

**ECONOMIC ASSESSMENT OF TRAINING AND USE OF INTEGRATED FRUIT
FLY MANAGEMENT STRATEGY AMONG MANGO FARMERS IN ELGEYO
MARAkwET, KENYA**

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**A Thesis Submitted to the Graduate School in Partial Fulfillment of the Requirements
for the Master of Science Degree in Agricultural and Applied Economics of Egerton
University**

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DECLARATION AND RECOMMENDATION

Declaration

This research thesis is my original work and has not been submitted for examination in this University or any other institution of higher learning for the award of a degree.

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Recommendation

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DEDICATION

This work is dedicated to my parents, who have always given me financial and moral support throughout my studies.

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ABSTRACT

Mango farmers in Elgeyo Marakwet were faced with the challenge of high fruit fly infestation that causes a 40-80% quality and quantity loss of mangoes. To address this challenge, ICIPE and partners implemented a Randomized Control Trial (RCT) experiment that involved three groups of farmers: farmers who received training only, farmers who received training and fruit fly Integrated Pest Management (IPM) materials and the control group (non-trained). The objective of this study was to determine if this particular IPM intervention (training and use of fruit fly IPM) had a significant influence on: the knowledge and perception of farmers towards fruit fly infestation and management, on the demand for IPM (fruit fly traps), and on mango loss due to fruit flies. The study involved a sample of 663 farmers that were interviewed during the baseline survey, and two follow-ups with 7% and 8% attrition respectively. Cross-sectional data obtained at baseline addressed the second objective of this study, while the first and third objectives utilized panel data. The Difference-in Difference (DiD) model revealed that farmers who received training and start-up IPM materials had a significant improvement in their knowledge and perception towards fruit fly IPM by 8 % and 5 %, while mango production loss substantially declined by 7 % and 8 % compared to the control group and farmers who received training only respectively. This suggests that training accompanied by the provision of start-up IPM materials used by farmers is a great stimulus to promote social and experiential learning. Further analysis from the zero-inflated negative binomial regression revealed that farmers who received training only significantly demanded more fruit fly traps compared to the control group. This indicated that training only was effective in upscaling adoption of fruit fly IPM even when accompanied with the provision of start-up IPM materials which was insignificant in this case.

TABLE OF CONTENTS

DECLARATION AND RECOMMENDATION	ii
COPYRIGHT	iii
DEDICATION.....	iv
ACKNOWLEDGEMENTS	v
ABSTRACT.....	vi
TABLE OF CONTENTS	vii
LIST OF TABLES	x
LIST OF FIGURES	xi
LIST OF ABBREVIATIONS AND ACRONYMS	xii
CHAPTER ONE	1
INTRODUCTION.....	1
1.1 Background of the Study	1
1.1.1 Fruit Fly IPM Intervention in Elgeyo Marakwet County	2
1.2 Statement of the Problem.....	3
1.3 Objectives of the Study.....	3
1.4 Hypotheses of the Study	4
1.5 Significance of the Study	4
1.6 Scope and Limitation of the Study.....	5
1.7 Operational Definition of Terms.....	5
CHAPTER TWO	6
LITERATURE REVIEW	6
2.1 Mango Production in Kenya	6
2.2 Economic Importance of Fruit Flies in Mango Production	7
2.3 Integrated Pest Management Training	8
2.3.1 Effect of training and use of IPM strategy on farmers’ knowledge and perception of pest infestation and management.	8
2.3.2 Effect of training and use of IPM strategy on the adoption of IPM technology.....	10
2.3.3 Economic impact of training and use of IPM strategy among farmers	11
2.4 Theories of Training	12

2.4.1	Expectancy Theory	12
2.4.2	Social Learning Theory.....	13
2.4.3	Behavioral Economic Theories.....	15
2.5	Theoretical Framework	17
2.5.1	Theory of Change	17
2.6	Conceptual Framework.....	17
CHAPTER THREE		20
METHODOLOGY		20
3.1	Study Area	20
3.2	Sampling Procedure	22
3.3	Data Collection	23
3.4	Analytical Framework	23
3.5	Data Analysis	25
3.6	Empirical Model of Estimation.....	25
3.6.1.	Difference in difference (DiD) model.....	25
3.6.2	Zero-inflated Negative Binomial (ZINB) Model.....	26
3.7	Description of Outcome and Independent Variables	27
CHAPTER FOUR.....		33
RESULTS AND DISCUSSION		33
4.1	Socio-Economic and Household Characteristics of Sampled Mango Farmers in Elgeyo Marakwet County	33
4.2	Farmers' Knowledge and Perception of Fruit Flies Infestation and Management	35
4.2.1	Farmers' knowledge of fruit fly infestation and management after IPM training intervention.....	37
4.2.2	Farmers' perception towards fruit fly infestation and management after IPM training intervention.....	37
4.2.3	Impact on knowledge and perception	38
4.3	Farmers' Demand Intensity for Fruit Fly Traps to Suppress Fruit Fly Infestation after IPM Intervention.....	41
4.3.1	Impact on demand of IPM technologies	42

4.4	Mango Production Loss due to Fruit Fly Infestation among Sampled Farmers in Elgeyo Marakwet	48
4.4.1	Farmers' Mango Production Loss due to Fruit Flies before (2017 main season) and after (2018 Main Season) the IPM Training Intervention.....	48
4.4.2	Impact on Mango Production Loss	49
CHAPTER FIVE		52
CONCLUSIONS AND RECOMMENDATIONS.....		52
5.1	Summary	52
5.3	Recommendations.....	54
5.4	Areas for Further Research	55
REFERENCES.....		56
APPENDICES		66
Appendix A: Questionnaire on Mango Production & Marketing in Elgeyo-Marakwet.....		66
Appendix B: Knowledge and Perception on Fruit Fly Infestation and Management.....		76
Appendix C: Variance Inflation Factor (VIF) (Knowledge and Perception)		76
Appendix D: Variance Inflation Factor (VIF) (Mango Production Loss)		77
Appendix E: Breusch-Pagan Test (Knowledge and Perception)		77
Appendix F: Breusch-Pagan Test (Mango Production Loss)		78
Appendix G: DiD Model (Knowledge and Perception)		79
Appendix H: ZINB Model (Demand for Fruit Fly Traps).....		85
Appendix I: DiD Model (Mango Production Loss).....		95

LIST OF TABLES

Table 1: Distribution of the sampled mango-growing households in Elgeyo Marakwet by Ward.....	23
Table 2: Definition of independent variables for DiD analysis (Knowledge and perception)	28
Table 3: Definition of variables for DiD analysis (Mango production loss)	30
Table 4: Definition of independent variables for ZINB regression analysis	32
Table 5: Socio-economic and household characteristics	34
Table 6: Farmers' knowledge and perception towards fruit fly infestation and management after IPM training intervention	36
Table 7: Difference in Difference regression (Knowledge and perception)	39
Table 8: Average number of fruit fly traps demanded in the year 2018	41
Table 9: Poisson regression and NBR results on the total number of fruit fly traps demanded after IPM intervention	43
Table 10: ZIP regression (Demand for fruit fly traps)	44
Table 11: ZINB regression (Demand for fruit fly traps).....	47
Table 12: Difference in Difference regression (Mango production loss)	51

LIST OF FIGURES

Figure 1: Conceptual Framework.....	19
Figure 2: Map of Elgeyo Marakwet County.....	21
Figure 3: Knowledge status of sampled farmers by treatment.....	37
Figure 4: Perception status of sampled farmers by treatment.....	38
Figure 5: Distribution of the number of traps purchased after IPM intervention.....	42
Figure 6: Symptoms of fruit fly infestation reported by mango farmers.....	48
Figure 7: Proportion of mango production loss due to fruit flies in 2017 (before) and 2018 (after) main season.....	49

LIST OF ABBREVIATIONS AND ACRONYMS

2SLS	Two-Stage Least Squares
AERC	African Economic Research Consortium
AFFP	African Fruit Fly Project
ANOVA	Analysis of Variance
ATT	Average Treatment Effect on the Treated
BCD	Behavior Centered Design
CIDP	County Integrated Development Plan
CSPro	Census and Survey Processing System
DiD	Difference in Difference
FFS	Farmer Field Schools
FSD	Financial Sector Deepening
GAP	Good Agricultural Practices
GDP	Gross Domestic Product
GoK	Government of Kenya
HCD	Horticulture Crops Directorate
HCDA	Horticultural Crops Development Authority
ICIPE	International Centre of Insect Physiology and Ecology
IPM	Integrated Pest Management
IV	Instrumental Variable
MAT	Male Annihilation Technique
MoALFI	Ministry of Agriculture, Livestock, Fisheries and Irrigation
NBR	Negative Binomial Regression
NGOs	Non-Governmental Organizations
OLS	Ordinary Least Squares
PPS	Probability Proportional to Size
RCT	Randomized Control Trial
SD	Standard Deviation
SSA	Sub-Saharan Africa
VIF	Variance Inflation Factor
ZINBR	Zero Inflated Negative Binomial Regression
ZIP	Zero Inflated Poisson

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Agriculture plays a major role in employment, food security and accounts for 65% of the country's export earnings in Kenya (Ministry of Agriculture, Livestock, Fisheries and Irrigation (MoALFI), 2017). The sector employs 61.1% of the total population and it contributes 32.4% of the Gross Domestic Product (GDP) (World Bank, 2016). According to World Bank (2016), developing the agricultural sector especially in rural areas of Kenya, where poverty is dominant, should be given a high priority. Research indicates that the agricultural sector accounts for 70% of informal employment in rural areas (Government of Kenya (GoK), 2010). Hence, to reduce unemployment rates in Kenya, there is a need to improve the agricultural sectors' performance by supporting smallholder farmers.

Within the agricultural sector, the horticultural industry is considered an important driver of growth whereby mango is ranked the second most important fruit after banana and contributes 20 % of the total fruit production value in Kenya (Horticulture Crops Directorate (HCD), 2018). Although the volume of mango production in the country has increased over time, from below 250,000 metric tonnes in 2003 to over 746, 377 metric tonnes in 2018 (Horticultural Crops Development Authority (HCDA), 2013; HCD, 2018), the productivity is still below its potential, estimated at 2.8 million metric tonnes per year. The low productivity is attributed to high pre-and post-harvest losses, mainly caused by pest infestation (e.g., the tephritid fruit flies) and lack of appropriate handling and storage practices (Griesbach, 2003; Alemayehu *et al.*, 2018).

Fruit fly infestation has been a significant challenge in mango production in Sub-Saharan Africa (SSA), including Kenya. In Africa, fruit flies cause annual losses of US\$2 billion due to quarantine restrictions on the pest (Ekesi *et al.*, 2016). Subsequently, fruit fly infestation reduces the income and profits gained by smallholders by limiting their access to high-value export markets. Henceforth, fruit flies are a major threat to global and local markets for mangoes in Kenya, and in Africa in general.

Farmers in developing countries, including Kenya, are overly reliant on chemical pesticides to intensify horticultural production (Carvalho, 2017) including the management of fruit flies. Although the average quantities may not be greater than in developed countries, unregulated pesticide use has led to pest resistance, high pesticide expenditure, and negative

health and environmental effects to producers and consumers (Gautam *et al.*, 2017; Midingoyi *et al.*, 2019; Mwangu *et al.*, 2020).

As a result of the above challenges, specific consideration has therefore been given to the development and promotion of environment-friendly integrated crop health management strategies such as the Integrated Pest Management (IPM) package for fruit flies. The International Centre of Insect Physiology and Ecology (ICIPE) has developed these management strategies in collaboration with partners from Europe, the United States of America, Africa, and Asia. The fruit fly IPM package comprises of male annihilation technique (MAT), biological control with biopesticides and parasitoids, the application of protein bait spray, and orchard sanitation that involves the use of augmentorium technique (Ekesi *et al.*, 2014; Ekesi, 2015).

The fruit fly IPM package is intended to reduce mango losses due to fruit fly infestation and minimize expenditure on pest control by farmers. Generally, the IPM strategy is expected to improve the competitiveness of the mango value chain by increasing the income of actors through the supply of quality mangoes. However, the adoption of the fruit fly IPM strategy in SSA is still low (Muriithi *et al.*, 2020). Thus, to promote the adoption of the strategy, training has been found effective from previous studies (Korir *et al.*, 2015; Gautam *et al.*, 2017). For example, Gautam *et al.* (2017) found that trained farmers have better knowledge about pests, they adopt more IPM methods, and reduce the frequency of spraying and mixing different pesticides. Hence, in the long-term, farmers need to be empowered through training on technology application and overall farm management to improve agricultural production in Africa.

1.1.1 Fruit Fly IPM Intervention in Elgeyo Marakwet County

An RCT experiment was designed in mango growing wards in Elgeyo Marakwet County to assess the impact of training and use of integrated fruit fly management strategy. As mentioned in the introduction section, the fruit fly IPM package is comprised of five different components. The first component is the male annihilation technique that involves the use of a male lure that traps the male flies to reduce their population to low levels such that mating does not occur (Ekesi&Billah,2007). The food bait spray, on the other hand, is an application of hydrolyzed proteins (attractant) combined with a killing agent (*spinosad* insecticide) that is applied in localized spots on the mango tree (Ekesi, 2010).

Biological control agents involve the use of red ants, parasitoid wasps, bio-pesticides and fungal pathogens (*Metarhizium*). The major natural enemy is the parasitoid eggs that hatch to produce larva that grows by feeding on the internal tissue of the flies' larva eventually killing the fruit flies (Ekesi, 2010). Lastly, the orchard or field sanitation involves cultural methods to reduce fruit fly infestation such as regular disposal of fallen rotten fruits by burning or burying them in a deep hole, feeding them to livestock or disposing of the fruits in an augmentorium. The augmentorium is a tent-like structure that traps fruit flies from the collected rotten fruits but allows parasitoids to escape from the tent through a fine mesh at the top (Ekesi *et al.*, 2014; Ekesi, 2015).

Although the fruit fly IPM is comprised of five different components, as mentioned in the previous paragraph, our RCT experiment involved three components of the strategy: - male annihilation technique or fruit fly traps, the spot spray of food bait, and orchard sanitation. This is because fruit fly traps and food bait are currently available in the market, while orchard sanitation is a simple practice that can be easily adopted by farmers.

1.2 Statement of the Problem

ICIPE under the African Fruit Fly Project (AFFP) has over the recent past developed and disseminated an eco-friendly integrated pest management strategy to suppress fruit fly infestation. To promote the use of the strategy, ICIPE offered training and start-up kit fruit fly IPM materials to smallholder farmers. However, it was not known if this particular intervention approach has a significant influence in improving mango farmers' knowledge and perception on fruit fly infestation, their management practices, and reduction of mango loss due to the pest. This study, therefore, aimed to fill this knowledge gap by assessing the economic significance of the training and use of the fruit fly IPM materials provided among mango growers using the case of Elgeyo Marakwet County of Kenya.

1.3 Objectives of the Study

The main objective of the study was to economically contribute to improved quality and quantity of mangoes in Kenya by emphasizing on the importance of training being accompanied by the provision of start-up IPM materials for farmers to use (experiential learning) to control fruit flies.

Specifically, the study sought:

- i) To determine the impact of training and use of fruit fly IPM on mango farmers' knowledge and perception of fruit flies' infestation and management in Elgeyo Marakwet County.
- ii) To assess the effect of training and use of fruit fly IPM on the demand for fruit fly traps by mango farmers in Elgeyo Marakwet County.
- iii) To determine the impact of training and use of fruit fly IPM on mango loss due to fruit flies in Elgeyo Marakwet County.

1.4 Hypotheses of the Study

- i) Training and use of fruit fly IPM have no significant impact on mango farmers' knowledge and perception of fruit flies' infestation and management in Elgeyo Marakwet.
- ii) Training and use of fruit fly IPM have no significant effect on the demand for fruit fly traps by mango farmers in Elgeyo Marakwet.
- iii) Training and use of fruit fly IPM have no significant impact on mango loss due to fruit flies in Elgeyo Marakwet.

1.5 Significance of the Study

Mango is one of the high-value fruits contributing to the economic and nutritional well-being of fruit value chain actors in SSA. However, mango production in Kenya is still below its potential due to high fruit fly infestation. Thus, to reduce mango losses caused by fruit flies, IPM has been found effective from previous research. More so, capacity building is vital for promoting IPM strategies and practices among smallholders to reduce over-reliance on pesticides that may have health and environmental risks. Therefore, this study contributes to limited literature on the adoption and impact of training and use of fruit fly IPM strategy on farmers' pest management practices, and overall farm performance in Kenya and other fruit fly affected countries in Africa. It was anticipated that this research study would help policymakers in the public and private sector understand the importance of training being accompanied by the use of fruit fly IPM to improve farmers' economic performance in fruit production. Funders of the project can be informed from the results of this study on the importance of strengthening technical support by providing farmers with start-up IPM technologies after training to intensify IPM adoption. Intensification of IPM adoption would

lead to better access to international markets by improving mango production through reduced mango losses caused by fruit flies. Furthermore, earlier studies that showed impressive returns from the use of the fruit fly IPM strategy were mainly focused in the Eastern region of Kenya, which limited the generalization of information. Nevertheless, this study was based in Elgeyo Marakwet, which is in the Rift Valley region of Kenya.

1.6 Scope and Limitation of the Study

This study was conducted in Elgeyo Marakwet County where the intervention of fruit fly IPM training and use of the strategy took place among small-holder mango farmers. The study only assessed the direct impact and effects of the intervention on only three outcome variables.

1.7 Operational Definition of Terms

Demand was measured by the number of fruit fly traps purchased by mango farmers in Elgeyo Marakwet.

IPM training intervention refers to the two IPM components (MAT, and food bait) given to the farmers who participated in the RCT experiment.

Experiential learning is the process of learning through the use of fruit fly IPM strategy (hands-on learning). Farmers who were trained and given fruit fly IPM materials went through this process, unlike farmers who received training alone.

