Kenyan Vegetable Farmers' IPM adoption: barriers and impacts

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ABSTRACT

This thesis analyzes factors affecting adoption of integrated pest management (IPM) techniques by Kenyan vegetable farmers, including the role of their risk preferences. It also analyzes factors affecting their pesticide applications and expenditures. A survey was administered to 450 Kenyan vegetable growers to identify their pest management practices, and a behavioral experiment was run to elicit their risk preferences utilizing. Cumulative Prospect Theory. Loss aversion was found to be correlated with higher likelihood of IPM adoption while risk aversion was associated with higher pesticide application rates and expenditures. The influence of IPM adoption on pesticide use differed by IPM technique.

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GENERAL AUDIENCE ABSTRACT

Integrated Pest Management (IPM) techniques can improve small holder farmers' livelihoods by lowering production costs and decreasing dependence on chemical pesticides. Even though some IPM techniques have been available to Kenyan vegetable farmers since the 1990's, IPM adoption remains relatively low while chemical pesticide use remains high. A farm-household survey and behavioral experiment were conducted to identify factors that influence farmer decisions to adopt IPM and to apply pesticides. Factors that influence IPM adoption were found to differ from those that influence pesticide decisions. Furthermore, IPM adoption by Kenyan farmers does not decrease use of chemical pesticides for all IPM techniques.

DEDICATION

I dedicate this work to my loving wife and family who supported me during every step of the journey.

ACKNOWLEDGEMENTS

I am grateful to my advisor Dr. George Norton, my committee members Jeff Alwang and Brad Mills, and my fellow student colleagues' instruction and guidance throughout my research.

TABLE OF CONTENTS

Chapter 1. Introduction

Sub-Saharan Africa's economic progress has been a focal point for international development agencies for decades. Billions of dollars of development aid have been targeted at the region for micro finance and entrepreneurship, environmental conservation, gender equality, education, sanitation, nutrition, health, political systems, trade, infrastructure, communication, agriculture, etc. (Ndikumana and Pickbourn 2017; World Bank 2018; Thirtle and Lin 2003). Progress has been made in recent years and is reflected in many areas such as literacy, agricultural development, and poverty. For many countries in Sub-Saharan Africa, agricultural production plays an important role in income generation, subsistence and nutrition. Considerable foreign assistance attention in recent decades has focused on Kenya's agricultural development, with programs such as USAID's Feed the Future being a good example (World Bank 2018).

The importance of Kenyan agriculture to the country's development and stability is multifaceted. With over 75% of Kenyans working at least part time in agriculture, and 75% of agricultural output derived from small scale, rain-fed production, the development of rural areas has been focal point for many development projects (World Bank 2018). The current population of 50 million, population growth rate of 1.57 percent, and dependency ratio of 78.3 percent poses a major challenge for Kenya's development. The country's vulnerability to economic shocks shows the immediate need to improve both agricultural and non-agricultural sectors. Especially during times of extended drought, such as 2008-2013, the high dependency ratio causes increased food insecurity and heavy reliance on international aid. International support has increased in recent years, and in 2019 the U.S. alone contributed $102.1 million dollars and 43,325 MT of food (USAID 2020). Furthermore, Kenya's high population growth rate has caused land parcels in areas of high productivity to shrink in size, pushing new farms to marginal lands, limiting the productivity of farmers, and contributing to the vulnerability of Kenyans (FAO 2012; Peter and Bukachi 2018). However, progress has been made since 2005, and Kenya has seen the proportion of its population living below the national poverty line, $1.90 a day, fall from 46.8 to 36.1 percent (World Bank 2018). Kenya's agricultural development will continue to be an integral part of the country's success.

Kenya's horticultural sector continues to be a major contributor to nutrition, income generation, and exports for the country (Kabaluk 2010; CARE 2016). Overall, the sector contributes the highest share of agriculture's GDP, with commercial large-scale operations dominating the export sector while domestic markets are supplied by small scale producers that account for 80 percent of all growers. Yet, the productivity and marketability of the country's horticultural sector has considerable room for improvement. Specifically, the industry is characterized with low fertilizer use, high crop losses, overuse of pesticides, and a changing dynamic of pests affecting horticulture in Kenya (Midega and Murage 2016; Datta and Mullainathan 2014; EAVCIPM-IL report; Peter and Bukachi 2018; CARE 2016). Integrated Pest Management (IPM) is a solution that can address some of these challenges and is actively being disseminated in Kenya.

IPM is a pest treatment portfolio of chemical, biological, and cultural pest management techniques that can be used to minimize pesticide use and reduce production costs to the farmer (Sparger and Alwang 2011**;** Carrión Yaguana and Alwang 2016; Lagnaoui and Santi 2004; Gautam and Schreinemachers 2017; Larochelle and Alwang 2017; Orr and Ritchie 2004; De Groote and Vanlauwe 2010; Abtew and Niassy 2016; Macharia and Ndegwa 2009; Parsa and Morse 2014). IPM programs began in southeast Asia in the 1980's with rice production and made their way to Africa in the early 1990's with assistance from the International Centre for

Insect Physiology and Ecology (ICIPE) (Bekele and Mithöfer 2011) and additional support from FAO and USAID. Studies have shown that reducing pesticide use through IPM adoption can lead to health benefits, reductions in pesticide resistance, and environmental conservation: improved biodiversity, soil quality, water quality (Abtew and Niassy 2016; Parsa and Morse 2014). However, as the data show, IPM adoption is not widespread world-wide. Adoption of IPM techniques by farmers depends on a variety of factors that make their farms unique (Carrión Yaguana and Alwang 2016; Orr and Ritchie 2004; Parsa and Morse 2014). Farm size, crops cultivated, type of production, household demographics, climate, distance from inputs and markets, credit restrictions, access to extension, time constraints, risk preferences, social networks is a non-exhaustive list that can contribute to a farmers' decisions to adopt, postpone adoption, or reject IPM techniques (Parsa and Morse 2014; Lagnaoui and Santi 2004).

The East African Vegetable Crop IPM Innovation Lab (EAVCIPM-IL) project was established to induce technology development in the *Feed the Future* priority areas in Tanzania, Ethiopia, and Kenya. The objective of the project is to work with local delegates to advise national and regional policy for agricultural technology development that is locally adaptable, gender-appropriate, reduces environmental degradation, and improves producer welfare. IPM techniques that meet the criteria set by the EAVCIPM-IL have been regionally adapted and actively disseminated since 2015. The priority crops for the program are tomato, onion, African eggplant, cabbage, chilies, and beans. The program was implemented in three countries with region specific objectives.

This study will focus on the crops and IPM technologies promoted by the EAVCIPM-IL in Kenya and evaluate the factors affecting adoption by Kenyan farmers. The Kenyan IPM techniques that were introduced in the region were tailored to cabbage, tomatoes, and French beans in vegetable producing areas around Mount Kenya. The priority crops were identified by the program during the initial year of the program with support from EAVCIPM-IL partner Kenyan Agriculture and Livestock Research Organization (KALRO). KALRO is a Kenyan led research organization established by the Kenya Agricultural and Livestock Research Act of 2013 to "establish suitable legal and institutional framework for coordination of agricultural research in Kenya." (Kenya 2014). The crops are susceptible to a wide range of pests, are grown extensively in Kenya under a variety of conditions, are a source of critical income for small-scale farmers, highly nutritional, and show new dynamics of pests affecting them. The changing pest dynamics, as stated by the program, has led to increased crop losses, synthetic pesticide use, pesticide resistance, production costs, and human exposure to pesticides, and a reduction in bio-diversity. The IPM techniques advocated by the program are the use of pest-resistant plant varieties (PRV), healthy seeds/sanitizing seed treatments, solarization, starting seedlings in growing trays, nursery nets to protect plants, removing damaged plants from fields, yellow sticky traps, microbial pesticides, bio-pesticides, Trichoderma, and mulching.

The underlying problem is that the IPM techniques advocated by the EAVCIPM-IL program have had a low adoption rate in the region, at least as indicated by the 2016 baseline survey. The critical question is whether adoption remains low in the region and why. A follow-up questionnaire was deployed June 2019 and tailored to understand the factors of IPM adoption and effects of adoption on pesticide use.