CHAPTER TWO

LITERATURE REVIEW

2.1 Mango Production in Kenya

In Kenya, farmers mainly carry out small-scale farming in high potential areas and agricultural production is mostly carried out on farms ranging from 0.2-3 hectares of land (GoK, 2010). Furthermore, small-scale agricultural production contributes 75% of the total agricultural output and 70% of agricultural produce marketed. According to the GoK (2010), the productivity in these farms can be increased if farmers adopt modern farming techniques. However, in the case of mangoes, productivity also depends on several other factors such as the weather and soil conditions, control of pests and diseases, altitude and the cultivar. In the case of weather conditions, mango yield differs significantly because the crop is usually grown under a wide range of agro-climatic conditions which allows mangoes in Kenya to be available almost all year round (Griesbach, 2003). Temperature, rainfall and humidity have a great influence on mango production (Griesbach, 2003). For example, in Kenya, a dry period is required at the time of flowering (this is mainly during August to October) and sufficient heat is needed during the time of fruit ripening. Additionally, for optimal productivity of mangoes, an altitude up to 1,500m above sea level with average temperatures ranging between 15°C and 30°C and an annual rainfall of 850-1,000mm is required (Financial Sector Deepening (FSD) Kenya, 2015).

Two types of mangoes are usually grown in Kenya, the local and the exotic or improved varieties (Msabeni *et al.*, 2010). Local mango varieties include: Ngowe, Boribo, Batawi and Dodo while the exotic varieties include: Apple, Van Dyke, Kent, Keit, Tommy Atkins, Haden, Sabre and Sabine (Griesbach, 2003). Growing these varieties has placed Kenya on the global map in mango production. Among the 90 countries worldwide that produce mangoes, Kenya is ranked 15th worldwide, contributing 1.7% of world production after Vietnam (contributes 1.8% of world production) (FSD Kenya, 2015). Furthermore, Kenya is the leading mango producer in East Africa and is ranked second to Nigeria in Africa, contributing 43% of East Africa's total production volume.

In Kenya, mangoes are consumed as fresh fruits, and as processed juice. The crop is mainly grown by small-scale farmers and a few commercial farmers for consumption in hotels and restaurants (Gor *et al.*, 2009). During the last 20-30 years, commercial production of mangoes has been developed based on locally adapted and imported cultivars (Griesbach, 2003). This has seen the production of mangoes in Kenya increase from 250,000 metric

tonnes in 2003 to over 746, 377 metric tonnes in 2018 (HCDA, 2013; HCD, 2018). However, mango producers are faced with several constraints such as inadequate clean and quality planting materials, pest and disease infestation, high cost of inputs and low adoption of improved technologies. Among the pests, fruit fly infestation has led to great losses which are incurred at the farm level and export points (Ekesi *et al.*, 2016).

2.2 Economic Importance of Fruit Flies in Mango Production

The economic importance of the damage caused by the mango fruit fly (*Diptera Tephritidae*) is growing in both small-scale and industrial mango orchards as well as in home garden mango trees. This is evident by the damage caused to mangoes that have increased by over 80% since the invasion by *Bactrocera dorsalis* in East Africa in 2003 (Ekesi *et al.*, 2009; Goergen *et al.*, 2011). In Kenya, fruit flies are regarded to be the major constraint of mango production and they can be divided into two categories, that is, indigenous and invasive species (Ekesi *et al.*, 2009). The most common species in Africa that are of economic importance belong to the genera *Dacus*, *Trirhithrum*, *Ceratitis* and *Bactrocera* (De Meyer *et al.*, 2014), while *Ceratitis*, *Dacus* and *Trirhithrum* are native species to Africa. Most of these fruit fly species have the same life cycle. First, the female lays its eggs on the young fruit of the mango tree that is attractive as it approaches maturity. Then the larvae create tunnels in the flesh of the untreated mango providing an opportunity for secondary infections. This hastens the maturation of the mango, which later falls to the ground. The larvae then leave the fruit and develop into pupae in the top layer of the soil. The pupae develop to an adult that starts to look for nourishment to reach sexual maturity, mate, and lay eggs (Ekesi&Billah,2007; Rattanapun, 2009).

These harmful *tephritidae diptera* species such as *Ceratitis cosyra* and *Bactrocera dorsalis* attack mangoes leading to 40-80% losses depending on the locality, variety and season (Rwomushana *et al.*, 2008). For instance, Vayssières *et al.* (2009) reported that losses were ranging from 17% to 73% of mango in West Africa, while Nankinga *et al.* (2014) emphasized that it is possible to experience 100% losses across agro-ecological zones in Uganda without control measures. Fruit flies do not only lead to direct damage of mangoes but also cause indirect losses to producers and exporters. This can be associated with quarantine restrictions whereby; the slightest trace of fruit fly bite may lead to economic losses when trade and export of mangoes from the host country are restricted to the international market. According to Ekesi *et al.* (2009), *Bactrocera dorsalis* responsible for

huge economic loss since its first detection in Africa in 2003. More so, fruit flies are estimated to cause annual losses of US\$ 2 billion in fruit and vegetable production in Africa (Ekesi *et al.*, 2016). This loss leads to reduced profits to fruit farmers and traders leading to high prices of fruits in the local urban markets (Nankinga *et al.*, 2014). Furthermore, the livelihood, income, and food security of mango farmers are affected leading to high poverty levels and subsequently affecting the country's potential GDP. Therefore, it is important to encourage farmers through training to use IPM measures to control fruit fly infestation in mango orchards and reduce economic losses faced by both mango farmers and traders in Kenya.

2.3 Integrated Pest Management Training

Integrated Pest Management is a method intended to manage pests and diseases with as little damage to people, the environment and natural enemies of pests. Different practices and products are used within IPM in combination as a package to keep pest populations below economically injurious levels as well as reduce pesticide expenditure (Orr, 2003). According to the MoALFI (2017), Good Agricultural Practices (GAP) and IPM are important components for sustainable agriculture. However, there is an unreliable supply of mangoes from farmers due to poor crop management practices, and low illiteracy levels in using new production techniques which is as a result of the high cost of farmer training and less involvement of farmers in the development of IPM strategies (Orr, 2003; Gautam *et al.*, 2017). This consequently leads to low adoption of IPM technology, therefore calling for interventions such as the training and provision of start-up IPM materials for farmers to use.

Training is a process through which skills are developed, information is provided and attitudes, knowledge or skill behaviour are modified through learning experiences to achieve effective performance in an activity. Furthermore, training helps in transferring skills to farmers and bringing about technological change and innovation in management practices to reduce pest infestation. Therefore, training services should be developed and enhanced to improve the economic status of farmers in Kenya.

2.3.1 Effect of Training and Use of IPM Strategy on Farmers' Knowledge and Perception of Pest Infestation and Management

Farmer-level knowledge and perception of pest infestation and management is an important component or variable in determining the effectiveness of training and use of IPM strategy. Research indicates that farmers barely use biological and nonchemical methods to

control pests for sustainable mango production (Akotsen-Mensah *et al.*, 2017). This is because the awareness of using these methods is very low among farmers in Africa (Materu *et al.*, 2016). Therefore, there is a need to develop and upscale pragmatic learning based IPM training modules to reach a larger audience of mango farmers. This is also in agreement with earlier work done by Erbaugh *et al.* (2001, 2007) and Heh (2014) who concluded that IPM training has a significant effect on farmers' perception and use of IPM practices in Ghana.

According to Abdullahi *et al.* (2011), Ghanaian farmers ranked *Bactrocera dorsalis* among the major pests of mango in Ghana. They generally perceived that the fruit fly species was more damaging than any other arthropod pest of mango in terms of loss of market value, rejection of mangoes at international markets and quarantine restrictions due to the presence of the pest. This clearly showed that farmers in Ghana were knowledgeable about *Bactrocera dorsalis* as a fruit fly species. However, in a similar study done by Benjamin *et al.* (2012) in Northern Ghana, a majority (80.9%) of farmers demonstrated poor knowledge in identifying the fruit fly species of economic importance especially *Bactrocera dorsalis*. The farmers were however familiar with the economic impact of the flies than their direct damage symptoms on mangoes. Hence, this showed the importance of training mango farmers through experiential learning by providing the IPM technology to improve their skills and knowledge on fruit fly management.

The effect of training alone on farmers' knowledge and perception is evident from previous studies. For example, a study on the effect of training on the acquisition of pest management knowledge and skills by small vegetable farmers conducted in Yunnan province, China from 2003 to 2007 found significant gains of knowledge on vegetable pests, natural enemies and pest management among the trained farmers (Yang *et al.* 2008). The farmer field school allowed farmers to acquire simple skills and knowledge as well as technical IPM knowledge. Results from a meta-analysis study also showed that training such as the farmer field schools (FFS) are beneficial in improving the knowledge of farmers, adoption of management practices as well as improving agricultural production and farmers' income (Waddington *et al.*, 2014). This is the same case for the effect of IPM strategy that has led to improved mango income, reduced mango losses due to fruit flies and reduced pesticide expenditure (Kibiri *et al.*, 2015; Muriithi *et al.*, 2016; Mwangi *et al.*, 2020). However, there is limited evidence on the effect of training and the use of IPM strategy to improve the knowledge and perceptions of farmers. Furthermore, training programs in Kenya are mainly focused on transferring technologies and the lack of pragmatic training programs that involve

the provision of the strategy may be the reason for the lack of innovative dissemination channels (Najjar, 2009). Therefore, providing training opportunities that involve the use of IPM strategies to farmers is important in improving their overall economic performance in a country.

2.3.2 Effect of Training and Use of IPM Strategy on the Adoption of IPM Technology

Research and training on IPM methods are important for creating a sustainable agricultural ecosystem (Alam *et al.*, 2016). Furthermore, knowledge and utilization of IPM methods can only be improved through training and the establishment of an IPM policy to promote the adoption of IPM technologies in Kenya (MoALFI, 2017). Training is essential to disseminate information on various IPM methods. Farmers who do not participate in training such as farmer field schools are not likely to experience improvements in IPM adoption and agricultural outcomes (Waddington *et al.*, 2014; Korir *et al.*, 2015). According to Benjamin *et al.* (2012), 39% of mango farmers in Northern Ghana took no action to control fruit flies in their orchards. This is because, fruit fly strategies like the bait application, pheromone traps, soil inoculation and biological control methods were either not known by the farmers or were inaccessible. Moreover, 72% of the farmers used chemicals that were not recommended to control fruit flies and did not consider their environmental and health dangers. This indicated the lack of knowledge on available IPM strategies, consequently leading to low adoption rates among farmers in Northern Ghana.

Korir *et al.* (2015) found out that farmers who received training had a higher probability of adopting more IPM components provided by ICIPE to reduce fruit fly infestation. This was plausible because IPM is a knowledge-intensive technology and disseminating accurate information among farmers about the various IPM components available is most likely to enhance its adoption. Moreover, in their study on basic socio-economic and institutional factors influencing the adoption of IPM in cotton and rice cultivation in Punjabi and in Haryana respectively, Singh *et al.* (2008) found that product specific IPM training was greatly effective in improving technological awareness among farmers. This indicated that training, as well as the use of IPM strategies, is most likely to have a positive influence on the adoption of IPM technologies by farmers. Therefore, an effect or change at farmer level is as a result of research, and effective training that encourages the adoption of new technologies. Hence, training farmers through experiential learning is important to bring about a behavioural change that is likely to encourage farmers to use IPM

practices over the use of harmful pesticides. Furthermore, strengthening existing knowledge and information through training on various IPM components is the best approach to upscale the use of IPM strategies among farmers in Kenya (Midigonyi *et al.*, 2018).

2.3.3 Economic Impact of Training and Use of IPM Strategy among Farmers

Mango farmers who adopt fruit fly IPM strategies successfully are more likely to generate economic benefits in terms of reduced mango rejections due to fruit fly infestation, reduced pesticide expenditure, improved net income from mango production and minimized environmental and health risks (Kibira *et al.*, 2015; Muriithi *et al.*, 2016; Midigonyi *et al.*, 2018; Mwangu *et al.*, 2020). It is reasonable to suggest that knowledge gained through training on fruit fly IPM methods could lead to fewer rejections of mango since pests will be managed appropriately (Akotsen-Mensah *et al.*, 2017). However, there is limited evidence of the effectiveness of training in improving agricultural outcomes among participating and non-participating farmers (Waddington *et al.*, 2014). In the Philippines, Sanglestsawai *et al.* (2015) examined the impact of integrated pest management-farmer field school (IPM-FFS) on yield, insecticide expenditure and profit using propensity score matching (PSM) and regression-based approaches to account for biases from selection problems from observable variables. They found that trained farmers had statistically lower insecticide expenditure compared to non-trained farmers, but they did not find any evidence that the training significantly affected yield. Additionally, trained farmers may have statistically gained higher profits than non-trained farmers, but these results may have been biased due to unobservable variables. Hence, the impact of training, in this case, may have been inconclusive. However, a study done in Tanzania on the impact of training on technology adoption and rice farming productivity by Nakano *et al.* (2018) indicated that as the technology adoption rates of key farmers increased immediately after the training, their yield increased from 3.1 to 5.3 tons per hectare. This result suggested the effectiveness of training farmers to improve their farm performance. Furthermore, Carlberg *et al.* (2012) had similar results. They concluded that farmers who participated in IPM training programs have significantly higher production levels. This would lead to improved income from an increased volume of sales and eventually improve the livelihoods of farmers. Training has also had an influence on reducing pesticide use which eventually reduces pesticide expenditure and improves the profits of farmers. As the number of training events increase, pesticide use is likely to decrease (Gautam *et al.*, 2017).

Training is beneficial in improving intermediate outcomes such as knowledge learned and the use of advantageous strategies as well as final outcomes like yield and profit (Waddington *et al.*, 2014). However, it is important to allow farmers to use the IPM technology to learn more about how to use them appropriately after training. This may result in more economic benefits compared to farmers who are trained alone. Nevertheless, there is limited impact evaluation evidence of training and IPM technology on agricultural outcomes especially in Africa (Waddington *et al.*, 2014). Therefore, this study contributes to growing literature on the economic impact of training and use of IPM strategy to inform farmers on the benefit of attending training programs as well as identify areas that require policy interventions to achieve higher dissemination of information to farmers. Furthermore, policymakers, funders of IPM projects and extension instructors can be informed on the importance of training programs being accompanied by the provision of start-up kits to improve the use of IPM methods. This may lead to efficient use of fruit fly integrated management components that may reduce total expenditures and eventually lead to higher incomes received by farmers in Kenya.

2.4 Theories of Training

2.4.1 Expectancy theory

Expectancy theory postulates that individuals have choices, and they make decisions based on which choice they believe will give them the best outcome. According to Vroom (1964), this theory involves three premises: expectancy, instrumentality, and valence. The motivational force that drives the behaviour of an individual is a product of these variables represented by the equation:

$$\text{Motivation} = \text{Expectancy} * \text{Instrumentality} * \text{Valence}$$

Expectancy

A farmers' expectancy is the anticipation that attending training and using IPM strategies on their part will lead to better farm performance. Vroom defines expectancy as an "action-outcome association" that takes the values ranging from 0 to 1. A farmers' motivation will range from 0 (no expectation) and 1 (full expectation) depending on whether they perceive that attending training and using IPM will help them achieve better farm or economic performance.

Instrumentality

Instrumentality is the perception that a given outcome of performance in the part of the farmer will lead to him or her receiving an expected reward. Vroom defines this as an “outcome-outcome association” and it ranges from 0, where there is no expectation of desired outcome delivery to 1, where a reasonable probability of the delivery of rewards is perceived. A farmer with a value of one is most likely to perceive that adopting IPM practices and technologies after training will enable him to gain economic benefits in terms of increased income and reduced damage caused by pests.

Valence

Valence is the degree to which a farmer prefers a given outcome. Vroom describes it as the “effective orientations toward particular outcomes.” Valence can be positive, whereby the attainment of the reward is desired, or negative whereby the attainment of the reward is something a farmer wishes to avoid. Therefore, valence can have values ranging from -1 to 1. Farmers are more likely to have a positive valence (value of 1) since they would prefer to reap economic benefits by learning how to use various IPM strategies to reduce pest infestations.

2.4.2 Social Learning Theory

According to Bandura *et al.* (1977), individuals learn through direct experience and by observing the behaviour of others.

Learning by Direct Experience

This form of learning is mainly governed by the rewarding and punishing consequences that follow a given action. Some of the outcomes may be unsuccessful, while others may be more promising effects. Through this process of differential reinforcement, successful modes of behaviour are selected from exploratory activities, while the ineffectual ones are discarded. During learning, farmers may not only attend training and use IPM strategies to reduce pest infestation, but they also observe the different consequences that come with their decision. If the response or outcome of attending training and using IPM strategies is successful (increased income and reduced pest infestation), these farmers continue to attend training and use IPM strategies to benefit economically.

Observational Learning

According to Bandura *et al.* (1977), four interrelated processes govern this form of learning:

Attentional Processes

An individual cannot learn much by observation if he or she does not attend to the important characteristics of behaviour. People have different associational preferences and they are most likely to select from the numerous characteristics of behaviour the most relevant ones. It is possible to have farmers with greater attention than other farmers. Hence, interested farmers are more likely to pay attention to behaviours that are interesting and that pose appealing characteristics to them.

Retention Processes

A farmer cannot be influenced by observing the behaviour of another farmer if he or she has no memory of it. If a farmer is to reproduce another farmer's behaviour when the latter is no longer present to serve as a guide, the response patterns should be represented in memory in symbolic form. This will help past influences to achieve permanence. This memory can be in the form of an image or a verbal one.

Motoric Reproduction Processes

To achieve behavioural reproduction, a farmer must acquire the component skills and finances to use the IPM strategies. Once he or she has the required elements for efficient reproduction of the action (attending training and using IPM strategies appropriately), he or she is most likely to benefit from his or her decision. Additionally, farmers should be physically and mentally stable to gain knowledge on IPM practices and use them appropriately to receive economic benefits.

Reinforcement and motivational processes

A farmer can acquire, retain, and possess the abilities for skillful implementation of modelled behaviour, but may not be motivated to act or perform (lack of reinforcement) if he or she has a negative attitude towards training and the use of IPM strategies. A farmer who does not give any importance to training and reducing the overreliance on pesticides is most likely not to attend training and use IPM strategies to reduce pest infestation. Therefore, a

farmer should be well informed of the economic benefits of training and the use IPM strategies to be motivated to reinforce and act appropriately.

2.4.3 Behavioral Economic Theories

Human beings are hardly rational economic agents; at least they do not conform to the classical economic theories of economic transactions (Kahneman, 2011). Some of the behavioral economics theories may help to justify the behaviour of farmers from the sampled group of interest for this study. They include:

1. Bounded Rationality

According to Kahneman (2003), there are restrictions to human information processing, due to limits in knowledge. The minds of human beings should be understood relative to the environment in which they developed. A farmer who evolved in an environment where IPM practices and strategies were adopted is most likely to attend training and use IPM strategies compared to a farmer who used pesticides throughout his life to reduce pest infestation.

2. Dual System Theory

Kahneman (2011) uses a dual-system theoretical framework to explain how decisions and judgements do not comply with the notions of rational behaviour. System 1 involves thinking processes that are intuitive, automatic, experienced-based and unconscious, while System 2 is more reflective, controlled, deliberative, and analytical. System 1 is based on several aspects, namely:

Availability and affect Heuristics (Cognitive Shortcut)

Availability heuristics is a mental shortcut if the possibility of an event occurring is perceived to be higher simply because an example comes to mind easily (Tversky & Kahneman, 1974). This occurs when a farmer may deem IPM investments to be economically beneficial because of remembering a farmer or neighbour who got increased income and reduced pest infestation after using IPM strategies. Finally, another heuristic is that of affect, that is a bad or a good feeling that surfaces automatically when one thinks about an object. For example, farmers may consider pesticide benefits as low and expenditure as high leading to a significant negative risk-benefit correlation. This will discourage farmers from using pesticides to control pests.

Salience

The availability and affect processes are internal to an individual and may be biased. Salience is whereby information that stands out, more relevant or novel is more likely to affect the thinking and actions of a person. A farmer is able to make a decision easily about adopting fruit fly traps and lures if either positive or negative information is provided about it. For example, fruit fly traps and lures can be framed as being 99% reliable or having only 1% failure rate.

Status Quo Bias and Inertia

System 1 is also reflected in human aversion to change. The preference to have things remain the same, such as the tendency not to change behaviour unless the incentive to do so is strong is referred to as the status quo bias (Samuelson & Zeckhauser, 1988). Inertia is termed as people's tendency to remain at the status quo (Madrian & Shea, 2001). A farmer who has a habit of spraying pesticides may not adopt IPM practices because he may not want to change his approach in reducing pest infestation on his farm.

3. Social Dimensions

Behavioural economics considers social forces that have an influence on people's decisions based on their social environments (Fehr, 2009).

Trust and Dishonesty

It is possible to have a community of farmers who do not trust one another. This is most likely to hinder the flow of information from the treatment group (trained farmers) to the control group (non-trained farmers).

Social Norms

Social norms signal actions taken by the majority of people (although these actions are deemed to change over time). A community of farmers that deem pesticides to be an effective way of reducing pest infestations are less likely to adopt IPM strategies.

Consistency and Commitment

Farmers (farmer representatives in the wards) who pre-commit especially publicly to using IPM practices after training are more likely to be consistent in the adoption of IPM technologies. This is because humans have the need for continuous and consistent self-image.

2.5 Theoretical Framework

2.5.1 Theory of Change

This study was based on the theory of change which is a chain working through various links necessary for a specific objective or outcome to be attained (Aunger *et al.*, 2016). Several models that explain the theory of change such as the Behavior Centered Design (BCD) theory of change. This is a learning model that assumes that for change to occur, a behavior change intervention such as training and use of IPM strategies is necessary. This intervention should bring about changes in perceptions that result in the selection and repeated adoption of the desired behaviour (use of IPM strategies) (Aunger *et al.*, 2016). These changes normally occur in stages. An individual first may have no interest in change (pre-contemplates), he or she may then think about change after a while (contemplates), then plan for change, act by adopting the IPM strategy and continue using it (maintenance). Hence, to encourage maintenance in the use of IPM strategies, the confidence of farmers needs to be improved through incentives such as increased income and reduced expenditures. This will boost the self-efficacy of an individual in his or her ability to act and to continue in that action regardless of difficulties or challenges (Bandura *et al.*, 1986). Therefore, a rigorous evaluation of the effect or impact of an intervention (training and the use of IPM strategies) requires a reliable counterfactual (White, 2009). Furthermore, theory-based impact evaluation is an important approach in determining why a program has or has not had an impact or effect. It involves examining the chain (theory of change) from inputs (intervention) to outcomes and testing each link (assumptions) from inputs to outcomes as well (White, 2009).

2.6 Conceptual Framework

The conceptual framework as shown by Figure 1 borrows mainly from the theory of change, which postulates that farmers learn because of training and use of IPM strategies. Training and use of IPM strategies are most likely to encourage farmers to adopt IPM strategies in the future and enables them to experience improvements in outcomes like revenue. This is consistent with Waddington *et al.* (2014) findings on farmer field schools in

improving farming practices and farmer outcomes in low and middle-income countries. They found that training promoting the use of IPM strategy and other practices are advantageous in improving intermediate outcomes such as knowledge learned and adoption of IPM strategies, as well as outcomes like improved agricultural production and farmers' revenue. Additionally, to realize an improvement in both intermediate and outcomes, facilitators of the training need to be effectively trained, farmers' perceptions and attitudes also should change in favour of the identified IPM strategy and, the strategy adopted should be available and suitable to reduce mango losses due to pest infestation.

The IPM intervention (training only, use of IPM strategies, training and use of IPM strategies), in this case, was the treatment variable that had a trickle-down effect. The results of the study revealed that the intervention improved farmers' knowledge and positively changed their perception towards fruit fly infestation and management practices, which led to the demand for fruit fly traps and lures subsequently leading to a significant reduction in mango losses due to fruit fly infestation as postulated by Figure 1.

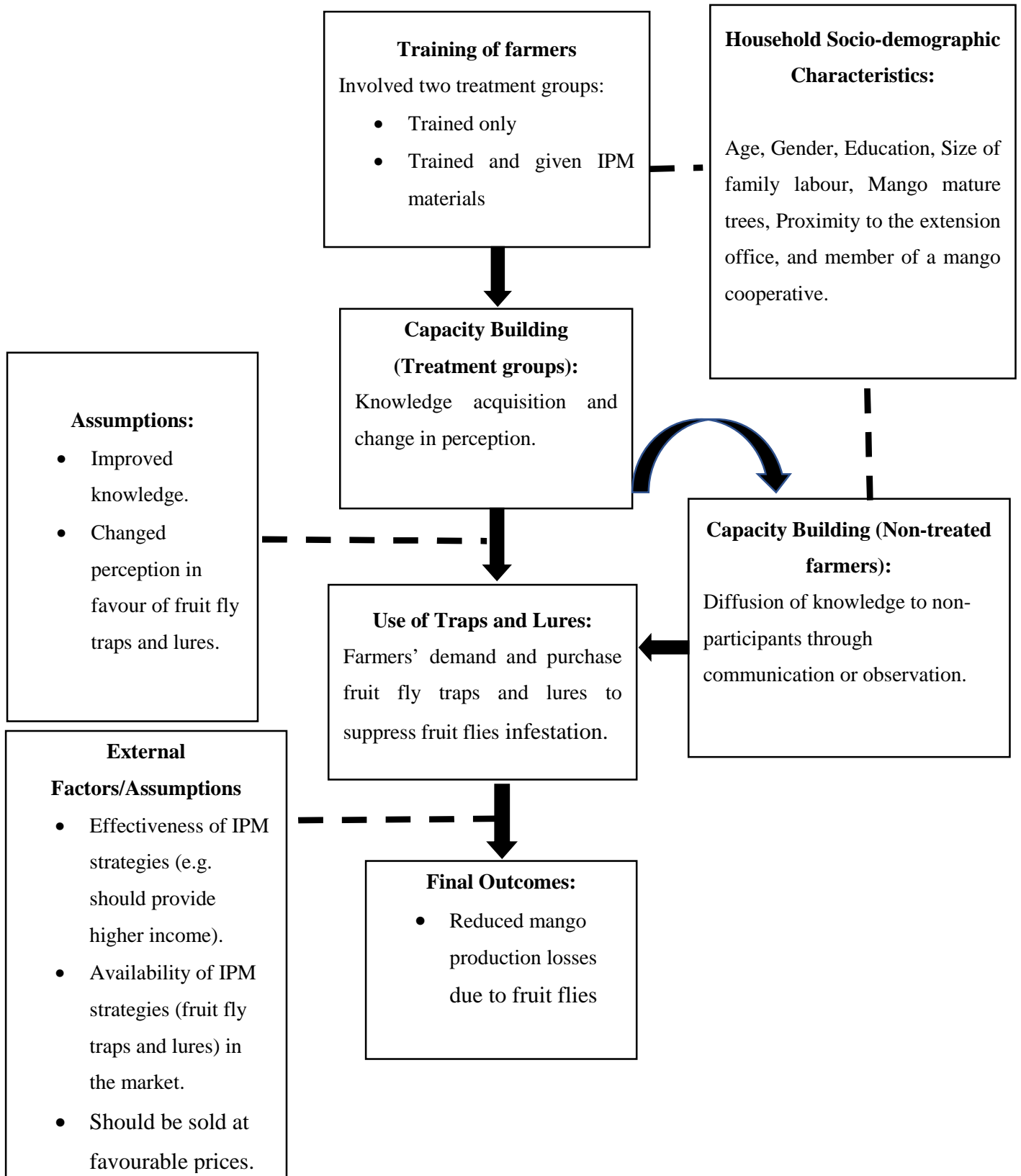


Figure 1: Conceptual Framework

Source: A Modification from Waddington *et al.* (2014).

CHAPTER THREE

METHODOLOGY

3.1 Study Area

In Elgeyo Marakwet County, mango farming is one of the most attractive economic activities due to the crops favourable climatic conditions. The County is in the North Rift of Kenya (1° 20' 0" N, 35° 40' 0" E) and covers an area of 3029.9 km². There are three topographical zones in the county namely; the Kerio Valley, the Highlands and the Escarpment. The altitude varies from 900m above sea level in Kerio Valley to 2700m above sea level in the highlands. This gives rise to different climatic conditions in the region. For instance, temperatures in the Highlands range between 15°C-23°C whereas on the Escarpment and Kerio Valley, temperatures can be as high as 30°C and as low as 17°C. Rainfall received in the Highlands range between 1200mm to 1500mm per annum while the Escarpment gets 1000mm to 1400mm of rainfall per annum. Kerio Valley receives less rainfall that ranges between 850mm to 1000mm per annum (Elgeyo Marakwet County Integrated Development Plan, 2019).

This study was conducted in Kerio Valley in six purposively selected mango-producing wards that border the Kerio River, namely: Endo, Sambirir, Arror, Emsoo, Soy North, and Soy South as shown in Figure 2.

3.2 Sampling Procedure

Elgeyo Marakwet County was purposively selected from the main mango growing Counties in Kenya due to the intensity of mango production in the area. The RCT was implemented following a multi-stage sampling procedure. Six wards in the major mango producing areas of Elgeyo Marakwet County were selected for this study. Villages and mango farmers were sampled from the census of mango growing wards prepared and compiled by the research team. Sixty-six (66) villages were randomly selected from the six wards using the probability proportional to size (PPS) sampling procedure, and 663 mango growing households were randomly selected for the interviews. The baseline data collection was conducted in October 2017. Of the total 663 farmers, 376 farmers from 34 villages were randomly selected and invited for intensive training by entomologists, and the remaining 287 belong to the control group. The training was conducted in a central place in each ward and involved both theory and practical sessions. The practical demonstrations were carried out on a farm belonging to one of the trainees. Using a lottery, 182 farmers who attended the training were selected to receive free fruit fly start-up IPM materials, while 194 farmers were assigned as farmers who received training only.

A follow-up survey, revisiting the same households interviewed at baseline, was conducted in September 2018. Six hundred and fourteen (614) mango growing households were successfully interviewed, leading to an attrition rate of about 7.4 %. A second follow-up survey was conducted in June 2019, reaching 608 households, leading to an attrition rate of 8.30 %. Table 1 shows the sample of mango growers interviewed across the three waves by Ward.

Table 1: Distribution of the sampled mango-growing households in Elgeyo Marakwet by Ward

Ward	Baseline Survey	Mid-line survey	End-line survey
		Follow-up survey 1	Follow-up survey 2
Endo	355	328	329
Sambrir	113	104	99
Arror	69	64	63
Emsoo	14	11	11
Soy South	22	23	22
Soy North	90	84	84
Total number of respondents	663	614	608

3.3 Data Collection

Data collection across the three waves was conducted by trained enumerators using structured close-ended questionnaires programmed in a Census and Survey Processing System (CSPRO) software. The baseline questionnaire captured information on mango farmers' knowledge and perception on mango pests and diseases, knowledge and use of proposed IPM practices, as well as several socio-economical, and demographic characteristics. Information collected during the first follow-up survey included fruit fly infestation between the periods 2017/2016 and 2018/2017, mango losses incurred in different seasons, 2018 short season production, use of pesticides, and practice of orchard sanitation, traps, lures, and food bait received and bought by farmers. The third wave captured data on fruit fly infestation and yield comparing 2017 and 2018 main season, mango income in 2018 main season, knowledge and perception of fruit fly infestation and management, and the demand for traps and lures for the 2018 main season.

3.4 Analytical Framework

Methods used to evaluate the impact of interventions in research include the Difference-in-Difference (DiD), propensity score matching, regression discontinuity design, and Instrumental Variable (IV) methods (Baker, 2000). The DiD method is an appropriate tool in evaluating changes in outcome variables as a result of an intervention. For instance, Kibira *et al.* (2015) used the DiD method to evaluate the impact of IPM fruit fly package on the

magnitude of mango rejection, insecticide expenditure, and net income. The results indicate that farmers who used the IPM package were better off in terms of reduced mango losses and insecticide expenditure and increased net income from mango production in Embu County, Kenya. Muriithi *et al.* (2016) as well adopted the DiD model to obtain estimates that differentiated the impact of five different combinations of fruit fly IPM practices in Meru County, Kenya. Findings from this study generally indicated a significant reduction in mango losses due to fruit fly infestation among farmers using the different combinations of fruit fly IPM treatments.

Therefore, this study employed the DiD regression model to evaluate the impact of training and use of fruit fly IPM strategy on the knowledge and perceptions of mango farmers and their mango production loss due to fruit flies in Elgeyo Marakwet. The DiD method explores the time dimension of data (panel data) and requires having data for both the treated and control groups, before and after the intervention (Khandker *et al.*, 2009). To evaluate the treatment effect on the treated, it is important to have a counterfactual or a control group to allow any change in the treatment group to be attributed to the intervention (Khandker *et al.*, 2009). This is only possible if the control group has similar observable and unobservable dimensions to those receiving the program and will not receive any spillover benefits. Once this is observed, the Average Treatment Effect on the Treated (ATT_{DiD}) can be estimated by comparing the difference in outcomes between the treated and control groups in some period after the intervention with the difference that existed before the intervention.

The first step is to get the difference between the treatment and control group before and after the intervention. We denote the group receiving treatment (with), Group I (I for intervention) and those not receiving treatment (without), Group C (C for the control group). The subscripts a and b denote after and before the intervention. Before the intervention, one would expect the average outcome to be similar for the two groups. Hence, the difference in outcome for the two groups ($I_b - C_b$) would be close to zero. However, once the intervention has been implemented, one would expect differences in the outcome for the two groups. Therefore, ($I_a - C_a$) would not be zero. The DiD estimate is then obtained by subtracting the pre-existing difference from the difference after the intervention: $ATT_{DiD} = (I_a - C_a) - (I_b - C_b)$ (Ahmed *et al.*, 2009). This method relies on two main assumptions that the unobserved heterogeneity is time-invariant and is cancelled out by comparing the before and after situations and secondly, that in the absence of the intervention, both the treated and control group would experience over time the same trend in the outcome variable (Common Trend).

3.5 Data Analysis

Descriptive statistics such as the mean, standard deviation, percentages, and frequencies of variables of interest were analyzed. This was primarily used to examine the socio-economic characteristics of the three groups of farmers. The zero-inflated negative binomial model, and the difference in difference model were used to determine the effect of training and use of fruit fly IPM strategy (intervention) on various outcome variables of interest. Prior data analysis, several tests were done using STATA (version 14) software. These tests included the multicollinearity test (Variance Inflation Factor (VIF)), serial correlation test using Cumby-Huizinga test, and the Breusch-Pagan test for heteroscedasticity (Gujarati, 2004). Both primary and secondary data were analyzed for this study.

3.6 Empirical Model of Estimation

3.6.1. Difference in Difference (DiD) Model

The study applied the DiD model to evaluate the impact of the IPM training intervention on farmers' knowledge and perception towards fruit fly IPM and mango production loss. The average treatment effect on the treated (ATT_{DID}) was estimated within a regression framework as follows:

$$Y_{it} = \alpha + \beta T_i + \pi S_t + \sigma (T_i * S_t) + \lambda X_i + \varepsilon_{it} \quad (1)$$

where, Y_{it} is the outcome variable (farmers' knowledge and perception score, and mango production loss due to fruit flies) for household i at time t . The treatment variable (training) is denoted by T_i (i.e., farmers received training and IPM, farmers received only training and control group); S_t is the time variable with the base year of 2017; X_i represents a vector of observed covariates, and ε_{it} is the error term. The interaction coefficient σ provides the difference in difference estimate (ATT_{DID}) which captures the treatment's impact. The year-specific effect π captures the changes in the outcome variables for the control group. Simultaneously, the constant term α is the mean outcome of the control group at baseline (2017). Hence $\alpha + \pi$ provides the mean outcome of the control group in the follow-up (2018). The coefficient β of the treatment variable captures the specific impact of the treatment (differences in Y_{it} between the treatment and control groups at baseline), and λ is a vector of the marginal coefficient effect of the observable explanatory variables (X_i).

3.6.2 Zero-inflated Negative Binomial (ZINB) Model

The number of fruit fly traps purchased was used as a proxy for the demand of fruit fly traps by mango farmers in Elgeyo Marakwet. The demand for fruit fly traps (dependent variable) was obtained by summing the number of traps purchased by the i^{th} farmer in the two mango seasons after the intervention (2018 short and main season). Given the nature of the dependent variable, count data models were the best option for this objective. Therefore, the first count data model that was considered was the Poisson model that has the probability density function (Greene, 2003) expressed as:

$$Prob(Y = y_i/x_i) = \frac{e^{-\theta} \theta^{y_i}}{y_i!}, y_i = 0, 1, 2 \quad (2)$$

for $\theta > 0$.