1.1 Significance and objectives of research

The agriculture technology adoption literature is large. A question that is commonplace for development agencies is: How are we going to meet the food demand of future populations with current land and water resource scarcities? One answer is to increase farmers' productivity by developing and disseminating agricultural technologies tailored to regional needs. However, as the literature shows, dissemination of productive technologies is not simple and poverty traps can inhibit development and speed of adoption of new productive technologies? Poverty traps are mechanisms that prevent the impoverished from earning enough capital to escape poverty. Restrictions that the literature identifies as sources for poverty traps are market inefficiencies in labor, land, credit, information, and human preferences such as risk aversion (Tanaka and Camerer 2010; Kostandini and Mills 2011; Foster and Rosenweig 2010; Dorward and Kydd 2004; B. Kelsey Jack 2013). The research presented here will add to this literature and add a new perspective on the factors affecting agricultural technology adoption in rural Kenya.

Few publications identify both social learning networks and risk preferences as factors affecting agricultural technology adoption. That being said, the impact that social networks have on agricultural technology adoption is not revolutionary and received increased attention over the years (Munshi 2004; Bandiera and Rasul 2006; Conley and Udry 2010; Maertens and Barret 2013). Additionally, Liu 2013, Shimamoto and Yamada 2018, and Schleight and Gassmann 2018 published research that elicited risk parameters, which they included as a factor affecting technology adoption. Only Schleight and Gassman used a variable that could capture social network effects on adoption. However, the research focused on adoption of energy efficient technologies in the EU. The primary objective of the current study is to identify the factors that influence Kenyan vegetable farmers' IPM adoption. There are six additional sub-objectives:

Sub-Objective 1

Assess the current state of adoption of vegetable IPM practices in eastern Kenya and whether adoption has increased over the life of the EAVCIPM-IL project.

Sub-Objective 2

Determine whether risk preference affects the level of vegetable IPM adoption

Sub-Objective 3

Determine whether risk preference affects pesticide use on vegetables

Sub-Objective 4

Determine whether IPM training reduces the number of seasonal vegetable pesticide applications

Sub-Objective 5

Determine whether farmer's trust towards people in general, agricultural extension officers, and agricultural input salespeople affects IPM adoption

Sub-Objective 6

Determine whether farmer's trust towards people in general, agricultural extension officers, and agricultural input salespeople is a factor in total pesticide application count and total pesticide expenditures

Hypotheses

Hypothesis 1: Vegetable IPM adoption in Eastern Kenya has not increased from 2016 to 2019.

Hypothesis 2: Risk averse farmers will adopt more vegetable IPM practices than risk neutral or preferring farmers.

Hypothesis 3: Risk averse farmers will have more pesticide applications on vegetables than risk neutral or preferring farmers.

Hypothesis 4: Risk averse farmers will spend more on pesticides for vegetables than will risk neutral or risk preferring farmers.

Hypothesis 5: Farmers who place higher values on prospects with higher probability will adopt fewer IPM practices than farmers who place more value on prospects with lower probability.

Hypothesis 6: Farmers who place higher values on prospects with higher probability will apply pesticides more times than farmers who place more value on prospects with lower probability.

Hypothesis 7: Farmers who place higher values on prospects with higher probability will have higher pesticides expenditures than farmers who place more value on prospects with lower probability.

Hypothesis 8: Loss averse farmers will adopt more vegetable IPM practices than loss neutral or loss preferring farmers.

Hypothesis 9: Loss averse farmers will make more pesticide applications than farmers who are loss neutral or loss preferring.

Hypothesis 10: Loss averse farmers will have higher pesticide expenditures on vegetables than farmers who are loss neutral or loss preferring.

Hypothesis 11: Farmers who have received more IPM training will apply less pesticides than farmers with less IPM training

Hypothesis 12: Farmer's trust in people in general does not affect IPM adoption

Hypothesis 13: Farmer's trust people in general does not affect the number of pesticide applications or pesticide expenditures

Hypothesis 14: Farmers who trust agricultural extension officers in general will adopt more IPM techniques than farmers who do not

Hypothesis 15: Farmers who trust agricultural extension officers in general will have fewer pesticide applications and lower pesticide expenditures than farmers who do not

Hypothesis 16: Farmers who trust agricultural salespeople in general will adopt fewer IPM techniques than farmers who do not

Hypothesis 17: Farmers who trust agricultural salespeople in general will apply more pesticide applications and have higher pesticide expenditures than farmers who do not

Hypothesis 18: Farmers from Tharaka-nithi adopt more IPM techniques than farmers from Kirinyaga and Nyeri.

Hypothesis 19: Farmers from Tharaka-nithi do not apply more pesticides than farmers from Kirinyaga and Nyeri.

Hypothesis 20: Farmers from Tharaka-nithi do not have more pesticides expenditures than farmers from Kirinyaga and Nyeri.

Chapter 2. Background on technology adoption

When agricultural technologies are disseminated, they must have a selling point that justifies their adoption by farmers. Promises of higher yields, lower production risk, lower health risk, better quality, lower costs, and or reducing environmental problems are selling points that can influence farmers to consider a technology or change intensity of use if the technology is already being utilized. However, new unfamiliar technologies may come with high risks since it is uncertain that the productivity of the technology will meet the promises of the salesperson. Some farmers will accept the risk and adopt them, placing their trust in the word of the individual or organization providing the product. Perhaps this trust originates from previous experiences the farmer has had purchasing products from the salesperson, or perhaps it is not trust that influences adoption but rather an ambitious entrepreneur eager to find the next best practice and willing to accept the risk ahead of his or her competitors. In either situation, if the technology truly is new to the farmer, before adopting they should know the full risk that adoption poses and the challenges that could lie ahead; i.e. market preferences, susceptibility to drought, pest resistance, input requirements, etc. Each farmer must assess the technology's potential benefits, costs, and production constraints before making a change in their production. However, to even arrive at this point of consideration the necessary conditions are that the product or practice be known and available to the farmer. Market inefficiencies that limit these necessary conditions will be addressed following the conceptual framework that models the adoption decision.

2.1 Conceptual Framework

The decision to make changes to a farm management plan can be portrayed using a utility framework in which the farmer maximizes expected utility from consumption of material and non-material goods and services (Moser and Barrett 2006). The farmer's agricultural production is assumed to be the sole source of income and the reference point for the decision to change the farm management plan will be the farmer's current level of wealth. The model portrays the farmer's decision process, where they select levels of choice variables with the objective of maximizing expected utility (EU) of material and non-material consumption subject to idiosyncratic constraints. This decision has been modeled many times previously, adding additional dynamics with each round of research (Pope and Just 1977; Antle 1989, Hurd 1994; Staal and Baltenweck 2002). Each study assumes that the farmer is trying to maximize expected utility subject to his or her production constraints and preferences. The general model, tailored to represent a decision between two crop varieties, is presented below. This model could be expanded to capture the decision to use various IPM technologies versus their conventional counterparts, or to apply more/less pesticides.

$Max_c\, EU(Y)\ s.t. [X_i, Z_i, L_i, K_{ic}(X_i, Z_i, L_i)]$……………………………………………….(1)

Equation 1 illustrates farmer *i's* production decision where expected utility is being maximized by selecting crop variety, *c,* to be planted on all of farmer *i's* arable land, in order to generate income, *Y*. The farmer's agricultural production is assumed to be their only source of income, while income is converted to utility through consumption of material and non-material goods. Expected utility of *Y* is a function of expected mean yield of crop *c* and variance of expected mean yield subject to expectations of *c's* productivity given the farmer's endowment of land X_i, exogenous factors Z_i (e.g. soil characteristics, pest intensity, weather, prices of commodities and inputs, proximity to other adopting farmers, etc.) and family labor L_i. The last variable $K_{i,c}(X_i, Z_i, L_i)$ is the farmer's knowledge of the variety, which shapes expectations of how the crop should perform on their farm in various growing scenarios. Similar to Moser and Barret, the model assumes that knowledge of crops, $K_{i,c}$, can only increase and not be reduced. Knowledge in this sense is used to determine expected utility, or the expected yield of crop$_c$, for all growing conditions.

Suppose that *c* represents two possible choices Rambo and Commando, two varieties of tomatoes cultivated in Kenya.

$EU_{Rambo} = \sum_0^N U(Y)\ s.t. \left[X_i, Z_i, L_i, K_{i,Rambo}(X_i, Z_i, L_i)\right]$..(2)

$EU_{Commando} = \sum_0^N U(Y) s.t. [X_i, Z_i, L_i, K_{i,Commando}(X_i, Z_i, L_i)]$ ....(3)

The expected utility of each crop's outcome for each possible growing scenario (i.e. quality of growing season is summed, with *N* possibilities. The farmer's decision of which crop to plant would be determined by the crop that yields the highest expected utility. If the Rambo variety's expected utility is higher than Commando's and is planted this year, that does not imply that Rambo will be planted instead of Commando every year. The farmer can choose to reject Commando entirely or choose to postpone adoption until they are certain the variety's expected utility exceeds that of Rambo's. Postponing adoption allows farmers to circumvent the risk associated with early adoption of an unfamiliar technique and gather information on the technology that will be utilized in the decision process for the next cropping season.

A 1957 paper by Zvi Griliches analyzed the adoption rate distribution of hybrid corn in the U.S. He assumed an S-shaped pattern of adoption (Griliches 1957). The exact shape of diffusion was linked to regional characteristics of the mid-western states such as profitability, communication, risk aversion, and other economic factors (Feder, Just, and Zilberman 1985). These same factors that served as a barrier to adoption in the U.S. have also been identified as challenges facing technology adoption in developing countries. B. Kelsey Jack (2013) provides a detailed review of the agriculture technology adoption literature in developing countries and identifies seven market inefficiencies that can limit diffusion of technologies.

1. Externalities
2. Input and output market inefficiencies
3. Land market inefficiencies
4. Labor market inefficiencies
5. Credit market inefficiencies
6. Informational inefficiencies
7. Risk market inefficiencies

Our study will focus on informational inefficiencies and risk market inefficiencies as they apply to decisions by Kenyan horticulture producers to adopt IPM techniques.

2.2 Social Learning Network

One of the assumptions for perfect markets is that there is perfect information. In reality we know that perfect information often if not always falls short regardless of the market. For IPM dissemination in rural Kenya several assumptions are made. Kenyan farmers like other farmers operate under uncertainty, whether it's about future input and commodity prices or the weather in the upcoming growing season. In order to make changes to the existing farm management plan, the farmer gathers information about the agricultural practice under consideration before making a decision. Sources of information flow from the farmers' on-farm trials and the sources in their social network such as friends/neighbors, family, agricultural extension officers, agricultural input suppliers, research organizations, etc. (Munshi 2004; Maertens and Barrett 2012).

Going back to the previous example of a farmer's decision between two tomato varieties, suppose that *c* represents two possible choices Rambo (equation 4) and Commando (equation 5).

$$EU_{Rambo} = \sum_0^N U(Y) \; s.t. \left[X_i, Z_i, L_i, K_{i,Rambo}(X_i, Z_i, L_i)\right] \quad (4)$$

$$EU_{Commando} = \sum_0^N U(Y) s.t. \left[X_i, Z_i, L_i, K_{i,Commando}(X_i, Z_i, L_i)\right] \quad (5)$$

The expected value of each crop is summed for each possible quality of growing season, with N possibilities. The farmer's decision about which crop to plant would be determined by the crop that yields the highest expected utility.

Figure 2.1 visualizes the farmer's decision comparing the expected utility of planting Rambo (blue secant line) to Commando (red secant line) for different income scenarios. The visualization assumes the farmer's only income source is his tomato crop, and the farmer is risk averse. In this depiction there are two expected utility scenarios for each crop, which are represented by the two points that touch the expected utility curve for each secant line. Each secant line, the point with the lowest expected utility represents the expected utility of crop c for a poor-quality growing season, while the point with the highest expected utility represents the expectations of expected utility for a high quality of growing season. The variance of expected utility from income/yield for crop c is represented by the length of the respective secant line. Points A and B represent the expected utility of Rambo and Commando respectively, which are functions of the varieties mean expected income/yield and variance of income/yield. Since point A lies above point B in this scenario, the farmer would choose to plant Rambo over Commando.

Figure 2.1

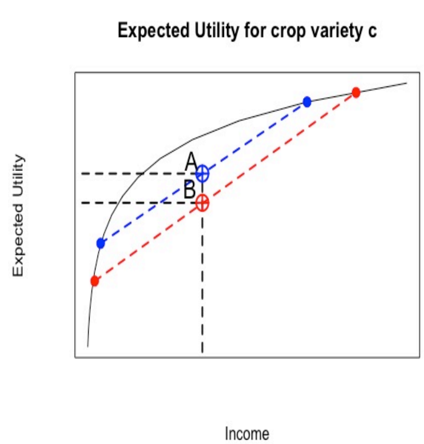
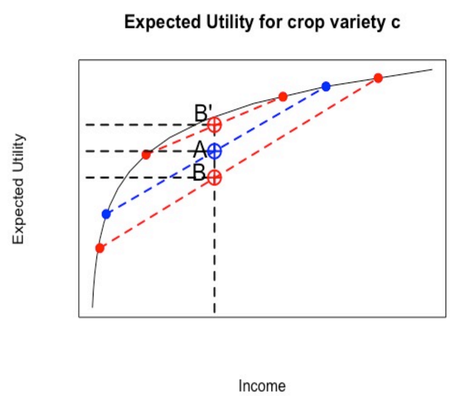


Figure 2.1 shows a much larger variance of expected utility of the Commando variety than Rambo's. The high variance could be due to unfamiliarity with the variety's outcome, which could cause some farmers to postpone adoption until the variance is reduced. Suppose the farmer attends a farmer field day (FFD) led by an agricultural extension officer where they are informed about the benefits and witness a plot of the Commando variety. This information update is depicted in figure 2.2. The new information from the FFD causes a change in $K_{i,Commando}(.)$ which reduces the variance of the expected utility of the variety and updates the expected utility of the Commando variety from B to B`. The farmer in this scenario would choose to plant the Commando variety over the Rambo variety.

Figure 2.2



In this simple model, the expected utility functions were drawn to represent a risk averse farmer, however, the functional form depends on each farmer's preference towards uncertainty. Each farmer has a unique risk preference, and as a result, differences in risk preferences could influence some farmers to adopt the Commando variety in the first scenario when the variance of Commando is high, while others postpone adoption until more information is gathered. Farmer's risk tolerance and how risk preference applies to their adoption decision will be addressed in the subsequent section.

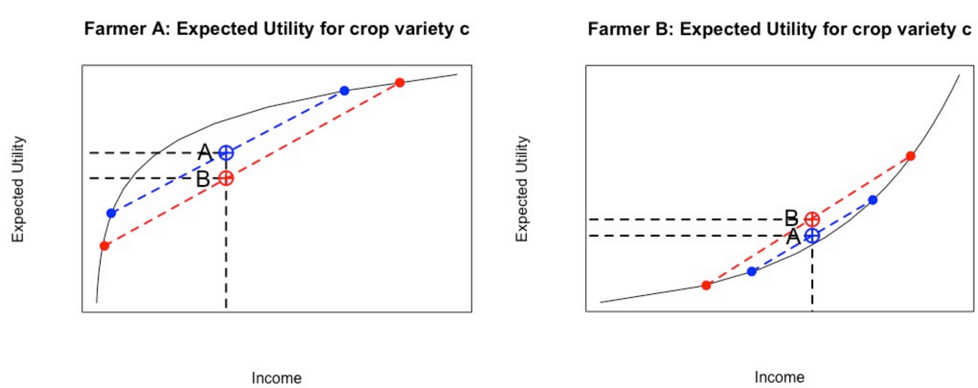
2.3 Risk-Individual Preference Towards Uncertainty

Uncertainty is all around us from the commute to work to the decision about where to travel over the holidays. Nevertheless, we learn to live with uncertainty and rationalize living within a threshold of acceptable risk. Some people are willing to accept more risk than others and risk comes in many forms from dangers inherent in deciding to ride a motorcycle to those associated with starting a business. Both activities involve a certain level of risk but those risks are clearly of different types. The type of risk addressed in this document will focus on income risks from making changes to farm management plans.

Farmers have a variety of factors that make their agricultural operations uncertain. Variability in weather, prices of inputs, commodity prices, and international trade relations all contribute to farmers' production uncertainty. Access to credit, government subsidies, crop insurance, improved crop varieties and improved farm management practices are tools that farmers use to mitigate production risks, yet these tools are not available to all farmers. However, even when the tools are available the agricultural technology adoption literature indicates that adoption rates and the factors influencing them vary by location (Cole and Gine 2013; Parsa and Morse 2014). Konstandini and Mills 2011 identify studies that assess how exposure to risk can establish poverty traps that restrict development and adoption of productive technologies of the rural poor. As the saying goes, if there is no risk there is no reward, but many of the individuals in developing countries live on less than $2 a day and in regions where susceptibility to climate change and violent conflict are high. Consequently, some households without access to financial and agricultural risk mitigation tools are on the tipping point where one mistake could put them in a situation where their household regresses even further into poverty. This vulnerability makes some households reluctant to try new technologies and could be one of the factors influencing the pace of IPM adoption in Kenya.