The mean and variance of this distribution is given as:

$$E(Y) = var(Y) = \theta \quad (3)$$

Where Y in equation (2) is the random variable representing the number of fruit fly traps purchased or demanded, y_i is the particular count value for the i^{th} farmer, x_i are the covariates influencing the number of traps purchased or demanded by the i^{th} farmer and θ is the parameter to be estimated (expected number of traps demanded). However, the main limitation of the Poisson regression is the assumption that the mean and variance functions of the dependent variable are equal as expressed by equation (3). This assumption implies that the conditional variance on the dependent variable is not constant; hence, the regression is heteroskedastic (Cameron & Trivedi, 2001). Therefore, the Negative Binomial Regression (NBR) was estimated and it was evident that there was a problem of overdispersion implying that the negative binomial regression was superior to the standard Poisson model. However, the NBR was not appropriate for this study because the dependent variable exhibited an overabundance of zeros (Figure 5).

The zero-inflated models can solve the problem of overdispersion and excess zeros (Lambert, 1992). They include two models, the zero-inflated Poisson (ZIP) and the zero-inflated negative binomial (ZINB). These models involve two regressions: a binary regression that describes zero outcomes in the first stage and a truncated Poisson or NBR that defines positive outcomes in the second stage (Lambert, 1992). According to Minami *et al.* (2007), the ZINB model is superior to the ZIP model because it solves for the problem of overdispersion and excess zeros simultaneously. Thus, the ZINB model was appropriate for this objective.

According to Long and Freese (2006), the probability density function that defines the binary variable is given as:

$$\psi_i = p(A_i/Z_i) = \frac{\exp(Z_i)}{1 + \exp(Z_i)} \quad (4)$$

Where A_i is equal to one if a farmer did not demand for fruit fly traps (always in the zero group), and zero otherwise. Z_i are explanatory variables of inflation that inflate the number of zeros in the observations.

The second probability is defined for the positive outcomes (including the zeros), which is computed by a negative binomial regression:

$$P(Y = y_i/x_i) = \frac{\Gamma(y_i + \alpha^{-1})}{y_i! \Gamma(\alpha^{-1})} \left(\frac{\alpha^{-1}}{\alpha^{-1} + \mu_i}\right)^{\alpha^{-1}} \left(\frac{\mu_i}{\alpha^{-1} + \mu_i}\right)^{y_i} \quad (5)$$

Where y_i is a discrete variable that represents the number of fruit fly traps demanded by a farmer over the two specified mango seasons (approximately one year) after the IPM intervention, Γ is the gamma function, and α is the parameter to be estimated. Lastly, μ_i is the expected number of fruit fly traps and lures purchased or demanded which is equal to:

$$\mu_i = \exp(X_i\beta) \quad (6)$$

The ZINB model has been used in various studies to assess adoption decisions made by individuals. For instance, Gido *et al.* (2017) used the model to assess the factors influencing the consumption intensity of leafy African indigenous vegetables in Kenya while Muñiz *et al.* (2014) also used the model to analyze individual decisions regarding sports and cultural activity participation in Spain. Therefore, in this study, the ZINB model was used to assess the effect of training and use of fruit fly IPM on the demand for fruit fly traps by mango farmers in Elgeyo Marakwet.

3.7 Description of Outcome and Independent Variables

Knowledge and perception scores: Table 2 presents the independent variables that were included in the regression to assess the impact of training and use of fruit fly IPM on the knowledge and perception of mango farmers. This was based on literature review (Ntawuruhunga *et al.*, 2016; Kassahun *et al.*, 2017).

Table 2: Definition of independent variables for DiD analysis (Knowledge and perception)

Variable	Definition and measurement	Expected sign
RTrain_None	Effect of training alone which is a dummy variable: 1= Trained only 0= Non-trained (control)	+
RTT_None	Effect of training and use of fruit fly IPM measured as a dummy variable: 1= Trained and given IPM materials 0= Non-trained (control)	+
RTT_RTrain	Effect of the use of fruit fly IPM alone which is measured as a dummy variable: 1= Trained and given IPM materials 0= Trained only (control)	+
Sex	Sex of the household head (dummy variable)	+/-
Age	Age of the household head in years.	+/-
Educ	Education of the household head in years	+
Mature_trees	Number of mature mango trees owned by a farmer	+
Family_labour	Number of family members who provide labour during mango production	+
Extnen_dist	Distance to the nearest extension office in walking minutes.	-
Member_coop	Member of a mango cooperative (dummy variable): 1= Yes, 0=No	+

The empirical model was given as:

$Y =$

$$\beta_0 + \beta_1 Treatment + \beta_2 Sex + \beta_3 Age + \beta_4 Educ + \beta_5 Mature_{trees} + \beta_6 Family_{labour} + \beta_7 Exten_{dist} + \beta_8 Member_{coop} + \varepsilon \quad (7)$$

Where Y refers to the knowledge and perception scores of farmers towards fruit fly IPM. The knowledge and perception scores were allocated based on three knowledge and four perception statements (Appendix 2). A value of 1 was given to farmers who provided a correct response, and a value of 0 for an incorrect response or no opinion. Farmers' knowledge and perception were then expressed as a single percentage score following Togbé *et al.* (2015) and Gautam *et al.* (2017).

Mango production loss: The outcome variable, mango production loss was captured as the proportion of mango damage caused by fruit flies out of the total mango production. Table 3 presents the independent variables that were included in the regression equation for mango production loss due to fruit flies (Kibira *et al.*, 2015; Muriithi *et al.*, 2016).

Table 3: Definition of variables for DiD analysis (Mango production loss)

Variables	Definition and measurement	Expected sign
<i>Dependent</i>		
Fruitfly_Loss	Proportion of mango loss due to fruit flies out of the total mango production (2017 & 2018 main season)	
<i>Independent</i>		
Treatment status (T_i)		
RTrain_None	Trained alone (Dummy): 1= Trained only 0= Non-trained (control)	-
RTT_None	Trained and given IPM materials (Dummy): 1= Trained and given IPM materials 0= Non-trained (control)	-
RTT_RTrain	Given IPM materials alone (Dummy): 1= Trained and given IPM materials 0= Trained only (control)	-
Time (t_i)		
Time	Time period survey was conducted (Dummy). 0= before the intervention, 1=after the intervention	+/-
Interaction (T_i*t_i)		
RTrain_None*t_i	Actual mango intervention variable (Dummy).	-
RTT_None*t_i	1= only after intervention if household was treated,	-
RTT_RTrain*t_i	0=otherwise	-
Sex	Sex of the household head (Dummy)	+/-
Age	Age of the household head in years.	+/-
Educ	Education of the household head in years	-
Mature_trees	Number of mature mango trees owned by a farmer.	+
Family_labour	Number of family members who provide labour during mango production.	-
KP_score	Knowledge and perception score of a farmer towards fruit fly IPM	-
Demand_IPM	Number of fruit fly traps demanded by a farmer to reduce fruit fly infestation	-

The empirical model for mango loss due to fruit flies was given as:

$$Y = \beta_0 + \beta_1 \text{Time} + \beta_2 \text{Treatment} + \beta_3 (\text{Treatment} * \text{Time}) + \beta_4 \text{Sex} + \beta_5 \text{Age} + \beta_6 \text{Educ} + \beta_7 \text{Mature}_{\text{trees}} + \beta_8 \text{Family}_{\text{labour}} + \beta_9 \text{KP}_{\text{score}} + \beta_{10} \text{Demand}_{\text{IPM}} + \varepsilon(8)$$

Where Y refers to the proportion of mango loss due to fruit flies out of the total mango produced during 2017 (before) and 2018 (after) main seasons.

Demand for fruit fly IPM: This outcome variable was measured as the number of fruit fly traps demanded by a farmer over two mango seasons after the IPM intervention. Some of the independent variables that were included in the regression according to Singh *et al.* (2008) and Korir *et al.* (2015) are presented in Table 4.

Table 4: Definition of independent variables for ZINB regression analysis

Variables	Definition and measurement	Expected sign
RTrain_None	Effect of training alone which is a dummy variable: 1= Trained only 0= Non-trained (control)	+
RTT_None	Effect of training and use of fruit fly IPM strategy measured as a dummy variable: 1= Trained and given IPM materials 0= Non-trained (control)	+
RTT_RTrain	Effect of the use of fruit fly IPM strategy alone which is measured as a dummy variable: 1= Trained and given IPM materials 0= Trained only (control)	+
Sex	Sex of the household head (dummy variable)	+/-
Age	Age of the household head in years	+/-
Educ	Education of the household head in years	+
Mature_tress	Number of mature mango trees owned by a farmer	+
Family_labour	Number of family members who provide labour during mango production	+/-
Member_coop	Member of a mango cooperative (dummy variable): 1= Yes, 0=No	+
KP_score	Knowledge and perception score of a farmer towards fruit fly IPM	+

The empirical model for the demand of fruit fly traps and lures was given as:

$$Y = \beta_0 + \beta_1 Treatment + \beta_2 Sex + \beta_3 Age + \beta_4 Educ + \beta_5 Mature_{trees} + \beta_6 Family_{labour} + \beta_7 Member_{coop} + \beta_8 KP_score + \varepsilon \quad (9)$$

Where Y is the number of fruit fly traps demanded by farmers after the IPM training intervention.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Socio-Economic and Household Characteristics of Sampled Mango Farmers in Elgeyo Marakwet County

The socio-economic and household characteristics of mango farmers in Elgeyo Marakwet are presented in Table 5 differentiated in three experiment groups (received training and start-up IPM materials, received training only and the control group). The results of the study reveal that household heads in Elgeyo Marakwet were fairly agile and young with an average of 44 years and are therefore more likely to adopt new labour-intensive technologies. This is because younger farmers are less-risk averse and more willing to adopt new technologies (Mwangi *et al.*, 2015). Furthermore, farmers in the three groups were fairly educated with an average of 9.61 years of formal education hence are more likely to make optimal decisions to invest in IPM technologies. The overall average size of family labour among the respondents was approximately four people and there was no significant difference among the three groups of farmers. The proportion of mango loss due to fruit flies at baseline was an average of 26.66 %, which was fairly high for the sampled mango farmers before the IPM training intervention.

The surveyed households produced an average of 7,359.96 kg of mangoes at baseline with no significant difference among the three groups of farmers. Mango income was not significantly different across the three groups of farmers; however, farmers who received training and IPM materials had a slightly higher income (Ksh80,282.16) compared to the other two groups. The total number of mature trees was statistically different among the three groups of farmers as determined by the one-way ANOVA ($F(2,659) = 3.32, P=0.036$). A Tukey post-hoc test revealed that the total number of mature trees was statistically higher for farmers who received training only compared to the control group (difference= -7.55, $P=0.052$). However, mango area was not statistically different among the three groups of farmers. The overall average was at 0.58 acres of land. Regarding distance to the nearest extension office, farmers in the control group lived further from the nearest extension office compared to the other two treatment groups.

As for the dummy variables, descriptive statistics show that 95.17% of the households are male-headed and 98.91% of the households were aware of fruit flies as a threat to mango production in Elgeyo Marakwet. Lastly, a greater proportion (15.70%) of farmers who received training and IPM materials were members of a mango cooperative.

Table 5: Socio-economic and household characteristics

Variable	Received Training and IPM (N=182)	Received Training only (N=194)	Control (N=286)	Pooled (N=662)	F-statistic
Continuous variable	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	
Age (years)	45.14 (12.72)	44.09 (12.35)	43.11 (11.59)	43.95 (12.15)	1.57
Education (years)	10.21 (7.90)	9.28 (4.15)	9.45 (4.39)	9.61 (5.53)	1.55
Family labour size (number)	3.72 (1.90)	4.07 (2.09)	3.78 (1.89)	3.85 (1.96)	1.79
Fruit fly loss (proportion)	26.75 (13.89)	26.14 (13.80)	26.95 (14.80)	26.66 (14.25)	0.19
Mango production (kg)	8,505.87 (29,942.52)	7,107.32 (14,181.64)	6,802.12 (13,138.74)	7,359.96 (19,472.28)	0.45
Mango income (ksh)	80,282.16 (162,639.43)	76,808.05 (160,700.79)	64,833.84 (136,455.79)	72,590.02 (151,193.39)	0.69
Mature trees (number)	31.32 (30.18)	32.49 (49.33)	24.94 (24.03)	28.91 (34.94)	3.32**
Mango area (acres)	0.61 (0.74)	0.60 (0.72)	0.56 (0.68)	0.58 (0.71)	0.35
Distance to nearest extension office (walking minutes)	126.02 (118.48)	110.82 (111.25)	206.80 (142.23)	156.46 (123.99)	0.74
Dummy variable	%	%	%	%	
Gender	95.05	94.33	95.80	95.17	
Aware of fruit flies	98.31	98.93	99.28	98.91	
Member of mango cooperative	15.70	12.43	9.69	12.19	

Significance level: *** p<0.01, ** p<0.05, * p<0.1

4.2 Farmers' Knowledge and Perception of Fruit Flies Infestation and Management

Mango farmers' knowledge and perception towards fruit flies' infestation and management were measured using a Likert scale. Descriptive statistics are presented in Table 6 for the three groups of sampled farmers interviewed during the end line survey. The results indicate that majority of farmers who received training and IPM materials agreed that spread of fruit flies could be prevented using fruit fly traps (98.84%). This was a comparable case for other statements such as reporting of fruit fly infestation, training, and extension services as appropriate channels for information dissemination, and fruit fly traps as better management alternatives to synthetic chemicals. However, regarding information on the risk posed by synthetic chemicals, farmers who received training (only), stated they were well informed that synthetic chemicals pose a great risk to human health (68.93%). Further analysis revealed that about a quarter (25.97%) of the surveyed farmers in the control group believed that synthetic chemicals alone could effectively control fruit flies as shown in Table 6.

Table 6: Farmers' knowledge and perception towards fruit fly infestation and management after IPM training intervention

Statement	Treatment status (3 groups)	Agree	No opinion/ don't know	Disagree
Spread of fruit flies can be prevented by the use of traps and lures.	Trained & given			
	IPM materials:	98.84%	1.16%	0.00%
	Trained only:	89.83%	9.60%	0.56%
Reporting fruit fly infestation to agricultural extension officers is important for government intervention.	Control:	85.27%	12.79%	1.94%
	Trained & given			
	IPM materials:	87.21%	5.23%	7.56%
Fruit fly traps and lures are better alternatives to synthetic chemicals for the control of mango fruit flies.	Trained only:	85.31%	7.34%	7.34%
	Control:	76.74%	9.30%	13.96%
	Trained & given			
Training and extension services are appropriate in providing information on fruit fly management.	IPM materials:	91.28%	7.56%	1.16%
	Trained only:	77.40%	19.21%	3.39%
	Control:	70.54%	22.09%	7.37%
Synthetic chemicals alone can effectively control fruit flies.	Trained & given			
	IPM materials:	94.76%	0.58%	4.65%
	Trained only:	93.79%	4.52%	1.69%
Synthetic chemicals pose a great risk to human health compared to the use of fruit fly traps and lures.	Control:	91.47%	3.88%	4.65%
	Trained & given			
	IPM materials:	15.69%	20.35%	63.96%
Infected fruits in the field can host a large number of fruit fly eggs that develop to maggots.	Trained only:	23.16%	22.03%	54.8%
	Control:	25.97%	22.48%	51.55%
	Trained & given			
Fruit fly traps reduce the use of chemicals in the farm to control pests	IPM materials:	66.86%	24.42%	8.73%
	Trained only:	68.93%	22.60%	8.47%
	Control:	62.40%	25.19%	12.41%
Fruit fly traps reduce the use of chemicals in the farm to control pests	Trained & given			
	IPM materials:	94.77%	5.23%	0.00%
	Trained only:	88.70%	10.17%	1.13%
Fruit fly traps reduce the use of chemicals in the farm to control pests	Control:	83.72%	14.73%	1.55%
	Trained & given			
	IPM materials:	93.61%	2.91%	3.49%
Fruit fly traps reduce the use of chemicals in the farm to control pests	Trained only:	77.40%	21.47%	1.13%
	Control:	73.26%	24.03%	2.71%

4.2.1 Farmers' Knowledge of Fruit Fly Infestation and Management after IPM Training Intervention

Based on the aggregate of the knowledge variables listed in Appendix 2, results indicate that 96.5% of farmers who received training and IPM materials were knowledgeable that spread of fruit flies can be prevented by the use of fruit fly traps, that infected fruits in the field can host a large number of fruit fly eggs and that synthetic chemicals pose a great risk to human health compared to the use of fruit fly traps. However, a greater percentage of farmers in the control group (15.5%) were not well informed on fruit fly infestation and management as shown in Figure 3. This implied that farmers who received training and IPM materials were better informed on fruit fly infestation and management compared to the other two treatment groups.

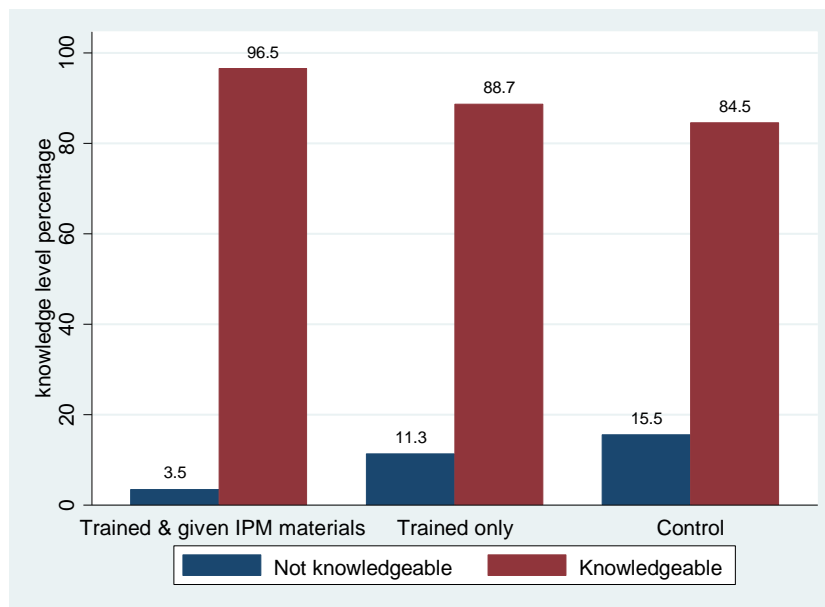


Figure 3: Knowledge status of sampled farmers by treatment

4.2.2 Farmers' Perception towards Fruit Fly Infestation and Management after IPM Training Intervention

Based on the aggregate of the perception variables in Appendix 2, mango farmers' perception of fruit fly infestation and management was categorized into two; farmers with good perception and those with poor perception. The results show that about 95.30% of farmers who were trained and given IPM materials had a good perception towards fruit fly traps as better management alternatives to synthetic chemicals, and training and extension services as appropriate channels for information dissemination. However, some farmers who received training only (16.40%) and the control group (22.10%) had a poor perception

towards using agricultural extension as a channel for reporting fruit fly infestation and using fruit fly traps as a pest management strategy. These results are presented in Figure 4.