Going back to the previous example with the two tomato varieties, suppose we have two Kenyan farmers, farmer A and farmer B, who are nearly identical and are considering planting the new Commando variety (red secant line) over a familiar Rambo variety (blue secant line). The farmers have the same farm characteristics, use the same practices, grow the same crops, both trust agricultural extension officers, and even receive the same information. However, even though the farmers are almost identical, farmer B plants the new variety right away while farmer A only adopts the new variety until the uncertainty in the variety's expected utility is reduced. One mechanism that would rationalize this decision is that the two farmers have different preference towards income risk. Figure 2.3 shows how different functional forms of the expected utility function would rationalize the decision to adopt right away, farmer B, or postpone adoption of the new variety, farmer A.

Figure 2.3



Through an international development lens, facilitation of agricultural development could be challenging in regions that are composed of many individuals like farmer A. Researchers over the years have tested the relationship between individuals decisions under uncertainty and technology adoption and have found evidence to support the theory that individual's risk preference, as elicited using Expected Utility Theory (EU) (Binswager 1980; Bocqueho and Jacquet, 2013; Cook 2013) or Cumulative Prospect Theory (CPT), an analog to EU, (Liu 2013; Bocqueho and Jacquet, 2013; Shimamoto and Yamada 2017; Schleich and Gassmann 2019), has inhibited adoption and slowed the pace of development in some communities. However, the literature that combines both the influence of social networks and risk preferences as factors affecting adoption is limited. Programs such as USAID's *Feed the Future* and EAVCIPM-IL Kenya have been working to reduce uncertainty associated with adopting productive agricultural technologies by tailoring the programs to disseminate the relevant knowledge needed to make an informed decision. The results of our analysis may provide information to help improve the speed of technology adoption in developing countries by enhancing the understanding how farmer's information networks and risk preferences effect their adoption process.

In summary, households can be stuck in poverty traps that limit their development, where a household's inability to accept the risk associated with adopting new technologies results in low marginal productivity and limits income generation and savings. With low income, the ability to save is difficult and households become vulnerable to income shocks that cause them to remain in the cycle of poverty. Therefore, if an agricultural technology or system has proven to improve the welfare of adopters, facilitating its adoption should be of the upmost importance for development groups. Due to the financial limitations of development groups, financial resources are often allocated to areas that have the highest social impact. In order to gauge the likelihood of programs to facilitate technology adoption, risk preference of a community or region could be one metric that determines the willingness to accept a technology and the investment needed to facilitate adoption. The work by Kahneman and Tversky (1979 and 1992) provided evidence that

Cumulative Prospect Theory (CPT) is a useful method for improving our understanding of human behavior. The risk parameters that CPT elicit have the ability to provide development groups with insight into their population's behavior under uncertainty. This knowledge may help improve the speed of adoption of agricultural technologies and systems and serve to raise incomes, reduce perceived production uncertainty, and improve resiliency by tailoring dissemination programs and marketing strategies. A comparison of the two leading methods for estimating risk aversion EU and CPT, the risk parameters used in this study, and the behavioral experiment used to elicit the risk parameters are provided in the *Methods* chapter.

Chapter 3. Methods

3.1 Social Learning Network

The agricultural technology adoption literature points to family, friends/neighbors, extension officers, farmer groups, salespeople, and non-governmental organizations as sources of agricultural information for farmers in developing countries (Munshi 2004; Maertens and Barrett 2012; Bandiera and Rasul 2006). Discussions about timing of planting/harvesting, severity of pest infestations, market information, or even observing a neighboring plot and their management practices all influence farmers' decisions. Yet, the confidence that one farmer might place in their agricultural extension officer for agricultural information is likely different than other farmers who are also served by that same officer. Coleman 1990 (as cited in Algan and Cuhuc 2014) defined trust as, 'an individual trusts if he or she voluntary places resources at the disposal of another party without any legal commitment from the latter, but with the expectation that the act of trust will pay off.'. The value that individuals place on an information source is a function of how much trust they have in the source and the quality of information provided. Algan and Cahuc provide a detailed review of the literature on trust, methods used to estimate trust in a survey setting, and how trust relates to development and friction in technology adoption.

Due to the time constraints of farmers and the fact that numerous IPM techniques have been disseminated in Kenya for many years by a multitude of organizations, we posed questions that assessed trust in general sources. An overview of IPM adoption and survey demographics in the region is presented in the results section *4.1. Survey Comparison: 2016 to 2019.*

The following set of questions were asked to understand the relationship between the previously mentioned sources and Kenyan farmers' adoption decisions.

Table 1: Social Learning Network Questions

1. Generally speaking, do you believe that most people can be trusted?
2. Generally speaking, do you believe that most agricultural extension workers can be trusted?
3. Generally speaking, do you believe that most agricultural salespeople can be trusted?

Notes: All responses to the questions were Yes or No

The generalized trust question first posed by Almond and Verba (1963) (as cited in Algan and Cuhuc 2014) gauge individuals trust towards IPM information sources. From the baseline survey and our colleagues in Kenya, the two sources deemed most important for disseminating information about agriculture technologies were extension and agricultural input salespeople. Thus, two specific questions were used to estimate the strength of connection that the farmers place on their information.

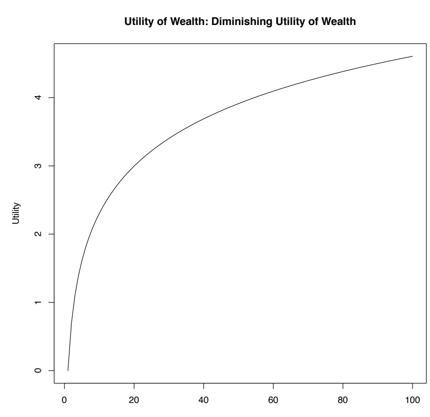
3.2 Risk-Introduction

Two leading methods of risk elicitation have been used to estimate the risk parameters of individuals: Expected utility theory (EU) and Cumulative Prospect Theory (CPT). It is the objective of this section to present the theory behind risk preferences, present the method most suitable for analysis of risk preferences of Kenyan farmers, and identify the impact that those preferences can have on their adoption decisions.

3.3 Early Behavioral Economics Theory

In order to understand theory and advanced economic models related to EU and CPT, it is best to start with the early developments and the assumptions in which the models found traction. The advanced risk elicitation methods took root with the St. Petersburg paradox in which mathematician Daniel Bernoulli proposed that individuals do not consider directly the dollar prizes of a gamble but rather the expected utility from participating in the gamble. Utility in an economic framework is the value an individual receives through his or her consumption of goods (consumable and non-consumable) and leisure. Bernoulli rationalized individuals lack of willingness to pay large amounts of money to participate in the gamble known as the St. Petersburg paradox, which entailed a series of coin flips, by determining that the utility of wealth increases at a decreasing rate as wealth increases as shown in figure 3.1. In other words, marginal utility of wealth decreases at an increasing rate as wealth increases.

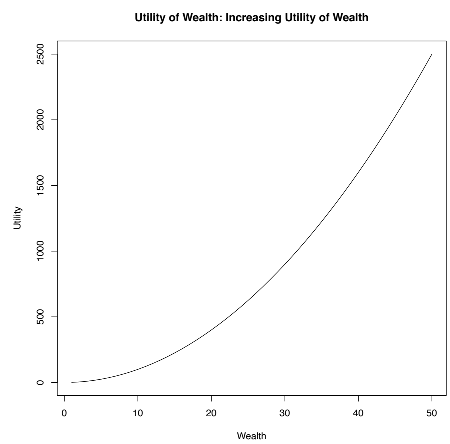
Figure 3.1: Marginal utility of wealth is decreasing at an increasing rate.