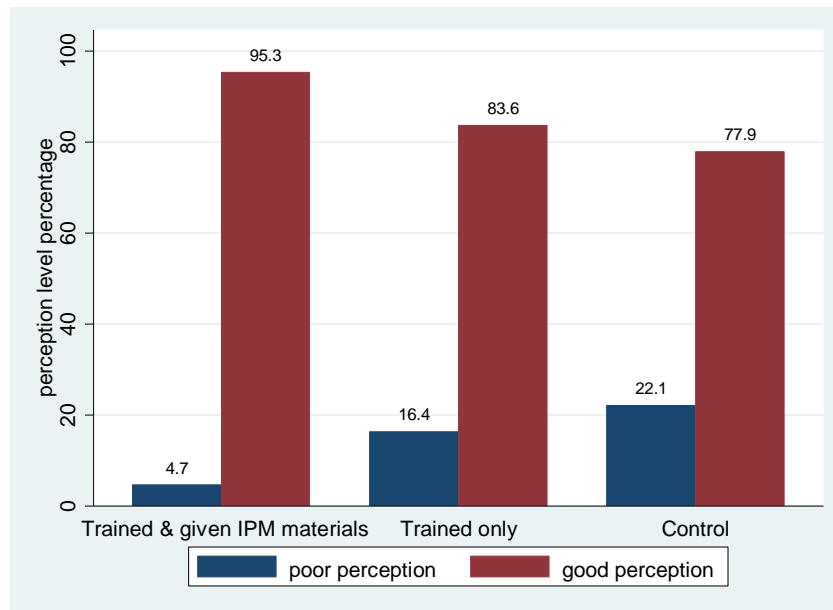


Figure 4: Perception status of sampled farmers by treatment

4.2.3 Impact on Knowledge and Perception

The DiD model presented in Chapter Three was estimated to determine the impact of fruit fly IPM intervention on the knowledge and perception of farmers towards fruit fly IPM. In Table 7, independent variables included in the DiD model had a variance inflation factor (VIF) less than 1.50, indicating the absence of serious multicollinearity. However, the three DiD regressions estimated experienced a problem of serial correlation and heteroscedasticity that was reported by the Cumby-Huizinga test and Breusch-Pagan test respectively. Serial correlation was solved by using the Prais-Winsten estimation and heteroscedasticity was solved using robust standard errors.

Over time, the knowledge and perception of farmers trained and given IPM start-up improved significantly by 15.81% (Table 7). They also had a significant increase in their knowledge and perception score by an average of 8.15% and 4.96% compared to the control group and farmers who only received training. This implied that apart from training, learning from the use of fruit fly IPM technologies provided is vital in improving the knowledge and perception of mango growers towards the adoption of fruit fly IPM. Our results coincide with Peshin *et al.* (2009) and Cockburn *et al.* (2014) who emphasize the importance of social and experiential learning for the dissemination of IPM strategies.

IPM training alone did not reveal a significant increase in farmers' knowledge and perception (Table 7). This can be explained by the fact that farmers who learn from their own experiences by using the technology tend to have a greater impact than knowledge articulated through training only (Kolb, 1984). However, over time the knowledge and perception of trained farmers improved significantly by 16.49%.

Table 7: Difference in Difference regression (Knowledge and perception)

Variables	Received training and IPM vs control	Received training and IPM vs received training only	Received training only vs control
Time (2017 vs 2018)	15.81*** (1.85)	19.67*** (2.10)	16.49*** (1.76)
Treatment	2.14 (2.08)	-0.05 (2.33)	2.51 (1.99)
Treatment*Time (DiD estimate)	8.15*** (2.90)	4.96* (2.87)	2.35 (2.73)
Sex of the household head (dummy)	7.27** (3.27)	5.18 (3.64)	9.02*** (3.33)
Age of the Household head (years)	-0.05 (0.06)	-0.08 (0.06)	0.05 (0.07)
Education of the household head (years)	0.16 (0.12)	0.15 (0.12)	0.72*** (0.19)
Mature mango trees (number)	0.03 (0.03)	0.06*** (0.02)	0.02 (0.02)
Size of family labour (number)	0.04 (0.38)	-0.38 (0.36)	-0.31 (0.35)
Distance to the nearest extension office	0.00 (0.00)	-0.01 (0.01)	-0.00 (0.00)
Member of a mango cooperative (dummy)	7.58*** (2.87)	3.55 (2.33)	9.55*** (2.83)
Constant	50.78*** (4.69)	58.59*** (4.91)	41.39*** (4.81)
Observations	860	698	870
R ²	0.2108	0.2288	0.1712
F-value	22.67***	19.47***	20.26***

Note: Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Robust standard errors estimated in parenthesis to solve the problem of heteroscedasticity for the three DiD regressions. Prais-Winsten estimated for the three regressions to control for the problem of autocorrelation exhibited in the data.

Other factors that positively influenced farmers' knowledge and perception include the sex and education of the household head, membership to a mango cooperative, and the number of mature mango trees. Male-led households significantly improved their knowledge and perceptions towards fruit fly IPM by an average of 7.27 and 9.02% for farmers who received training and IPM start-up and farmers who received training only, respectively. Educated farmers had an improvement in their knowledge and perceptions towards fruit fly IPM by 0.72%. Better educated farmers are more conscious of agricultural technologies including pest management strategies in their communities (Cockburn *et al.*, 2014; Adam *et al.*, 2015).

Farmers who were members of a mango cooperative had a substantial increase in their knowledge and perceptions towards fruit fly IPM by an average of 7.58 and 9.55%, respectively for those who received training and IPM start-up and those who received training only. This reveals the importance of rural institutions in enhancing knowledge and diffusion of technologies. Creating awareness is the first step to changing the knowledge and perceptions of farmers. This can be achieved through various mechanisms like farmer groups as also emphasized in the previous studies (Cockburn *et al.*, 2014; Adam *et al.*, 2015).

Mango growers who own a higher number of mature mango trees are more concerned and experienced in mango production. Hence, they are more likely to be knowledgeable about various pest management strategies. Their knowledge and perceptions towards fruit fly IPM improved by 0.06% (second column of Table 7), thus they are more likely to adopt fruit fly IPM strategies than farmers with fewer mature trees.

In conclusion, farmers who received training and start-up IPM materials had a significant improvement in their knowledge and perception of fruit fly IPM compared to the control group and farmers who received training only. This means that training and the use of fruit fly IPM materials provided was effective in improving the knowledge and perception of farmers in Elgeyo Marakwet.

4.3 Farmers' Demand Intensity for Fruit Fly Traps to Suppress Fruit Fly Infestation after IPM Intervention

Descriptive statistics on the demand intensity for fruit fly traps across the three treatment groups are presented in Table 8. The number of fruit fly traps purchased is over one year after the IPM training intervention. That is the total number of traps purchased during the 2018 short and main mango season by farmers in Elgeyo Marakwet. The average number of traps purchased was statistically different among the three groups of farmers as determined by the One-way ANOVA ($F(2, 604) = 7.59, P=0.0006$).

Farmers who received training only and those who received training and IPM materials had a higher demand intensity of about two traps compared to the control group. The demand intensity for farmers in the control group was approximately one trap only as shown in Table 8.

Table 8: Average number of fruit fly traps demanded in the year 2018

Variable	Pooled N=607	Trained and given IPM materials N= 172	Trained only N= 177	Control group N= 258	F-statistic
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	
Average number of traps demanded in 2018 (after intervention)	1.60 (3.15)	1.99 (3.86)	2.06 (3.69)	1.03 (1.88)	7.59***

Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

According to Cameron & Trivedi (2009), the dependent variable of a count data model usually takes small values. In this case, there are respondents with high frequencies of demand intensity for traps because the dependent variable is defined as an aggregate over two mango seasons. However, the histogram for the endogenous variable that is displayed in Figure 5 evidently shows that the distribution of values is skewed to the left with a high proportion of zeros. Furthermore, it is important to note that this sample is mainly concentrated in the small values whereby approximately 96.38% of the sampled farmers purchased traps less than 10. Further analysis revealed that more than half (64.73%) of the farmers in the control group did not purchase traps. This was followed by farmers who received training only (54.80%) and then by farmers who received training and IPM materials

(52.91%). The infrequency in the demand for traps by the three treatment groups can be explained by the fact that 48.47% of the farmers reported difficulties in purchasing or accessing the traps and lures in Elgeyo Marakwet, which posed as a challenge. This might be due to the supply shortage of fruit fly traps and lures to meet its rising demand among mango farmers in Elgeyo Marakwet. A solution to this problem would be for suppliers of IPM technologies to increase their supply and ease the distribution of fruit fly traps and lures by establishing more agrovets in the rural areas of Marakwet, Kenya.

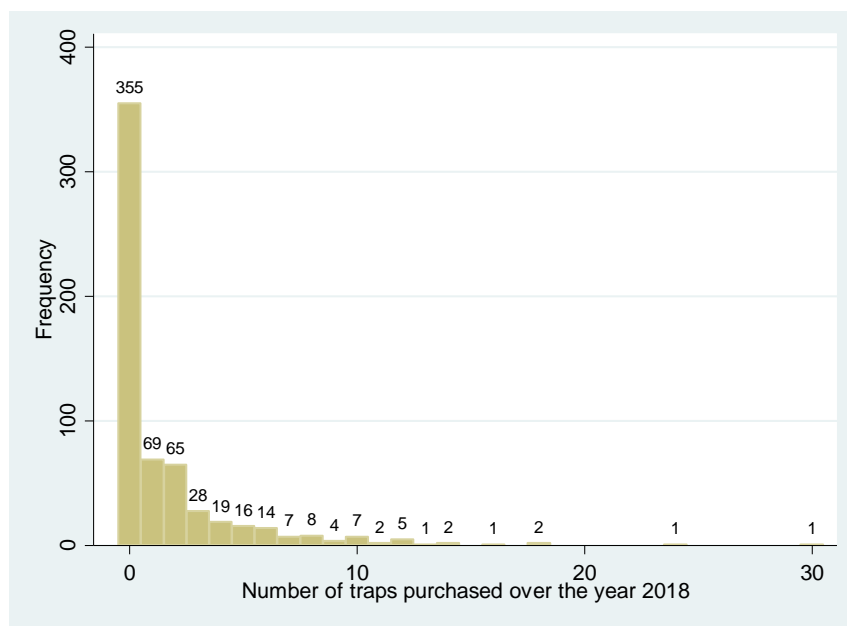


Figure 5: Distribution of the number of traps purchased after IPM intervention

4.3.1 Impact on Demand of IPM Technologies

Four count data models were estimated, and tests were performed to compare them and conclude on the most appropriate model for the data. A standard Poisson regression was first estimated for the three comparison groups of farmers as shown in Table 9. The appropriateness of the Poisson model was determined by estimating three corresponding negative binomial regressions (Table 9). The results from the Negative Binomial Regression (NBR) revealed that there was the presence of overdispersion. This was evident from the value of alpha that was greater than zero and the likelihood ratio test for an alpha, which was significant for the three negative binomial regressions. Therefore, this implied that the NBR was more appropriate than the standard Poisson model as shown in Table 9.

Table 9: Poisson regression and NBR results on the total number of fruit fly traps demanded after IPM intervention

Variables	Poisson regression			NBR regression		
	Received training and IPM vs Control	Received training and IPM vs Received training only	Received training only vs Control	Received training and IPM vs Control	Received training and IPM vs Received training only	Received training only vs Control
=1 if a farmer received training and IPM (dummy)	0.42*** (0.89)	-0.12 (0.08)		0.37* (0.20)	-0.03 (0.19)	
=1 if a farmer received training only (dummy)			0.55*** (0.09)			0.34* (0.21)
Sex of the household head (dummy)	-0.30* (0.18)	0.01 (0.19)	0.98*** (0.36)	-0.12 (0.46)	0.17 (0.47)	0.63 (0.56)
Age of household head (years)	0.00 (0.00)	-0.00 (0.00)	0.01*** (0.00)	0.00 (0.01)	0.00 (0.01)	0.01* (0.01)
Education of the household head (years)	-0.00 (0.01)	0.01** (0.01)	0.04*** (0.01)	-0.00 (0.02)	0.03 (0.02)	0.04 (0.02)
Mature trees (number)	0.01*** (0.00)	0.00*** (0.00)	0.00*** (0.02)	0.01** (0.00)	0.01** (0.00)	0.00 (0.00)
Family labour (number)	0.02 (0.02)	0.07*** (0.02)	-0.02 (0.02)	0.52* (0.29)	0.79*** (0.26)	-0.03 (0.05)
Member of cooperative (dummy)	0.60*** (0.10)	0.77*** (0.09)	0.37*** (0.11)	0.01 (0.01)	0.02*** (0.01)	0.40 (0.28)
% Knowledge and perception score	0.01*** (0.00)	0.01 (0.00)	0.02*** (0.00)	0.01 (0.01)		0.02*** (0.01)
Constant	-0.57* (0.33)	-1.23*** (0.36)	-3.43*** (0.46)	-0.89*** (0.81)	-2.04** (0.91)	-3.28*** (0.84)
Alpha				2.84	2.31	2.58
LR test of alpha=0				Prob>= 2 = 0.000***	Prob>= 2 = 0.000***	Prob>= 2 = 0.000***
(Standard error in parenthesis)	Significance level	*** p<0.01	** p<0.05	* p<0.1		

Note: The χ^2 -test is significant across, indicating that the NBR model is more appropriate than the standard Poisson regression.

Further tests revealed that the Zero-Inflated Poisson (ZIP) model was more appropriate than the standard Poisson regression. This was evident from the Vuong z-test, which was significant at 1% as shown in Table 10.

Table 10: ZIP regression (Demand for fruit fly traps)

Variables	Received training and IPM vs control	Received training and IPM vs received training only	Received training only vs control
<i>Standard poisson model</i>			
=1 if a farmer received training and IPM (dummy)	0.24** (0.09)	-0.05 (0.09)	
=1 if a farmer received training only (dummy)			0.35*** (0.10)
Sex of the household head(dummy)	-0.37* (0.19)	-0.43** (0.21)	0.47 (0.55)
Age of the household head (years)	-0.00 (0.00)	0.00 (0.00)	0.01*** (0.00)
Education of the household head (years)	0.02** (0.01)	0.05*** (0.01)	0.04*** (0.01)
Mature mango trees (number)	0.01*** (0.00)	0.00*** (0.00)	0.00*** (0.00)
Size of family labour (number)	0.04* (0.02)	0.06*** (0.02)	-0.03 (0.02)
Member of a mango cooperative (dummy)	0.08 (0.12)	0.30*** (0.09)	0.17 (0.11)
Knowledgeable and good perception (% score)	-0.00 (0.00)	0.01*** (0.00)	0.00 (0.00)
Constant	1.06** (0.42)	0.06 (0.43)	-0.53 (0.65)
<i>Logistic regression for zero inflation</i>			
=1 if a farmer received training and IPM or if farmer received training only	-0.28 (0.23)	0.11 (0.24)	-0.31 (0.23)
Age of the household head (years)	-0.01 (0.01)	-0.00 (0.01)	0.00 (0.10)
Education of the household head (years)	0.03 (0.03)	0.01 (0.02)	0.01 (0.03)
Mature mango trees (number)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Size of family labour (number)	0.04 (0.06)	-0.02 (0.06)	-0.00 (0.06)
Member of a mango cooperative (dummy)	-0.96*** (0.35)	-1.06*** (0.35)	-0.63** (0.36)
Knowledgeable and good perception (%score)	-0.02** (0.01)	-0.01* (0.01)	-0.03*** (0.01)
Constant	1.63** (0.75)	1.49* (6.89)	2.82*** (0.81)
<i>LR test of alpha =0 (²)</i>	59.31***	85.52***	68.67***
<i>Vuong test (Z)</i>	7.27***	6.84***	7.04***
<i>Observations</i>	420	324	404

Note: The z-test is significant across, indicating that the ZIP model is more appropriate than the standard Poisson model.

The fourth model estimated was the zero-inflated negative binomial regression and its suitability was tested using the zip option and the Vuong test (Table 11). The zip command test had a significant likelihood ratio of alpha equal to zero, indicating that the Zero-Inflated Negative Binomial (ZINB) model was more appropriate than the ZIP model (Table 11). This was also similar for the Vuong z-test that was significant at 10%, suggesting that the ZINB model was more suitable than the NBR. Thus, the ZINB model was chosen for this study.

It is hypothesized that improved IPM knowledge and perception through training would enhance the demand for fruit fly IPM technologies. This premise is tested using a ZINB regression. The ZINB regression is divided into two: the negative binomial regression and the logistic regression (Table 11). The demand for fruit fly IPM among farmers who received training and IPM start-up was positive compared to the control group, although the difference was insignificant when compared with farmers who received only training. Farmers who received only training had a higher demand intensity for fruit fly IPM than the control group, implying that training only was an effective approach in creating demand for IPM. Farmers' participation in IPM training and demonstration activities improves their confidence in the technology, thus increasing the probability of adopting it. This result supports previous studies that have shown a strong correlation between IPM training and adoption (Waddington *et al.*, 2014; Korir *et al.*, 2015; Midingoyi *et al.*, 2019; Mwangi *et al.*, 2020). Furthermore, product-specific training effectively improves technological awareness among farmers (Sing *et al.*, 2008).

Other factors that are likely to increase the demand for fruit fly IPM include the household head's education, the number of mature mango trees, and membership to a mango cooperative. IPM is a knowledge-intensive technology, thus may be favorable among better-educated farmers (Kassie *et al.*, 2018; Korir *et al.*, 2015). The finding on the number of mango trees is obvious as farmers endeavor to maximize returns from their mango production investments, as similarly observed by Korir *et al.*(2015) and Mwangi *et al.*(2020). Social network platforms like group membership are essential to creating awareness of new agricultural technologies. Our finding collaborates with Baumgrat-Getz *et al.* (2012) and Midingoyi *et al.* (2019). Furthermore, most farmer groups have better linkages to extension services conducive to the implementation of agricultural innovations (Adam *et al.*, 2015), such as fruit fly IPM technology.