Even though the expected monetary value of the Bernoulli's gamble was infinite, the fact that individuals would only pay a finite amount of money to play provided rationalization for his theory. Neumann and Morgenstern continued to build on the Bernoulli's work with their book *The Theory of Games and Economic Behavior*. The book presented the basic axioms of rationality and expected utility maximization theory, which is the basis on which the risk aversion elicitation methods find ground. Utility maximization theory states that individuals will try to maximize their utility through consumption of goods and leisure subject to their budget and time constraints. Although individuals do not receive utility directly from money but rather the goods they purchase with the money, utility functions are often portrayed as a function of wealth rather than goods and leisure to facilitate discussion. Bernoulli's discovery of the curvature of the utility function and Neumann and Morgenstern's utility maximization theory are used to define risk preferences and to rationalize individuals' decisions which is the basis of both EU and CPT (Snyder and Nicholson 2012).

As stated previously, when making a decision, individuals compare the respective expected values of prospects in order to determine the option that is most likely to maximize their utility. A prospect as defined by Kahneman and Tversky as (x_1, $p_{1;}$ …;$x_{n,}$ p_n), where x_i represents the outcome (value) of the prospect and p_i its respective probability such that $p_{1.+}$ p_2+…+ p_n = 1 (In the context of comparing two agricultural practices, p_1 could be the Rambo tomato variety previously mentioned and x_1 its expected value for a certain quality of a growing season). Assuming individuals behave rationally, their subjective utility curves can be estimated by asking participants to select between options of varying probability of outcomes and monetary values or both; which is in fact how both EU and CPT estimate their risk parameters. The estimates that the models derive can be used model an individual's behavioral response to goods with varying levels of uncertainty and value. Their behavioral response towards risk is categorized into three thresholds of risk preference: risk averse, risk neutral, and risk loving. A person who is risk averse, as defined by Nicholson and Snyder, is “an individual who always refuses fair bets” or similarly an individual whose marginal utility of wealth is increasing at a decreasing rate (figure 3.1). A fair bet is where the expected value of a gamble is equal to zero (e.g. coin flip gamble where if heads individual receives $1 and if tails individual pays $1). A person who is risk loving is characterized with the value function portrayed in figure 3.2.

Figure 3.2: Utility of wealth is increasing at an increasing rate.



As figure 3.1 becomes more concave, the individual’s level of risk aversion increases and as figure 3.2 becomes more convex the value that the individual receives from participating in a gamble also increases, as does the individuals risk loving preference. However, the two methods EU and CPT vary greatly in regard to the reference point of the decision process, valuation of prospects, and domain of risk preferences. For these reasons, the two methods rely on different assumptions to rationalize decisions and define the respective risk parameters.

3.4 Expected Utility or Cumulative Prospect Theory

In the 1979 article by Kahneman and Tversky (KT), the assumptions that EU was based on were put to the test. The three assumptions were:

$E[U(x_1, p_{1;} \dots ;x_n, p_n) = p_1u(x_1)+\dots+ p_nu(x_n)]$……………………………………………….…….(6)

$U(w+x_1, p_{1;} \dots ;w+x_n, p_n) > u(w)\dots$ ……………………………………………………….....(7)

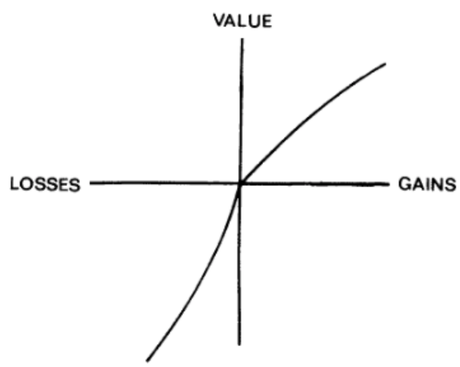
U is concave (u" < 0)………… ……………………………………………... …………….(8)

The first equality (equation 6) shows that the expected value (utility; U) of a prospect is a function of the probability of the respective prospect's outcomes and their subjective utilities. Equality 2 (equation 7) represent the subject's asset integration equality. It states that the subject will accept a prospect if and only if the utility from its consumption plus the utility of their assets (wealth), w, is greater than the utility of their assets alone. The third equality (equation 8) defines risk aversion and the subject is determined to be risk averse if the rate of change of the utility function is decreasing.

Through a series of questions, the KT study asked Israeli students to select between two prospects of varying degrees of uncertainty and payouts. The findings of the KT study determined that some of the tenants underlying EU theory were not consistent with participants' choices in their behavioral experiment. The questions and results of the study relevant to our choice of CPT over EU are shown in the Appendix: *Kahneman and Tversky Behavioral Experiment 1979*. The KT findings are summarized below.

Equation six above indicates that individuals weight the prospects' outcomes solely by their probabilities. However, KT discovered that this principle was consistently violated. They found that individuals overweight outcomes with certainty and small probabilities, which implies that outcomes are weighted not by their probabilities but by decision weights, π_i, where i is an indicator for the decision weights applied to the respective prospects' n outcomes. In order to satisfy stochastic dominance and allow utilization of the weighting function for prospects with many outcomes, the decision weights are normalized such that $\sum_{i=1}^{n} \pi_i$ (Tversky and Kahneman, 1992). Additionally, the KT study discovered further deviation from EU with regard to individuals' reference point used in the decision process. Specifically, they found that individuals' decisions between prospects did not use their final assets as the reference point but rather only the gains and losses of the prospects themselves. Furthermore, KT found that the value function was consistently concave in the domain of gains and convex for losses, while the rate of change of the value function was greater in absolute value in the loss domain than in the domain for gains. They also make the assumption that the value function is centered at zero (the reference point) (figure 3.4).

Figure 3.4: CPT value function



In review, the empirical results suggest that: 1) the value of outcomes are multiplied by their respective decision weights, not their probabilities; 2) the reference point for a decision is not final assets but the values of the prospects; 3) the value function tends to be convex in the domain of losses and concave in the domain of gains, and steeper in the domain of losses than in the domain of gains.

3.5 Cumulative Prospect Theory Methodology

In order to capture the unique characteristics that shape an individual's respective value function and weighting function, which rationalize the individual's preference between prospects, Kahneman and Tversky developed a system of equations. The parameters of interest that define an individual's preferences are σ, λ, and α. For this study, the α parameter will be derived using the Drazen Prelec's method, which has been used consistently in the literature

(Campos-Vazquez and Cuilty 2014; Tanaka and Camerer; 2010, Bocqueho and Jacquet 2013). Their system of equations is presented below, which will be followed by the risk elicitation behavioral experiment.

Equation 9 represents the value of a prospect.

$v(y) + \pi(p)(v(x) - v(y))$ for xy > 0 and |x| > |y| or $v(y) + \pi(p)v(x) + \pi(q)v(y)$……..…(9)

Variables p and q are the probabilities of outcomes x and y, respectively, with values of $v(x)$and $v(y)$. Additionally, a piecewise power function is used to represent the value for each individual in the domain of gains and losses.

Gains $v(x) = x^{\sigma}$ [x > 0]…………………………………………………………(10)

Losses $v(x) = -\lambda(-x^{\sigma})$ [x < 0]…………………………………………………………(11)

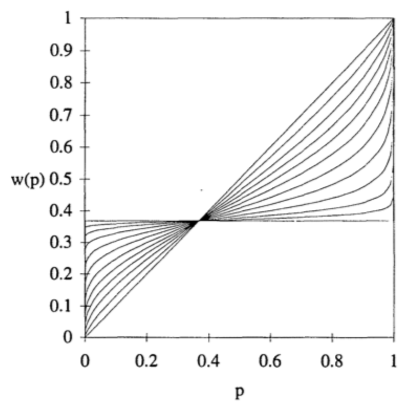
Parameters σ and λ are estimates that identify the concavity of the value function in the domain of gains (degree of risk aversion), and the convexity of the function in the domain of loss (degree of loss aversion). The greater σ the less risk averse an individual is and the less concave the value function is in the domain of gains. The greater λ, the more loss averse an individual is and the more convex the value function is in the domain of loss.

The probability weighting function is

$\pi(p) = [\frac{1}{\exp{(ln\frac{1}{p})}}]^{\alpha}$……………….…………………….……………………..…...………..(12)

Equation 12's is shown in figure 3.5 below with varying values for α. If α = 1, the probability weighting function is linear and the individual would weight decisions solely on the probability of their prospects. If α < 1, the function is an inverted S-shape implying that the individual overweight small probabilities and underweights large probabilities and conversely if α > 1.

Figure 3.5: Drazen Prelecs' weighting function.