Table 11 also shows the logistic regression providing the probability of observing a zero in the sample, which is the probability of farmers not demanding fruit fly IPM. Farmers

who had good knowledge and perception towards fruit fly IPM were less likely not to demand fruit fly IPM. This is plausible as farmers' awareness and mindsets are key drivers to adopting IPM technologies and needs to be improved. This can be achieved through training, which has proven effective in up-scaling adoption. Furthermore, membership to a mango group also significantly reduced the chance of not demanding the IPM since these farmers are more likely to be aware of the technology.

These results, therefore, indicate that training only was effective in increasing the demand for fruit fly IPM. Farmers who were trained only significantly demanded more fruit fly traps than farmers in the control group and farmers who received training and IPM materials.

Table 11: ZINB regression (Demand for fruit fly traps)

Variables	Received training and IPM vs control	Received training and IPM vs received training only	Received training only vs control
<i>Negative binomial model</i>			
=1 if a farmer received training and IPM (dummy)	0.23 (0.20)	-0.29 (0.21)	
=1 if a farmer received training only (dummy)			0.41** (0.20)
Sex of the household head(dummy)	-0.30 (0.30)	-0.47 (0.72)	0.36 (1.14)
Age of the household head (years)	-0.01 (0.01)	0.01 (0.01)	0.01 (0.01)
Education of the household head (years)	0.01 (0.05)	0.04 (0.05)	0.03* (0.02)
Mature mango trees (number)	0.01*** (0.01)	0.01 (0.00)	0.00 (0.00)
Size of family labour (number)	0.04 (0.04)	0.04 (0.05)	-0.04 (0.04)
Member of a mango cooperative (dummy)	0.06 (0.36)	0.56* (0.31)	0.18 (0.23)
Knowledgeable and good perception (% score)	-0.00 (0.01)	0.00 (0.01)	0.00 (0.01)
Constant	0.96 (1.21)	0.07 (1.10)	-0.55 (1.30)
<i>Logistic regression for zero inflation</i>			
=1 if a farmer received training and IPM or if farmer received training only	-0.28 (0.45)	-1.68 (3.03)	-0.20 (0.36)
Sex of the household head (dummy)	-0.47 (0.84)	-2.02 (2.16)	-0.99 (1.31)
Age of the household head (years)	-0.03 (0.03)	0.02 (0.04)	-0.00 (0.01)
Mature mango trees (number)	0.00 (0.01)	-0.05 (0.04)	-0.00 (0.00)
Size of family labour (number)	0.13 (0.10)	-0.03 (0.28)	-0.00 (0.08)
Member of a mango cooperative (dummy)	-1.84 (1.23)	-28.75*** (1.76)	0.76 (0.70)
Knowledgeable and good perception (%score)	-0.03* (0.02)	-0.08 (0.07)	-0.04*** (0.01)
Constant	2.98 (1.99)	7.39 (6.89)	3.92 (1.54)
<i>LR test of alpha =0 (χ^2)</i>	95.09***	128.24***	82.88***
<i>Vuong test (Z)</i>	2.55***	2.05**	3.12***
<i>Observations</i>	420	324	404

Note: Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Robust standard errors in parenthesis; The χ^2 and z- test is significant across, indicating that the ZINB model is more appropriate than the ZIP regression and the standard NBR model respectively.

4.4 Mango Production Loss due to Fruit Fly Infestation among Sampled Farmers in Elgeyo Marakwet

Descriptive statistics revealed that about 98.76 % of the sampled farmers were aware of fruit flies as a pest that caused mango damage. Furthermore, 83.61 % of the farmers reported that the severity of mango damage caused by fruit flies was high. Most of these farmers (95.78%) ranked fruit flies as a major pest that caused mango damage, followed by the mango weevil (3.85%) and then the mango white scale (0.37%). Therefore, this implied that fruit flies were a major challenge to farmers in Elgeyo Marakwet before the IPM training intervention took place. Further analysis revealed that the main mango fruit fly infestation symptom that farmers identified was infested fruits that contained maggots (33.1%). Other symptoms identified by farmers were fruits falling off the plant prematurely (31.6%), rotten fruits (20.5%), punctured fruits (14.6%) and lastly mangoes changing yellow (0.20%) due to over-ripening caused by fruit fly infestation(Figure 6).

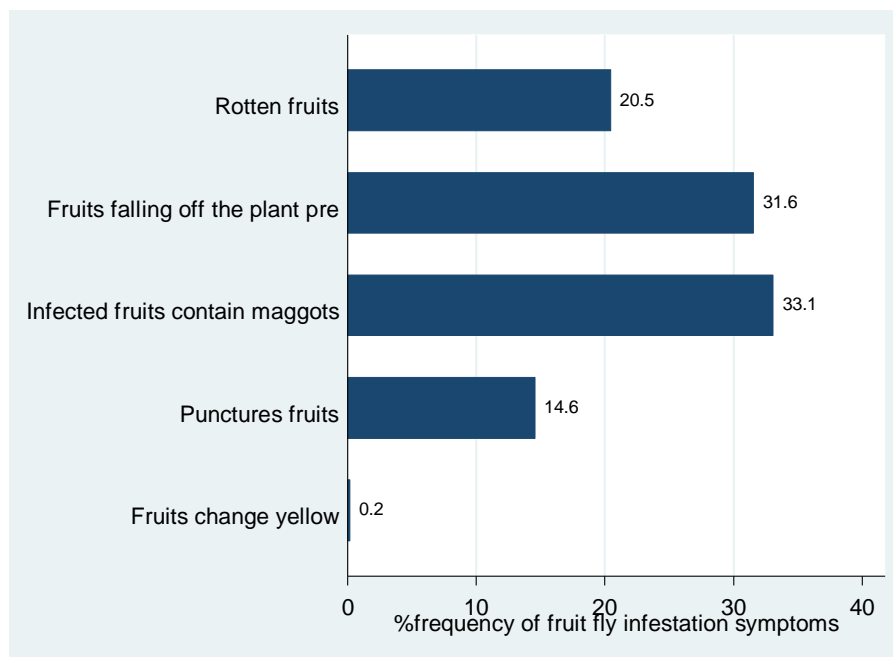


Figure 6: Symptoms of fruit fly infestation reported by mango farmers

4.4.1 Farmers' Mango Production Loss due to Fruit Flies before (2017 Main Season) and after (2018 Main Season) the IPM Training Intervention

Figure 7 presents the proportion of mango loss due to fruit flies in the year 2017 (before) and 2018 (after) main mango seasons. The difference in mango loss between the two years revealed that farmers who received training and IPM materials had a greater decline in their proportion of mango loss due to fruit flies by 20.70 %. This was followed by farmers in

the control group who had a decline of 13.20 % followed by farmers who received training only (-11.20%)

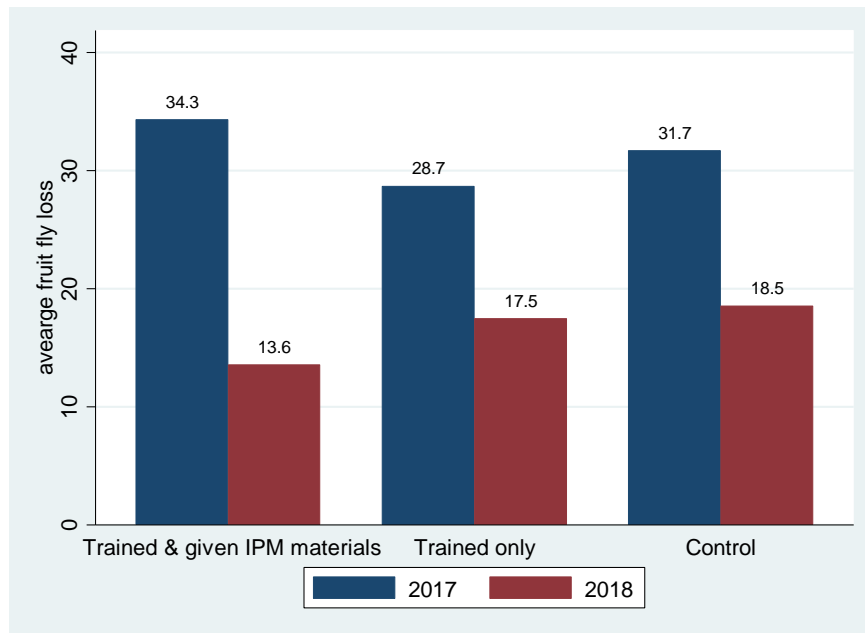


Figure 7: Proportion of mango production loss due to fruit flies in 2017 (before) and 2018 (after) main season.

4.4.2 Impact on Mango Production Loss

An ordinary least square DiD model presented in Chapter Three (equation 10) was estimated to determine the impact of fruit fly IPM intervention on the proportion of mango production loss due to fruit flies. In Table 12, independent variables included in the DiD model had a variance inflation factor (VIF) less than 1.50, indicating the absence of serious multicollinearity. Furthermore, there was the absence of autocorrelation. However, the three DiD regressions estimated experienced a problem of heteroscedasticity that was reported by the Breusch-Pagan test. This was solved by using robust standard errors.

Table 12 reports the DiD estimates for the impact of IPM training and start-up materials on mango production loss. Overtime, mango production loss for farmers who received training and IPM start-up decreased significantly compared to both the control group and those that received training only, by 6.89 and 8.07 % respectively. No significant change was generated among those that received training only relative to the change exhibited by the control group apart from the time effect. Hence, these findings suggest improving farmer's knowledge and perceptions about an agricultural innovation are not sufficient for adoption. Facilitating farmer's initial experience and ease of trying out new technologies through the

provision of start-ups may enhance their confidence about the technology, and hence widespread adoption (Yigezu *et al.*, 2018).

Besides, the covariates of interest, the number of fruit fly traps demanded among those who received training only significantly reduced mango production loss in comparison to the control group. This is plausible since the reduction of mango production loss is one of the main objectives of the technology's development and dissemination (Kibira *et al.*, 2015; Muriithi *et al.*, 2016). Thus, it is evident that training accompanied with the provision of start-up IPM materials used by farmers effectively reduced mango production loss caused by fruit flies in Elgeyo Marakwet.

Table 12: Difference in Difference regression (Mango production loss)

Variables	Received training and IPM vs control	Received training and IPM vs received training only	Received training only vs control
Time (2017 vs 2018)	-13.43 ^{***} (1.24)	-11.71 ^{***} (1.55)	-12.90 ^{***} (1.24)
Treatment	2.38 (1.48)	5.33 ^{***} (1.65)	-2.54 (1.51)
Treatment*Time (DiD estimate)	-6.89 ^{***} (1.82)	-8.07 ^{***} (2.00)	1.37 (1.87)
Sex of the household head (dummy)	-2.65 (2.01)	0.93 (2.01)	2.57 (1.92)
Age of the household head (years)	0.06 (0.04)	0.02 (0.04)	0.05 (0.04)
Education of the household head (years)	0.07 (0.06)	0.07 (0.06)	-0.11 (0.12)
Mature mango trees (number)	0.01 (0.02)	0.01 (0.01)	0.01 (0.01)
Size of family labour (number)	-0.14 (0.26)	-0.09 (0.27)	-0.40 (0.26)
Knowledgeable and good perception (% score)	-0.01 (0.02)	-0.03 (0.03)	-0.04 (0.02)
Demand for fruit fly IPM (number of fruit fly traps demanded)	-0.24 (0.18)	-0.09 (0.16)	-0.30 [*] (0.17)
Constant	31.91 ^{***} (3.16)	27.68 ^{***} (3.38)	32.02 ^{***} (3.14)
<i>Observations</i>	848	654	818
<i>R²</i>	0.2929	0.3149	0.2125
<i>F-value</i>	39.34 ^{***}	30.43 ^{***}	22.69 ^{***}

*Note: Significance level: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; Robust standard errors estimated in parenthesis to solve the problem of heteroscedasticity for the three DiD regressions.*

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

This section presents the summary of major findings for this study, conclusion drawn and policy recommendation.

5.1 Summary

Fruit flies (*Diptera Tephritidae*) are of economic importance to fruit production. They are known as “quarantine insects.” A consignment of mango exports to Europe is most likely to be rejected and destroyed by European phytosanitary services if a single fruit is infested with the insect’s larvae. Therefore, fruit fly infestation has been a major challenge faced by mango farmers, particularly in Elgeyo Marakwet as well other mango producing areas in Kenya. From previous studies, fruit fly IPM strategy has been found to be effective, though there is limited evidence to up-sale its adoption in Kenya. To promote the use of IPM, a training intervention was implemented that involved a randomized control trial experiment with three groups of farmers: farmers who received training and start-up IPM materials, farmers who received training only, and the control group.

The results of the study revealed that farmers in the three groups were agile with an average age of 44 years and were therefore amenable to adopting new labour-intensive technologies. Furthermore, farmers in the three groups were fairly educated with approximately 10 years of formal education hence were more likely to appreciate the benefits of a knowledge-intensive technology such as IPM. This study aimed at assessing if the training intervention (training and provision of start-up IPM technologies) in Marakwet had a significant impact in improving mango farmers’ knowledge and perception towards fruit fly IPM , their management practices (demand for fruit fly traps), and generally in improving their mango production by reducing mango damage caused by fruit flies.

This study sought to determine the impact and effect of training and fruit fly IPM on three outcome variables, namely, the knowledge and perceptions of mango farmers, their demand for fruit fly IPM and on farmers’ mango production loss caused by fruit flies. The difference in difference model was used to analyze the first and third objective of the study, while the zero-inflated negative binomial regression was used to analyze the demand for fruit fly IPM.

Data analyzed for the study was both based on panel data and cross-sectional data for the demand of fruit fly IPM after the training intervention. The data was transferred and analyzed using STATA version 14.

Based on the results of the study, farmers who received training and fruit fly IPM start-ups were better off than farmers who received training only and the control group in terms of improved knowledge and perceptions towards fruit fly IPM and reduced mango production loss due to fruit flies. Their knowledge and perceptions towards fruit fly IPM significantly improved by an average of 8% and 5%, while mango production loss substantially declined by 7% and 8% compared to the control group and farmers who received training only respectively. This suggests that training accompanied by the provision of start-up IPM is a great stimulus to promote social and experiential learning among farmers.

Regarding the demand for fruit fly IPM strategy, farmers who received training and IPM start-up and farmers who received training only demanded more fruit fly traps than the control group. However, this was only significant when comparing farmers who received only training with the control group. Thus, training only is effective in up scaling IPM adoption in developing countries. Apart from training, it is evident that social network platforms such as membership to farmer groups are important in improving farmer's attitudes towards using IPM technologies. It is vital to acknowledge that creating awareness and changing farmers' perceptions are key drivers of technology adoption, which can be improved by allowing farmers to try out new technologies at low or no cost and thus learn from their own experiences.

5.2 Conclusions

This paper is an important contribution to the limited literature on the impact of IPM training in Sub-Saharan Africa, using the case of fruit fly IPM strategy, implemented through a randomized control trial experiment among mango growers in Elgeyo Marakwet in Kenya. The study used panel data from three waves.

The results of the study emphasize the importance of IPM training being accompanied by the provision of start-up fruit fly IPM technologies. Once farmers are trained and receive IPM start-ups, they are more likely to benefit economically. The results of this study, therefore, provide significant highlights for researchers and policymakers to come up with effective training programs that can improve the knowledge and perception of farmers towards the use of agricultural technologies, up-scale the demand for these technologies and

subsequently improve the economic performance of farmers in Africa. This study suggests that product-specific training programs accompanied by the provision of start-up product packages are effective incentives for fast and widespread adoption of new technologies.

5.3 Recommendations

1. Provide training and start-up IPM technologies to significantly improve the knowledge and perceptions of farmers on IPM

Objective 1: Creating awareness of IPM technologies and changing the perception of farmers towards the use of IPM are key drivers to the adoption of IPM technologies. This study indicates that the knowledge and perception of farmers towards fruit fly IPM can be improved significantly through training and the provision of start-up fruit fly IPM technologies. Training alone is not effective enough in improving the knowledge and perceptions of farmers. Providing farmers with start-up technologies to learn through their own experiences of using the technology is the best approach to improving their knowledge and perceptions towards an agricultural technology.

2. Improve access to training centres in various Counties of Kenya to up-scale the adoption of IPM technologies

Objective 2: Training alone is effective in upscaling the demand of fruit fly IPM. Thus, to improve access to training centers, more training centres need to be established at ward-level in Kenya where farmers can walk in and acquire information on available agricultural technologies. Furthermore, a training centre will provide an avenue where farmers can provide feedback on the use of various agricultural technologies for research purposes.

3. Encourage farmers to join farmer groups or associations

Objective 1 & 2: Social network platforms such as farmer groups are essential to create awareness among farmers about available and new agricultural technologies. Through this study, it is evident that farmers who belong to a mango cooperative were knowledgeable and had a good perception towards fruit fly IPM. Furthermore, they demanded more fruit fly traps to reduce fruit fly infestation in their mango orchards. Thus, to significantly improve the knowledge and perceptions of farmers towards agricultural technologies and up-scale the

adoption of these technologies, farmers need to be encouraged to join farmer groups or associations.

4. Provide training and start-up IPM technologies to effectively reduce pest infestation

Objective 3: Training accompanied with the provision of start-up IPM technologies significantly reduced mango production loss caused by fruit flies among farmers in Elgeyo Marakwet. Therefore, to significantly reduce pest infestation and improve agricultural production in Africa, funders of projects should accompany training with the provision of start-up IPM technologies to allow the farmer to learn from his or her own experience and effectively reduce pest infestation levels.

5.4 Areas for Further Research

This study was not able to assess if there were spillover effects of training and use of fruit fly IPM specifically towards the control group involved in the randomized control trial experiment. Furthermore, it would be interesting to assess the factors that influence the diffusion of knowledge from trained farmers to the control group. This would determine the factors that motivate farmers to share information on IPM. Apart from fruit fly infestation, it is also important to determine other factors that influence mango production to inform literature.