The three Series used in the behavioral experiment for this study are presented in figure 3.6 below. The values of the respective options are based on the monthly earnings of Kenyan farmers and are most similar to the percentages of monthly income used in the Tanaka CPT experiment in Vietnam. It is important to note that during the actual experiment the column titled expected payout was not shown. However, it is depicted here to show that the expected payoffs of the prospects are decreasing as we go down in the series for Series 1 and 2 and increasing in expected payoffs for Series 3. Each row represents a choice to participate in the gamble presented in Option A or Option B. Participants were asked to identify the row where they would "switch" from participating in the gamble presented in Option A to Option B. This switching point is used to determine the parameters of interest. The switching points of Series 1 and Series 2 mutually determine parameters α and σ by the intersection of the combination possibilities of the two parameters that rationalize the individual's decision. For example, suppose an individual switches in Series 1 and Series 2 at the seventh question. For both series this implies that the subjective value of Option A question 6 is greater than the value of Option B question 6 and that in all following rows the value of Option A is less than that of Option B for that individual. The non-linear system of equations would use equations 9, 10, and 12 to determine all combinations of α and σ that would satisfy the system of equations. Each series switching point creates two equations with two unknowns, the parameters of interest. The union of parameters that satisfy the inequalities for the participant's switching point in Series 1 and Series 2 determines that individual's α and σ, which defines the uniqueness of their utility function in the domain of gains. The same process is used for determining λ, however the solution uses equations 9, 10, 11, and 12.

Figure 3.6: Behavioral Experiment Kenya 2019

Behavioral Experiment: Revealed Choice					
			Series 1		
	Option A		Option B		
	30%	70%	10%	90%	Expected payoff
1	300	70	500	35	57.41
2	300	70	550	35	52.41
3	300	70	600	35	47.41
4	300	70	650	35	42.41
5	300	70	750	35	32.41
6	300	70	850	35	22.41
7	300	70	1000	35	7.41
8	300	70	1300	35	-22.59
9	300	70	1550	35	-47.59
10	300	70	2000	35	-92.59
11	300	70	3000	35	-192.59
12	300	70	4000	35	-292.59
13	300	70	7000	35	-592.59
14	300	70	12000	35	-1092.59
			Series 2		
	Option A		Option B		
	90%	10%	70%	30%	Expected payoff
1	300	200	380	35	14
2	300	200	400	35	-1
3	300	200	420	35	-15
4	300	200	440	35	-29
5	300	200	480	35	-57
6	300	200	520	35	-85
7	300	200	560	35	-113
8	300	200	600	35	-141
9	300	200	680	35	-197
10	300	200	760	35	-253
11	300	200	840	35	-309
12	300	200	940	35	-379
13	300	200	1040	35	-449
14	300	200	1200	35	-561
			Series 3		
	Option A		Option B		
	50%	50%	50%	50%	Expected payoff
1	180	30	210	-150	75
2	30	30	210	-150	0
3	10	30	210	-150	-10
4	10	30	210	-110	-30
5	10	60	210	-110	-15
6	10	60	210	-100	-20
7	10	60	210	-80	-30

3.6 CPT Behavioral Experiment Implementation

The literature shows that monetary versus theoretical incentives, participant comprehension, and model assumptions should be fully acknowledged when determining the best experiment for the elicitation of participant's risk preferences (Tanaka and Camerer 2010; Binswager 1980; Cook and Chaterjee 2013; Dohmen and Falk 2010). With regard to monetary incentives, two approaches have been used. Some studies have offered explicit monetary incentives for participation in behavioral experiments (Epper and Fehr-Duda 2009; Tanaka and Camerer 2010; Binswager 1980h). Often payments or partial monetary incentives are given to control groups as an additional robustness check of data validity (Schleich and Gassmann 2018;

Sarin and Wieland 2015; Bocqueho and Jacquet 2013; Harrison and Johnson 2005). However, some studies have argued that monetary incentives do not have a significant impact on the validity of the risk parameters and support use of hypothetical values (Camerer and Hogarth 1999).

For our study, we offered partial monetary incentives following the approach by Bocqueho and Jacquet 2013. Starting out the experiment Bocqueho and Jacquet gave each participant 15 euros and they advised them that they would only receive a percentage of the payoffs that were presented in the behavioral experiment. The actual percentage amount was placed in a sealed envelope on the table and would be revealed after the experiment had concluded. Participants could either win or lose money. However, the experiment was constructed in such a way that participants could not lose more than the 15 euros provided to them for participation. The behavioral experiment used for this study was conducted in Kenya 2019 and followed Bocqueho and Jacquet's method. Participants were given 100KSH (roughly $1 USD) and an opaque sealed bag was laid on the table that concealed the percentage amount of 2% that would be used to determine final payouts. After the experiment was completed, a number was drawn at random that represented each row in the series (1-35), and participant's choices for that row would determine which option would be played for real money. The enumerators script for the behavioral experiment is provided in the APPENDIX: Behavioral Experiment.

Participant comprehension has been an issue with these types of behavioral experiments. Binswager 1980 used "risk inefficient" selections of participants to identify whether or not they comprehended the task. If the risk inefficient option was selected, the participant's results would be excluded from the analysis. Multiple Price List (MPL) elicitation is another method that can used to test participant comprehension and is the most similar to the method used in Kenya. MPL has individuals identify their preference between Option A and Option B for each row. Provided that the rows hold probabilities constant and increase monetary incentives for Option B ascending in the series, a participant that switched multiple times in the series would identify confusion with the experiment, thus identifying an observation to exclude from analysis (Cook and Chatterjee 2011). Additionally, for further MPL experiment robustness, question order randomization or establishment of control groups with different question ordering could be used (Harrison and Humphrey 2010). This would protect the validity of the results by reducing framing bias. Once again, if the participant switched multiple times this would identify a lack of comprehension and the observation should be thrown out.

For the sake of time of completion of each survey, the experiment conducted in Kenya followed the method presented by Tanaka 2010, which enforced monotonicity by asking participants to identify a single switching point for each series, held probabilities constant, and listed prospects in order of increasing monetary incentives. In order to identify individuals who did not understand the experiment, our experiment added two processes. First, to identify individuals who did not understand probability enumerators presented the participant with a bag of colored stones (9 white stones and 1 black stone of equal sizes). The enumerator then asked if one stone was to be pulled at random from the bag which color is most likely to be drawn. The same process was repeated for a second bag of colored stones (7 orange and 3 green stones of equal sizes) and responses were recorded. If the participant got either question that tested their probability wrong, the enumerators would not proceed with the experiment. Second, prior to survey deployment, practice questions were drawn at random from Series 1 and Series 2 using a random number generator. Row 1 Series 1 and Row 7 Series 2 were selected to be the practice questions for the respective series. The participant's practice question responses would be compared to their switching point for the respective series and if both of their practice question responses differed, this indicated that the farmer could have had difficulty understanding the behavioral experiment. Upon completion of the survey, a subset of the data would be created using only the farmers that got at least one of the practice questions correct. This subset of observations would be used for additional analysis which would serve as a robustness check of CPT results.

The techniques used in the behavioral experiment were selected to ensure each CPT parameter's validity. As a result, inclusion of the CPT parameters in the proceeding econometric analysis should represent each farmer's value function respectively and identify on average how risk aversion, loss aversion, and probability weighting is affecting Kenyan horticulture grower's IPM adoption and pest management decisions.

3.7 Modeling IPM adoption

The IPM adoption decision ties into utility maximization theory when the farmer is evaluating his or her adoption decision (accept, reject, or post-pone adoption). Following Staal and Baltenweck 2002, the adoption decision for farmer *i* is represented by $Y_{i,k}$ where the expected benefits (income), $B_{i,k}$, from adopting an agricultural technology, k, must exceed a certain threshold, $T_{i,k}$, that is determined from the farmer's perception of the technology under consideration and its substitutes. Where $Y_{i,k}$ is 1 if the farmer adopts technology *k* (equation 13), and 0 if the farmer rejects or postpones adoption of technology *k* (equation 14). If the expected benefit of the new technology exceeds the threshold, $T_{i,k}$, the farmer will adopt and if it does not, the farmer will either reject adoption or post-pone adoption until they are confident that the expected benefits of the technology exceeds $T_{i,k}$. The theoretical model is presented below.

$Y_{i,k} = 1 \; if \; B_{i,k} > T_{i,k} \rightarrow \; B_{i,k}X + \varepsilon_{i,k} \; > T_{i,k}$ ………..……………………………………..(13)

Farmer adopts

$Y_{i,k_i} = 0 \; if \; B_{i,k} < T_{i,k} \rightarrow \; B_{i,k}X + \varepsilon_{i,k} \; < T_{i,k}$ ………………………………..…………....(14)

Farmer does not adopt

Where *X* is a vector of explanatory variables and $B_{i,k}$ their respective estimated effects on farmer *i's* adoption decision of technology *k*. The error term $\varepsilon_{i,k}$, represents farmer *i's* uncertainty with the expected benefit of technology *k.* With regard to IPM adoption of Kenyan farmers, *X* represents the independent variables elicited through survey responses and $B_{i,k}$ their marginal effects on the adoption decision. The literature shows that a variety regression models (linear regression, logit, probit, order logit, log-log models, multinomial logit, Poisson, negative binomial, double hurdle, etc.) can be used to regress adoption of a technology or technologies on factors of adoption (Norton and Swinton 2001; Bandiera and Rasul 2006; Amudavi and Khan 2009; Joachim Schleich 2018; Fleiter and Schleich 2012; Owusu and Kakraba 2015; Sharma and Peshin 2015; Ainembabazi and van Asten 2017; Gautam and Schreinemachers 2017). The dependent and independent variables along with their interpretations are presented in the next three sections.

3.8 Response Variable

Three response variable categories are used to estimate IPM adoption. The categories were constructed so the study could identify differences in the factors that affect adoption of IPM practices in general, advanced IPM practices, and basic IPM practices. The response variable categories represent the number of IPM techniques used last season and is aggregated across the three crops: tomato, cabbage, and French beans. The aggregation methodology for the response variables is described below. The dependent variable takes on three different specifications.

1. *IPM Count*
2. *Advanced IPM*
3. *Basic IPM*

The first specification is a count variable of all IPM techniques used. The possibilities are use of a pest resistant variety (*PRV*), selecting healthy seeds or sanitizing seed treatment (*Select/Sanitize*), *Trichoderma*, starter trays (*Trays)*, soil solarization (*Solarization*), sticky traps (*Sticky*), microbial pesticide (*Microbial*), bio-pesticide (*Bio*), nursery nets (*Nets*), mulching (*Mulch*), and removing damaged plants (*Removed*). For French beans, nursery trays and nursery nets were excluded because French beans are not transplanted. The aggregation methodology for the three categories does not double count the same technique across crops, e.g. if we had a farmer that used *Trichoderma* on their tomato crop and cabbage crop and a *PRV* for their tomato crop, that farmer's *IPM Count* would be 2. The maximum *IPM Count* a farmer could have is 11.

The second specification, *Advanced IPM*, represents the count of all advanced IPM practices used last season across the three crops. They are considered advanced because they require significant knowledge to implement the practice effectively. The *Advanced IPM* are *Bio*, *Select/Sanitize*, *Microbial*, use of *Trichoderma*, *Solarization*, *Trays*, and *Nets*. Going back to the previous example, if we had a farmer that used *Trichoderma* on their tomato crop and cabbage crop and a *PRV* for their tomato crop, that farmer's *Advanced IPM* would be 1. The maximum *Advanced IPM* count a farmer could have is 7.

The last specification, *Basic Practices*, represents the count of all basic IPM practices used last season across the three crops. The practices are considered basic because the practices require little knowledge for successful implementation. These technologies are use of *PRV*'s, *Sticky*, *Mulch*, and *Removed*. If we had a farmer that used *Trichoderma* on their tomato crop and cabbage crop and a *PRV* for their tomato crop, that farmer's *Basic IPM* would be 1. The maximum *Basic IPM* count a farmer could have is 4.

3.9 Definitions, variable specifications, and expectations

Given the main objective of the study, to identify the factors of IPM adoption, the covariates of our models will consist of demographic variables, farm characteristics, social network variables, risk preferences, county level controls, and IPM training count.

Farmer *i's* adoption level of IPM category a is represented by $y_{i,a}$, where $y_{i,a} = \sum_0^{N_a} y_{i,k_a}$. The variable k_a is a vector of all IPM techniques within IPM category a. y_{i,k_a} represents the individual adoption decision of each IPM practice within category *a* with a maximum count of N_a (N_a = 11, 7, and 4 for *IPM Count, Advanced IPM*, and *Basic IPM* respectively). The factors used to estimate $y_{i,a}$ are represented by *X*. Where *X* is a vector of demographic variables, farm characteristics, risk preferences, social network variables, and county level controls. The independent variables used in the IPM adoption regressions, binary variables' reference category, and expected relationship with IPM are discussed below. Table 2 provides a concise version of the independent variables used and expected relationship with the response variables.

The demographic variables used are the primary decision maker's education level (*Education*), gender, number of workable dependents (*Working Age)*, and horticulture *Experience* in years. *Education* has two levels: 1 if the farmer's education is less than or equal to primary or 0 if their education level is greater than completed primary. It is expected that farmers with an education higher than completed primary school will be more likely to adopt *Advanced IPM* techniques than their less educated counterparts, while *Education* is not expected to be a significant factor in predicting *Basic IPM* count. Due to the complex nature of *Advanced IPM* we expect less educated farmers to have difficulty implementing *Advanced IPM* successfully. Over time, less educated farmers who did not see crop production results that met their pre-season expectations would switch away from *Advanced IPM* to a substitute with lower complexity where the expected benefits would exceed the previously mentioned threshold, $T_{i,k}$. Conversely, having an education higher than completed primary school is expected to increase the likelihood of successful implementation; hence farmers with *Education* = 0 are expected to have higher counts *Advanced IPM* than farmers with *Education* = 1. Therefore, we expect *Education*'s estimated effect to be negative in the *Advanced IPM* regression. The variable that controls for the primary decision maker's gender can take on three options: *Male*, *Female*, and *Both Male and Female*. The last option was used if the male and female of the household make farm decisions jointly. The gender category, *Male*, is used as the reference category for all preceding regressions. If gender was indicated as *Both Male and Female*, the enumerator would interview both partners jointly and the behavioral experiment would be completed together. If their partner was unavailable, they would interview the farmer that was available. Furthermore, with regard to education level, the partner with the highest education was used to determine the independent variable *Education. Females* are expected to adopt fewer practices in each IPM category than their male counterparts due to the time burden of child rearing restricting the likelihood of higher education, ability to implement practices, and learn about new pest management practices. *Experience* was determined by taking the farmer's highest level of experience across the three crops. For example, if the farmer grew tomatoes, cabbages, and French beans for 10, 5, and 4 years respectively, that farmer's *Experience* would be 10. *Experience* is expected to increase the likelihood of adoption for all IPM categories.

Farm characteristics that are used as factors affecting IPM adoption are: total acres farmed (*Acres)*, number of working age dependents (*Working age),* whether the farmer borrowed to finance last year's agricultural production (*Borrowed),* and vegetable production's revenue as a percent of total income *(% Income)*. *Acres* is the total acres farmed for the three crops of interest. It is expected that as the number of acres farmed increases, vegetable revenue would also increase, which would cause the farmer to seek out new pest management strategies to protect revenue from volatility. As a result, the likelihood of finding at least one IPM technique that exceeds $T_{i,k}$ is expected to increase, leading to higher levels of IPM adoption on average for each IPM category. A farmer's ability to borrow to finance their horticulture production is expected to relax financial constraints that may have deterred IPM adoption. Hence, we expect *Borrow* to have a positive relationship with all IPM adoption categories. We expect labor to be a substitute for IPM practices; thus we expect *Working age* to have a negative relationship with the three adoption response variables. Similar to the argument made for *Acres, % Income* is expected to have a positive relationship with the dependent variables because as *% Income* increases so too does the farmer's dependence on their vegetable production, which could influence the search pest management practices that yield higher net benefits.

Social network variables consist of three trust variables that represent farmers' responses to the following questions: Generally speaking, do you believe that most people can be trusted? (*Trust Gen.)*; Generally speaking, do you believe that most agricultural extension workers can be trusted? (*Trust Ext.)*; Generally speaking, do you believe that most agricultural salespeople can be trusted? (*Trust Sales).* The responses could either be Yes or No and the reference category for each trust variable is No. We believe that *Trust Gen.* could both increase and decrease the likelihood of IPM adoption and that the effect really depends on the social network that surrounds each individual farmer. However, given Kenyan horticulture's notoriety for high pesticide levels, we expect the effect of *Trust Gen.* to reflect preference towards conventional pest management methods over IPM adoption. Hence, we expect the effect to decrease the likelihood of IPM adoption on average. *Trust Ext.* is expected to increase the likelihood of IPM adoption for two reasons. One, all foreign Kenyan IPM dissemination efforts/programs are required to have government extension officers present when meeting with farmers. Two, extension officers are expected to have a strong working knowledge of agronomy as it applies to production in their region. Both would increase government extension officers' understanding of the benefits of IPM and advocate for the IPM practices that best meet the needs of the farmers they serve leading to higher IPM counts for farmers with *Trust Ext. = 1*. *Trust Sales* is expected to have a negative relationship with the response variables. Though agricultural salespeople's wages are tied to sales of horticulture inputs, with both IPM and pesticide practices sales included in their wages, given the low rate of IPM adoption observed in the 2016 survey (Methods: *Survey Comparison: 2016 to 2019*), it is expected that agricultural salespeople promote conventional pest management methods more than IPM practices on average.