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MODULE 2: HOUSEHOLD COMPOSITION AND CHARACTERISTICS AND HOUSING CONDITIONS

2.1 What is the age of the household head (complete years)?

2.2 What is the marital status of the household head? CODE 2

2.3 What is the education in years of the household head? CODE 3

2.4 What is the primary occupation of the household head? CODE 4

CODE 2	CODE 3	CODE 4
1.Married living with spouse 2.Married living without spouse 3.Divorced/separated 4.Widow/widower 5.Never married	0. None/illiterate 1. Adult education or 1 year of education * Give other education in years (e.g. 2 yrs for std 2, 8 yrs for class 8 etc) 100. Religious education	1.Farming (crop+ livestock) 2.Salaried employment 3.Self-employed off-farm 4.Casual labourer on-farm 5.Casual labourer off-farm 6.School/college child 7.Non-school child 8. Other, specify.....

2.5 INFRASTRUCTURE (all distances in walking minutes)

1. Distance to the village market from residence
2. Distance to nearest source of herbicides and pesticides dealer from residence.....
3. Distance to the nearest source of other inputs (seeds, fertilizer,) from residence
4. Distance to the nearest main output market from residence
5. Distance to the nearest agricultural extension office from residence
6. Distance to the nearest credit source from residence
7. Number of community activities (e.g. merry go round, farmers group, etc) head of household is currently participating.....
8. Number of community activities (e.g. merry go round, farmers group, etc) the spouse is currently participating.....

9. Total current family size in the household (household size).....
10. How many family members are above the working age or provide family labour during mango production?

MODULE 3: MANGO PRODUCTION AND MARKETING

3.1. What percentage of your total annual income is from farm income (crops including fruit & vegetable and animals)? [_____]%



3.2. What proportion of your total annual income comes from Mango production? [_____]%



3.3. Have you ever been visited by agricultural extension agents or others, who discussed non-pesticides means of controlling pests? [_____] 0=No, 1=Yes

3.4 KNOWLEDGE OF MANGO FRUIT FLIES, CONTROL STRATEGIES AND CONSTRAINTS IN ACCESSING KEY INPUTS AND CROP PRODUCTION

- 3.4.1. Are you aware of fruit flies? 1=yes; 0=no
- 3.4.2. Does fruit flies cause mango damage? 1=yes; 0=no
- 3.4.3. How severe do you believe fruit flies affect your yield/quality of your mango crops? 1=high ; 2=medium ; 3=low

3.4.4. Please match the above-named pests with their larvae or nymphs using photos provided:

Larvae/nymphs	Pest name (Code A)	Larvae/nymphs	Pest name (Code A)
1	2	1	2
			

			
Code A:			
1=Fruit flies	2=Mango weevil	3=Mango scale	4=Mealybug 5=Do not know

3.4.5. What proportion of the mango production do you believe you lose to all types of pests? _____%

3.4.6. What proportion of the mango production do you believe you lose to **fruit flies**? _____ %

3.4.7. Tell us the symptoms that you identify mango fruit flies' infestation and rank them starting with the most common ones (*Enumerator: If farmer does not state the given examples, show the farmer the photos and ask if he knows the symptoms*)

Mango fruit fly infestation symptoms	Rank (1= most common)	Common symptoms
1	2	1.Rotten fruits, 2.Fruits falling off the plant prematurely, 3. Infected fruits contain maggots 4. Punctured fruits 5. Other(specify)_____

3.4.8. Fruit fly knowledge and perception on prevention and control of mango fruit flies

	Fruit fly knowledge and perception	5=strongly agree 4=Agree 3=Neither/no opinion/don't know 2=Disagree 1=Strongly disagree	Did ICIPE's training change your knowledge and perception in relation to the question? 0=No, 1=Yes.
	1	2	
1.	Spread of fruit flies can be prevented by the use of traps and lures.		

2.	Infected fruits in the field can host large number of fruit fly eggs that develop to maggots		
3.	Reporting fruit fly infestation to agricultural extension officers is important for government intervention.		
4.	Training and extension services are appropriate in providing information on fruit fly management.		
5.	Synthetic chemicals alone can effectively control fruit flies		
6.	Synthetic chemicals pose a great risk to human health compared to the use of fruit fly traps and lures.		
7.	Fruit fly traps and lures are better alternatives to synthetic chemicals for the control of mango fruit flies.		
8.	Fruit fly traps reduce the use of chemicals in the farm to control pests.		

3.4.9. Who do you consult on questions related to management and control of fruit flies? (Code A) [____][____][____][____][____]

Code A			
1. Government extension officers	3. Agrovet owners/ agro-dealers	5. Private extension officers	7. Others (specify) _____
2. Neighbours/fellow farmers	4. Self/none	6. Farmer group	

3.5 IPM KNOWLEDGE, SOURCES OF INFORMATION, PERCEPTIONS AND ADOPTION

3.5.1. Have you heard about **Integrated Pest Management or NON-PESTICIDE** practices for control of Mango fruit flies? [_____] 1=Yes; 0=No

3.5.2. If YES, are you aware of fruit fly traps/ Male Annihilation Technique (MAT)? 1=Yes; 0=No

3.5.3. Have you or your household member used it? 1=Yes; 0=No

3.5.4. Did you buy any traps during the short season of 2018? [_____] 0=No 1=Yes.

3.5.5. If YES, how many traps were bought?

3.5.6. Did you buy any lures during the short season of 2018? [_____] 0=No 1=Yes.

3.5.7. If YES, how many lures were bought?

3.5.8. Did you buy any traps during the main season of 2018? [_____] 0=No 1=Yes.

3.5.9. If YES, how many traps were bought?

3.5.10. Did you buy any lures during the main season of 2018? [_____] 0=No 1=Yes.

3.5.11. If YES, how many lures were bought?

MODULE 4: CROP PRODUCTION FOR MANGO CROP GROWN BY THE HOUSEHOLD DURING THE 2016/17 AND 2018 CROPPING SEASON

Serial No	Plot ID (start with one next to residence)	Plot area (acres)	Sub-plot ID	Sub-plot area (acres)	Plot location name	Distance from homestead to sub-plot (walking minutes)	Inter-cropping on this sub-plot? (Other crops or improved & local mango varieties)? 0=No 1=Yes	If different mango varieties, which ones are intercropped or in this sub-plot? CODE 3	If inter cropping with other crops, what is area under mango (acres)?	Total number of mango trees on a plot	Total number of young mango trees (less than 3 years)	Total number of mango trees in production	Land quality CODE 1	plot tenure CODE 2
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1														
2														
3														
4														
5														
6														
7														

CODE 1 No1.Fertile 2.Moderately fertile 3.Infertile	CODE 2 1. Owned 2. Rented/shared in 3. Rented/shared out 4. Borrowed in 5. Borrowed out 6. Other specify _____	CODE 3 1. Apple 2. Tommy atkins 3. Ngowe 4. Kent 5. Van dyke 6. Keitt 7. Sensation 8. Haden 9. Sabine 10. Local varieties	Note 1. 1 acre = 4046.86m ² 2.1 hectares=2.47acres
---	---	--	--

4.1.2. Mango production in 2016/2017 SEASONS: Main season; Aug-Dec 2016 and Short-season March- April 2017

Serial No	Plot ID (as given in 4.2.1 above)	Sub-plot ID (as given in 4.2.1 above)	Total mango production by plot			
			MAIN SEASON		SHORT SEASON	
			Quantity	Unit: Codes A	Quantity	Unit: Codes A
	40	41	42a	42b	43c	43d
1						
2						
3						
4						
5						
6						
7						
8						
9						

CODES A
1=pieces
2=crate (specify Kgs) _____ kgs
3=4kgs carton
4= 6kgs carton
5=17kgs bucket
6=50 kgs bag
7=90kgs bag
8=120 kg bag
9=Quintal (1Qt=48.95Kgs)
10. 40kgs net
11.Other (specify

4.1.3. Utilization & Marketing of Mango production in 2016/2017 SEASONS: (Main season; Aug-Dec 2016 and Short-season March- April 2017) and 2018 short and main season

Mango varieties	Total production		Total quantity sold			Total consumed at home		Gift/donation		Post-harvest loss (this refers to loss only after harvest)		Main buyer Codes B	Actual transport cost (Ksh)	
	Quantity	Unit Codes A	Qty	Unit Codes A	Price per unit	Qty	Unit Codes A	Quantity	Unit Codes A	Qty	Unit Codes A			
43	44a	44b	45a	45b	45c	46a	46b	47a	47b	48a	48b	49	49	
1	Total mango production in 2016/2017 (sum of all plots production in table 4.11) and for 2018 short and main season.													
2	Apple													
3	Tommy atkins													
4	Ngowe													
5	Kent													
6	Van dyke													
7	Keitt													
8	Sensation													
9	Haden													
10	Sabine local varley													
13	Local varieties (Round)													
14	Other (specify)													

CODES A						CODES B			
1=pieces	3=4kgs carton	5=17kgs bucket	7=90kgs bag	9=Quintal	10. Other (specify)	1. Farmer group	3. Consumer or other farmer(s)	5. Non-local trader	7. Other, specify...
2=crate (specify kgs__40___kgs	4=6kgs carton	6=50 kgs bag	8=120 kg bag	10.40kgs net	_____	2. Farmer Union or Coop	4. Local trader	6. Exporter	

4.1.4. Do you have a contract for Mango production/ marketing? [_____] **1. Yes 0.NO**

4.1.5. Are you or any other household member currently a member of any mango production and marketing association group? [_____] **0=No; 1=Yes**

MODULE 5: HOUSEHOLD CREDIT NEED AND SOURCES

5.1 HOUSEHOLD CREDIT NEED AND SOURCES DURING 2016/17 AND 2018 CROPPING YEAR

Reason for Loan	Did your household need credit? 0=No>>3 1=Yes>>4	Why did your household not need credit? CODE 1	Did your household receive credit? 0=No>>5 1=Yes >>6	Why did your household not receive credit (Rank 3 reasons)? CODE 2			If Yes to col 4		
							What was the source of the credit? CODE 3	What was the amount of credit received? (KSh)	Did you receive the amount you requested? 0=No 1=Yes
1	2	3	4	5a	5b	5c	6a	6b	6c
1 Buying agricultural input for MANGO including IPM technologies									

CODE 1	CODE 2			CODE 3	
1=Not cash constrained	1=Borrowing is risky	5=I have no asset for collateral	8=No credit association	1=Money lender	5=Bank
2=Activity is not profitable	2=Interest rate is high	6=No money lenders in this area for this purpose	9=Not available on time	2=Farmer group/coop	6=Relative
3=Never thought of this investment	3=Too much paper work/ procedures	7=Lenders don't provide the amount needed	10=Other, specify.....	3=Merry go round	7= Other, specify.....
4=Had own source	4=Expected to be rejected, did not try			4=Microfinance	
5=Other, specify.....					

Thank you very much for your time and participation (Please remember to thank the farmer genuinely)

Time end: (24hrs) _____

Appendix B: Knowledge and Perception on Fruit Fly Infestation and Management

Knowledge section	Questions
	<ol style="list-style-type: none"> 1. Spread of fruit flies can be prevented by the use of traps and lures. 2. Infected fruits in the field can host large number of fruit fly eggs that develop to maggots. 3. Synthetic chemicals pose a great risk to human health compared to the use of fruit fly traps and lures.
Perception section	
	<ol style="list-style-type: none"> 1. Reporting fruit fly infestation to agricultural extension officers is important for government intervention. 2. Training and extension services are appropriate in providing information on fruit fly management. 3. Synthetic chemicals alone can effectively control fruit flies. 4. Fruit fly traps and lures are better alternatives to synthetic chemicals for the control of mango fruit flies. 5. Fruit fly traps reduce the use of chemicals in the farm to control pests.

Appendix C: Variance Inflation Factor (VIF) (Knowledge and Perception)

Variable	Received training and IPM vs control	Received training and IPM vs received training only	Received training only vs control
Sex of the household head	1.04	1.06	1.07
Age of the household head	1.16	1.16	1.27
Education of the household head	1.09	1.07	1.26
Mature mango trees	1.47	1.54	1.57
Size of family labour	1.11	1.11	1.08
Distance to the nearest extension office	1.13	1.03	1.05
Member of a mango cooperative	1.01	1.03	1.01
Mean VIF	1.14	1.16	1.19

Note: There is no presence of serious multicollinearity among the independent variables used in the DiD regression.

Appendix D: Variance Inflation Factor (VIF) (Mango Production Loss)

Variable	Received training and IPM vs control	Received training and IPM vs received training only	Received training only vs control
Sex of the household head	1.05	1.04	1.07
Age of the household head	1.14	1.13	1.26
Education of the household head	1.08	1.05	1.24
Mature mango trees	1.40	1.66	1.56
Size of family labour	1.09	1.10	1.08
Knowledge and perception score	1.04	1.03	1.06
Demand for fruit fly IPM	1.09	1.08	1.13
Mean VIF	1.14	1.19	1.22

Note: There is no presence of serious multicollinearity among the independent variables used in the DiD regression.

Appendix E: Breusch-Pagan Test (Knowledge and Perception)

	Received training and IPM vs control	Received training and IPM vs received training only	Received training only vs control
Chi2(1)	6.38	11.44	4.45
Prob> Chi2	0.0115	0.0007	0.0349

Note: There is presence of heteroskedasticity in the three regressions. We reject the null hypothesis that the variance is constant since the P-value of the three regressions is below 5% significance level.

Appendix F: Breusch-Pagan Test (Mango Production Loss)

	Received training and IPM vs control	Received training and IPM vs received training only	Received training only vs control
Chi2(1)	29.98	20.54	8.61
Prob> Chi2	0.0000	0.0000	0.0033

Note: There is presence of heteroskedasticity in the three regressions. We reject the null hypothesis that the variance is constant since the P-value of the three regressions is below 5% significance level.

Appendix G: DiD Model (Knowledge and Perception)

Notes:

tssethousehold_id Year

panel variable: household_id (strongly balanced)

time variable: Year, 2017 to 2018

delta: 1 unit

***Regression 1(Received training and trap (RTT) VS Received training only (RTrain))**

praispercent_KPscore

time##

RTT_RTrainSex_headage_headyearseducation_headtotal_Mat_treesfamily_labourextofficedistancemango_grp,r

Number of gaps in sample: 348 (gap count includes panel changes)

(note: computations for rho restarted at each gap)

Iteration 0: rho = 0.0000

Iteration 1: rho = 0.0461

Iteration 2: rho = 0.0466

Iteration 3: rho = 0.0466

Iteration 4: rho = 0.0466

Prais-WinstenAR(1) regression -- iterated estimates

Linear regression

Number of observations = 698

F(10, 687) = 28.12

```

Prob> F          =      0.0000
R-squared        =      0.2288
Root MSE        =      19.472

```

```

-----+-----
                |                Semirobust
percent_KPscore |      Coef.   Std. Err.      t    P>|t|      [95% Conf. Interval]
-----+-----
                |
                |      1.time |      19.6709   2.098516     9.37   0.000   15.55062   23.79117
RTT_RTrain |
  Received trap and training |      -.0494617   2.32871   -0.02   0.983   -4.621704   4.522781
time#RTT_RTrain |
1#Received trap and training |      4.964657   2.865957     1.73   0.084   -.6624295   10.59174
Sex_head |      5.180233   3.64272    1.42   0.155   -1.971967   12.33243
age_head|      -.0787996   .0645339   -1.22   0.222   -.205507    .0479077
yearseducation_head |      .149265    .1183729    1.26   0.208   -.0831512    .3816812
total_Mat_trees |      .0597036    .0169866    3.51   0.000    .0263517    .0930555
family_labour|      -.3800609    .3600689   -1.06   0.292   -1.087028    .3269066
extofficedistance|      -.0096868    .0063223   -1.53   0.126   -.0221002    .0027265
mango_grp |      3.545548    2.329064    1.52   0.128   -1.027389    8.118486
                |      _cons |      58.59429    4.90693   11.94   0.000   48.95991   68.22867
-----+-----
                |
                |      rho |      .0466036
-----+-----

```

Durbin-Watson statistic (original) 0.943053

Durbin-Watson statistic (transformed) 1.000000

***Regression 2 (RTT VS Control group (None))**

praispercent_KPscore

time##

RTT_NoneSex_headage_headyearseducation_headtotal_Mat_treesfamily_labouextofficedistancemango_grp

Number of gaps in sample: 429 (gap count includes panel changes)

(note: computations for rho restarted at each gap)

Iteration 0: rho = 0.0000

Iteration 1: rho = 0.0086

Iteration 2: rho = 0.0087

Iteration 3: rho = 0.0087

Prais-WinstenAR(1) regression -- iterated estimates

Number of observations = 860

F(10, 849) = 22.67

Prob> F = 0.0000

R-squared = 0.2108

Adj R-squared = 0.2015

Root MSE = 20.905

percent_KPscore	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
1.time		15.81296	1.850508	8.55	0.000	12.18085 19.44507
RTT_None						
Received trap and training		2.141994	2.076429	1.03	0.303	-1.933543 6.21753
time#RTT_None						
1#Received trap and training		8.152214	2.903335	2.81	0.005	2.453658 13.85077
Sex_head	7.277391	3.270011	2.23	0.026	.8591369	13.69565
age_head	-.0462533	.0628458	-0.74	0.462	-.1696046	.0770981
yearseducation_head	.1572254	.1227462	1.28	0.201	-.0836962	.3981469
total_Mat_trees	.0310694	.0277313	1.12	0.263	-.0233606	.0854994
family_labour	.037585	.3808265	0.10	0.921	-.7098869	.7850568
extofficedistance	.0000522	.0006231	0.08	0.933	-.0011708	.0012751
mango_grp	7.583504	2.872327	2.64	0.008	1.945809	13.2212
_cons		50.78474	4.686086	10.84	0.000	41.58706 59.98241
rho		.0087023				

Durbin-Watson statistic (original) 0.990507

Durbin-Watson statistic (transformed) 1.000000

***Regression 3 (RTrain VS None)**

praispercent_KPscore time##

RTrain_NoneSex_headage_headyearseducation_headtotal_Mat_treesfamily_labourextofficedistancemango_grp

Number of gaps in sample: 434 (gap count includes panel changes)

(note: computations for rho restarted at each gap)

Iteration 0: rho = 0.0000

Iteration 1: rho = 0.0510

Iteration 2: rho = 0.0513

Iteration 3: rho = 0.0513

Iteration 4: rho = 0.0513

Prais-WinstenAR(1) regression -- iterated estimates

Number of observations = 870

F(10, 859) = 17.75

Prob> F = 0.0000

R-squared = 0.1712

Adj R-squared = 0.1616

Root MSE = 20.257

percent_KPscore	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
1.time	16.48776	1.758429	9.38	0.000	13.03644	19.93908
RTrain_Noneb						
Received training	2.507995	1.991661	1.26	0.208	1.401097	6.417086
time#RTrain_Noneb						
1#Received training	2.353164	2.72777	0.86	0.389	3.000711	7.707039
Sex_head	9.019966	3.331517	2.71	0.007	2.481099	15.55883
age_head	.048747	.0659914	0.74	0.460	.0807764	.1782703
yearseducation_head	.7234384	.1860292	3.89	0.000	.3583134	1.088563
total_Mat_trees	.0151826	.0192992	0.79	0.432	.0226966	.0530617
family_labour	-.3125739	.3513265	-0.89	0.374	1.002133	.3769849
extofficedistance	-.0002081	.000617	-0.34	0.736	.0014191	.0010029
mango_grp	9.546063	2.831961	3.37	0.001	3.987689	15.10444
_cons	41.38635	4.812357	8.60	0.000	31.941	50.83171
rho	.0512802					
Durbin-Watson statistic (original)		0.942414				
Durbin-Watson statistic (transformed)		1.000000				

Appendix H: ZINB Model (Demand for Fruit Fly Traps)

Notes:

*Regression 1 (RTT VS RTrain)

```
zinzib      real_total_traps18      i.RTT_RTraini.sex_headage_headyearseducation_head      total_Mat_trees2018
family_labouri.MemberCoop2018      percent_KPscore,      inflate(      i.RTT_RTrainbi.sex_headage_head
total_Mat_trees2018 family_labour i.MemberCoop2018 percent_KPscore) robust
```

Fitting constant-only model:

```
Iteration 0:  log pseudolikelihood = -611.47404
Iteration 1:  log pseudolikelihood = -588.26331
Iteration 2:  log pseudolikelihood = -573.66978
Iteration 3:  log pseudolikelihood=  -570.4673
Iteration 4:  log pseudolikelihood = -569.13095
Iteration 5:  log pseudolikelihood = -568.77612
Iteration 6:  log pseudolikelihood=  -568.7269
Iteration 7:  log pseudolikelihood=  -568.7175
Iteration 8:  log pseudolikelihood = -568.71544
Iteration 9:  log pseudolikelihood = -568.71495
Iteration 10: log pseudolikelihood = -568.71484
Iteration 11: log pseudolikelihood = -568.71482
```

Fitting full model:

Iteration 0: log pseudolikelihood = -568.71482
Iteration 1: log pseudolikelihood = -561.24836
Iteration 2: log pseudolikelihood = -559.81601
Iteration 3: log pseudolikelihood = -559.53222
Iteration 4: log pseudolikelihood = -559.39361
Iteration 5: log pseudolikelihood = -559.34025
Iteration 6: log pseudolikelihood = -559.33969
Iteration 7: log pseudolikelihood = -559.33969

Zero-inflated negative binomial regression

Number of obs = 324

Nonzero obs = 156

Zero obs = 168

Inflation model = logit Wald chi2(8) = 23.09

Log pseudolikelihood = -559.3397 Prob> chi2 = 0.0033

```

-----+-----
                |               Robust
                |   Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
real_total_traps18 |
RTT_RTrain |
Received trap and training |  -.2936101   .2099039   -1.40   0.162   - .7050142   .117794

sex_head |
Male |  -.4686707   .7170631   -0.65   0.513   -1.874089   .9367471
age_head |   .0065119   .0090826    0.72   0.473   -.0112897   .0243135
yearseducation_head |   .0429093   .0501657    0.86   0.392   -.0554136   .1412322
    total_Mat_trees2018 |   .005356   .0042878    1.25   0.212   -.0030479   .0137599
family_labour |   .0362799   .0503721    0.72   0.471   -.0624477   .1350074

                |
                |   MemberCoop2018 |
Yes |   .555743   .3116954    1.78   0.075   -.0551688   1.166655
percent_KPscore |   .0019387   .0070923    0.27   0.785   -.0119619   .0158393
    _cons |   .0746015   1.09731    0.07   0.946   -2.076087   2.22529
-----+-----
inflate |
RTT_RTrainb |

```

```

Received trap and training | -1.677465  3.032493  -0.55  0.580  -7.621041  4.266112
sex_head |
Male | -2.024266  2.158989  -0.94  0.348  -6.255808  2.207275
age_head | .0159686  .0404455  0.39  0.693  -.063303  .0952403
      total_Mat_trees2018 | -.0455669  .0374025  -1.22  0.223  -.1188743  .0277406
family_labour| -.0257807  .2794975  -0.09  0.927  -.5735858  .5220244
      |
      MemberCoop2018 |
Yes | -28.74693  1.757301  -16.36  0.000  -32.19118  -25.30269
percent_KPscore| -.0777331  .0708445  -1.10  0.273  -.2165856  .0611195
      _cons | 7.391966  6.89299  1.07  0.284  -6.118046  20.90198
-----+-----
      /lnalpha | .5771553  .2800663  2.06  0.039  .0282356  1.126075
-----+-----
      alpha | 1.780965  .4987882  1.028638  3.08353
-----+-----

```

***Regression 2 (RTT VS None)**

```

zinb      real_total_traps18      i.RTT_Nonei.sex_headage_headyearseducation_head      total_Mat_trees2018
family_labouri.MemberCoop2018 percent_KPscore, inflate( i.RTT_Nonebi.sex_headage_head to
> tal_Mat_trees2018 family_labouri.MemberCoop2018 percent_KPscore) robust

```

Fitting constant-only model:

```
Iteration 0:  log pseudolikelihood=  -662.5943
Iteration 1:  log pseudolikelihood = -642.33095
Iteration 2:  log pseudolikelihood = -621.67851
Iteration 3:  log pseudolikelihood = -617.58578
Iteration 4:  log pseudolikelihood = -616.78591
Iteration 5:  log pseudolikelihood = -616.69137
Iteration 6:  log pseudolikelihood = -616.68763
Iteration 7:  log pseudolikelihood = -616.68761
```

Fitting full model:

```
Iteration 0:  log pseudolikelihood = -616.68761
Iteration 1:  log pseudolikelihood = -615.39448
Iteration 2:  log pseudolikelihood = -608.67712
Iteration 3:  log pseudolikelihood = -608.05125
Iteration 4:  log pseudolikelihood = -607.98336
Iteration 5:  log pseudolikelihood = -607.98221
Iteration 6:  log pseudolikelihood = -607.98221
```

Zero-inflated negative binomial regression

Number of obs = 420

Nonzero obs = 16

Zero obs = 252

Inflation model = logit Wald chi2(8) = 22.49

Log pseudolikelihood = -607.9822 Prob> chi2 = 0.0041

```

-----+-----
                |               Robust
                |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----+-----
real_total_traps18 |
RTT_None |
Received trap and training |   .2276201   .1961773    1.16   0.246   -.1568803   .6121206
sex_head |
Male |  -.2996061   .2997683   -1.00   0.318   -.8871411   .2879289
age_head|  -.0062475   .0134745   -0.46   0.643   -.032657    .020162
yearseducation_head |   .0099056   .0527891    0.19   0.851   -.0935591   .1133704
    total_Mat_trees2018 |   .0108948   .0032108    3.39   0.001   .0046018   .0171879
family_labour |   .0395122   .0395677    1.00   0.318   -.0380391   .1170636
                |
    
```

```

MemberCoop2018 |
Yes | .0646646 .3618432 0.18 0.858 -.644535 .7738642
percent_KPscore| -.0035046 .0061408 -0.57 0.568 -.0155403 .0085312
      _cons | .9607545 1.210933 0.79 0.428 -1.412631 3.33414
-----+-----
inflate |
RTT_None |
Received trap and training | -.2823421 .4457987 -0.63 0.527 -1.156091 .5914072
      |
sex_head |
Male | -.4683339 .8409609 -0.56 0.578 -2.116587 1.179919
age_head| -.0254221 .0270033 -0.94 0.346 -.0783476 .0275033
      total_Mat_trees2018 | .0019597 .0060654 0.32 0.747 -.0099283 .0138477
family_labour | .1256943 .0966802 1.30 0.194 -.0637954 .3151839
      |
      MemberCoop2018 |
Yes | -1.840845 1.22848 -1.50 0.134 -4.248621 .5669307
percent_KPscore | -.026706 .0159648 -1.67 0.094 -.0579965 .0045845
      _cons | 2.975719 1.991474 1.49 0.135 -.927497 6.878936
-----+-----
      /lnalpha | .0619566 .533755 0.12 0.908 -.9841839 1.108097
-----+-----
      alpha | 1.063916 .5678705 .3737441 3.02859

```

***Regression 3 (RTrain_None)**

```
zinb      real_total_traps18      i.RTrain_Nonei.sex_headage_headyearseducation_head      total_Mat_trees2018  
family_labouri.MemberCoop2018      percent_KPscore,      inflate(      i.RTrain_Nonebi.sex_headage_head  
total_Mat_trees2018 family_labour i.MemberCoop2018 percent_KPscore) robust
```

Fitting constant-only model:

```
Iteration 0:  log pseudolikelihood = -650.05156  
Iteration 1:  log pseudolikelihood=  -633.8788  
Iteration 2:  log pseudolikelihood = -598.75583  
Iteration 3:  log pseudolikelihood = -595.00341  
Iteration 4:  log pseudolikelihood=  -594.7015  
Iteration 5:  log pseudolikelihood = -594.68733  
Iteration 6:  log pseudolikelihood = -594.68725  
Iteration 7:  log pseudolikelihood = -594.68725
```

Fitting full model:

```
Iteration 0:  log pseudolikelihood = -594.68725  
Iteration 1:  log pseudolikelihood = -586.66398  
Iteration 2:  log pseudolikelihood = -583.83074  
Iteration 3:  log pseudolikelihood = -583.75514  
Iteration 4:  log pseudolikelihood = -583.75453  
Iteration 5:  log pseudolikelihood = -583.75453
```


Zero-inflated negative binomial regression

Number of obs = 404

Nonzero obs = 162

Zero obs = 242

Inflation model = logit Wald chi2(8) = 24.28

Log pseudolikelihood = -583.7545 Prob> chi2 = 0.0021

```
-----
```

	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
real_total_traps18						
RTrain_None						
Received training	.411549	.196752	2.09	0.036	.0259221	.7971758
sex_head						
Male	.3613406	1.138047	0.32	0.751	1.869191	2.591873
age_head	.0118995	.0076047	1.56	0.118	.0030055	.0268045
yearseducation_head	.0347922	.0203999	1.71	0.088	.0051909	.0747752
total_Mat_trees2018	.0036053	.0030289	1.19	0.234	.0023313	.0095418
family_labour	-.0380622	.0391576	-0.97	0.331	.1148096	.0386853

```
-----
```

```

MemberCoop2018 |
Yes | .1754747 .2321433 0.76 0.450 .2795177 .6304672
percent_KPscore | .0014023 .0057986 0.24 0.809 .0099628 .0127674
      _cons | -.5505676 1.303093 -0.42 0.673 3.104584 2.003449
-----+-----
inflate |
RTrain_None |
Received training | -.2042764 .3634508 -0.56 0.574 .9166269 .508074
sex_head |
Male | -.9929215 1.311444 -0.76 0.449 3.563305 1.577462
age_head| -.0011029 .0145347 -0.08 0.940 .0295905 .0273847
total_Mat_trees2018 | -.00086 .0034655 -0.25 0.804 .0076523 .0059323
family_labour| -.0042673 .0838968 -0.05 0.959 .168702 .1601674
      |
      MemberCoop2018 |
Yes | -.7607538 .703464 -1.08 0.280 2.139518 .6180102
percent_KPscore| -.0364326 .0103581 -3.52 0.000 .0567341 -.0161312
      _cons | 3.924225 1.539649 2.55 0.011 .9065678 6.941882
-----+-----
      /lnalpha| -.3251249 .3203531 -1.01 0.310 .9530055 .3027557
-----+-----
      alpha | .7224371 .231435 .3855804 1.353584
-----+-----

```

Appendix I: DiD Model (Mango Production Loss)

Notes:

***Regression 1 (RTT VS RTrain)**

regreal_fruitflyloss

time##RTT_RTrainsex_headage_headyearseducation_headMaturetreesfamily_labourpercent_KPscore total_traps18,

r

Linear regression

Number of observations = 654

F(10, 643) = 30.43

Prob> F = 0.0000

R-squared = 0.3149

Root MSE = 12.741

```

-----
                |
real_fruitflyloss |          Coef.   Std. Err.      Robust
                  |          t      P>|t|      [95% Conf. Interval]
-----+-----
                |
1.time           | -11.70561   1.547257   -7.57   0.000   -14.74389   -8.667318
                |
    
```

```

RTT_RTrainb |
  Received trap and training | 5.332484 1.64588 3.24 0.001 2.100536 8.564433
                                |
time#RTT_RTrainb |
1#Received trap and training | -8.068795 1.996584 -4.04 0.000 -11.98941 -4.148182
                                |
sex_head | .9328687 2.005208 0.47 0.642 -3.004679 4.870416
age_head | .0227359 .0442959 0.51 0.608 -.0642462 .109718
yearseducation_head | .0722029 .0567967 1.27 0.204 -.0393266 .1837324
Maturetrees | .0129027 .0111924 1.15 0.249 -.0090753 .0348807
family_labour| -.0928053 .2715506 -0.34 0.733 -.6260385 .4404279
percent_KPscore| -.0262304 .0270108 -0.97 0.332 -.0792704 .0268097
      total_traps18 | -.085948 .1578567 -0.54 0.586 -.395925 .2240289
      _cons | 27.679 3.384072 8.18 0.000 21.03384 34.32417

```

***Regression 2 (RTT VS NONE)**

```

regreal_fruitflyloss time##
RTT_Nonesex_headage_headyearseducation_headMaturetreesfamily_labourpercent_KPscore total_traps18, r
Linear regression
Number of observations = 848

```

F(10, 837) = 39.34
 Prob> F = 0.0000
 R-squared = 0.2929
 Root MSE = 13.11

```

-----
                |
real_fruitflyloss |          Coef.   Std. Err.      Robust
                |          t      P>|t|      [95% Conf. Interval]
-----+-----
                |
                |          1.time |   -13.43052    1.23518   -10.87    0.000   -15.85493   -11.0061
                |
RTT_Noneb |
  Received trap and training |   2.384024    1.478373    1.61    0.107   -0.5177294    5.285777
                |
time#RTT_Noneb |
1#Received trap and training |   -6.894359    1.820701   -3.79    0.000   -10.46803   -3.320684
                |
sex_head |   -2.64887    2.008059   -1.32    0.187   -6.590293    1.292553
age_head |    .0571145    .0394181    1.45    0.148   -0.0202554    .1344844
yearseducation_head |    .0673236    .0555684    1.21    0.226   -0.0417462    .1763934
Maturetrees |    .0097971    .0174329    0.56    0.574   -0.0244202    .0440143
family_labour |   -0.137108    .2630442   -0.52    0.602   -0.6534118    .3791958
percent_KPscore |   -0.006875    .0230442   -0.30    0.766   -0.0521063    .0383563
                |
                |   total_traps18 |   -0.2388797    .183342   -1.30    0.193   -0.5987437    .1209843
  
```

_cons | 31.90748 3.16413 10.08 0.000 25.69692 38.11804

***Regression 3 (RTrain VS None)**

regreal_fruitflyloss

time##RTrain_Nonesex_headage_headyearseducation_headMaturetreesfamily_labourpercent_KPscore

total_traps18,r

Linear regression

Number of obs = 818

F(10, 807) = 22.69

Prob> F = 0.0000

R-squared = 0.2125






Root MSE = 13.168

```

-----
                |
                |           Robust
real_fruitflyloss |   Coef.   Std. Err.   t   P>|t|   [95% Conf. Interval]
-----+-----
                |
                |
                |           1.time |   -12.89546   1.240938   -10.39   0.000   15.33131   -10.45961
                |
RTrain_Noneb |
  Received training |   -2.542522   1.511634   -1.68   0.093   5.50972   .424675
                |
time#RTrain_Noneb |
1#Received training |   1.367404   1.873803    0.73   0.466   2.310698   5.045507
                |
sex_head |   2.566604   1.924601    1.33   0.183   1.21121   6.344419
age_head |   .0405785   .0441402    0.92   0.358   .0460648   .1272217
yearseducation_head|  -.1148426   .1157252   -0.99   0.321   .3420006   .1123154
Maturetrees |   .0145829   .0112297    1.30   0.194   .00746   .0366257
family_labour|  -.4005771   .2565279   -1.56   0.119   .9041178   .1029636
percent_KPscore|  -.0365366   .0240284   -1.52   0.129   .0837021   .0106289
  total_traps18 |  -.3011022   .1714107   -1.76   0.079   .6375656   .0353611
    _cons |   32.02371   3.139535   10.20   0.000   25.86109   38.18633
-----

```

Appendix J: NACOSTI Research Permit

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This is to Certify that Miss.. Stephie Mwangi of Egerton University, has been licensed to conduct research in Elgeyo-Marakwet on the topic: Economic Assessment of Training and Use of Integrated Fruit Fly Management Strategy among Mango Farmers in Elgeyo Marakwet, Kenya for the period ending : 07/January/2021.	
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Appendix K: Publication Abstract

Impact of Training Mango Farmers in Kenya on Integrated Pest Management Uptake:

Evidence from A Randomized Controlled Trial

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Abstract

This study evaluates the impact of training mango growers in Kenya in Integrated Pest Management (IPM) using a Randomized Controlled Trial (RCT). We compare farmers' knowledge and perception about fruit fly IPM, the adoption of the IPM, and mango production losses among three categories of farmers: Trained only, who receive fruit fly training; trained and IPM, who receive fruit fly training and start-up IPM materials; and ordinary farmers (control). We find that farmers who received fruit fly IPM training and start-up IPM materials had a significant improvement in their knowledge and perception of IPM. They also had a substantial reduction in mango production loss caused by fruit flies than those who received training only and the control group. Those who only received training did not have a significant increase in their knowledge and perception towards IPM, nor a decline in mango production loss compared to the control group. This suggests that training alone may not bring the anticipated impact unless combined with hands-on experience with IPM technologies. However, farmers who received training and IPM materials, and those who only received training demanded more fruit fly IPM technologies than the control group, implying that raising awareness and knowledge are instrumental in creating demand for IPM technologies.

Keywords: *Randomized controlled trial, Mango fruit fly, Training, Mango production, Adoption, Integrated Pest Management*