Cumulative Prospect Theory was used to elicit farmer's risk preference. Following Tanaka 2010, the three parameters used to estimate farmer's risk preference are α, σ, and λ. Liu and Huang 2013 identify the pathways CPT variables connect with decisions to spray pesticides and the potential ambiguity that can arise from risk preference and the decision to spray pesticides (Liu and Huang 2013 studied Chinese cotton farmer's pesticide decisions). They posit that there are two pathways where the CPT parameters can affect farmer's utility functions. The pathways are risk to farmer's income and health associated with apply pesticides. They find that more risk averse farmers use higher pesticide quantities while farmers that are loss averse use less pesticides quantities. Since IPM techniques can be used both as a substitute for and a complement to pesticides, we believe that the effect of the parameters can have an ambiguous effect with IPM adoption. However, given the low IPM adoption identified in the 2016 survey and the high levels of pesticide use characterized by Kenyan horticulture, we expect the health risks of pesticide applications to play a minimal role in the IPM decision process, leading us to the following expectations. As α increases, so does the weight farmers place on prospects with higher probabilities (certainty). Given the low rate of IPM adoption indicated by the 2016 survey, it is expected that IPM techniques are associated with high levels of uncertainty and low probabilities of success. As a result, α is expected to have a negative relationship with all IPM adoption dependent variable specifications. Holding all else constant, IPM adoption will diversify the pest management portfolio, which can increase the probability of generating higher incomes and lower the risk of pesticide poisoning associated with IPM alternatives. Both effects lead us to expect that σ will have a positive effect on IPM adoption. We also expect a positive effect from the loss aversion parameter, λ, because as farmers diversify pest management practices, they decrease the likelihood of income losses from pest infestations.

Variables used to control for regional differences are dummy variables for the three counties sampled in the 2019 survey (*Nyeri*, *Kirinyaga*, and *Tharaka-nithi*). The reference category for the county variables is *Tharaka-nithi*. It is expected that farmers from Tharaka-nithi will adopt more IPM techniques than the other counties.

Table 2: Definition of variables in the IPM adoption model

Variable	*Definition*	*Expected sign*
Education	1 if the farmer's education is less or equal to completed primary school	Negative
Gender*	Gender of primary decision maker	See notes
Experience	Horticulture Experience (in years)	Positive

Acres	Total Acres Farmed	Positive
Borrow	1 if the farmer borrows to finance their agricultural production last year	Positive
Working age	Number of working age dependents	Negative
Veg Sales % of Income	Vegetable sales as percent of income	Positive
Trust General	1 if the farmer believes in general most people can be trusted	Positive
Trust Extension	1 if the farmer believes government agricultural extension workers can be trusted	Positive
Trust Sales	1 if the farmer believes agricultural salespeople can be trusted	Negative
α	CPT Parameter: The larger α becomes the more weight the individual places on large probabilities and less weight on small probabilities	Negative
σ	CPT Parameter: The greater σ, the less risk averse an individual is	Positive
λ	CPT Parameter: The greater λ, the more loss averse the individual is	Positive
County*	1 indicating the farmers county of residence	See notes
Training count	Count of the number of times the farmer was trained on IPM	Positive

Notes: Gender can take on three forms. Male, Female, and Both Male and Female if the partners share equal responsibility in making decisions. The reference category for gender for all the regressions is Male. It is expected that both Male, and Both Male and Female will have a positive relationship with IPM adoption. The County variable represents the three counties: Tharaka-Nithi, Nyeri, and Kirinyaga. The reference county for each regression is Tharaka-nithi. It is expected that the highest level of IPM adoption will be in Tharaka-Nithi due to the work done by KALRO in the county since 2015.

3.10 Estimation Strategy

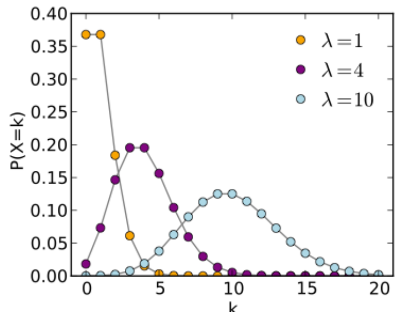
Estimation Strategy: Poisson

A Poisson regression is used to model IPM adoption since the dependent variable can only take on positive values and the level of adoption is measured by a count of IPM practices used (equation 15).

$$E(y_{i,a}|x_1 + x_2, \dots, x_{k_a}) = \exp\,(\beta_{i,a}X + \epsilon_{i,a}) \qquad (15)$$

Where the left-hand side (LHS) is the expected count of IPM category, *a,* for farmer *i.* The righthand side (RHS) represents the exponentiated marginal effects β of IPM category a with respect to X, a vector of independent variables, and the error term $\epsilon_{i,a}$ for farmer *i.* The Poisson model requires that the latent variable takes on a Poisson distribution. This distribution is presented in figure 3.7, where the parameter λ controls the distributions portrayed in the figure.

Figure 3.7: Examples of Poisson Distribution



Since, the count variable cannot be negative, maximum likelihood estimation is used and independent variables are exponentiated to ensure that the predicted values for the response variable remain positive. This can make estimate interpretation a bit challenging and often research that estimates count data converts the estimates to incident rate ratios (IRR). IRR's are constructed by exponentiating the estimates and converting to a percentage. All Poisson estimates are presented as estimates from equation 15 but are converted to IRR in the discussion to improve interpretation. Wooldridge 2016 states that "all of the higher moments of the Poisson distribution are determined entirely by the mean.". Specifically, the mean variance assumption that is presented in equation 16.

Var(y|x) = E(y|x)……..……………………………………………………………………..(16)

Equation 16 shows that the variance of y given x is equal the expected count of y given x. If this assumption does not hold the model's standard errors can either be too high or too low. One way to correct for this is to check for the presence of over or under dispersion and adjust the standard errors accordingly. This is done by the solving for an unknown non-negative parameter σ^2, which is shown in equation 17.

$\text{Var}(y|x) = \sigma^2 E(y|x)$……………………………………………………………….……..(17)

If $\sigma^2 > 1$, the variance is greater than the mean for all predictor variables which causes the standard errors to be inflated, conversely for $\sigma^2 < 1$. A $\sigma^2 = 1$ causes equation 2 to hold.

Estimation strategy: selecting model most appropriate response variables

Another hurdle that using count data must address is selecting the most appropriate model given the distribution of the response variable. The density of 0's (no IPM adoption) with respect to density of positive counts is one example that could result in misleading maximum likelihood estimates provided by the Poisson model. One way to test the goodness-of-fit of a Poisson model is to check the significance of the deviance and Pearson's chi^2. If the tests are highly significant, this indicates that the Poisson model is inappropriate, and another model could be more appropriate given the distribution of the response variable. Thus, a high presence of no IPM adoption could cause a violation in the mean variance assumption of the Poisson model, which could bias our model's estimates. Negative binomial and Double Hurdle models are two options for count data regressions in which a high presence of zero counts (no adoption) is observed.

Estimation strategy: Negative Binomial model

Similar to the Poisson regression, negative binomial regression (NegBin) model is used for nonnegative count dependent variables. However, variance in the model is allowed to be greater than what the Poisson model allows, which relaxes the equi-dispersion assumption of the Poisson model (equation 17). The negative binomial model specification is shown below.

$E\left(y_{i,a}\middle|x_1 + x_2, \dots, x_k, \epsilon_{i,a}\right) = \exp\left(\beta_1 \text{X} + d_{i,a} + \epsilon_{i,a}\right) = h_{i,a}\tilde{y}_{i,a}$……………………..……..(18)

The parameter $d_{i,a}$ in equation 18 controls for overdispersion (underdispersion), and thus could be a better model selection if the Poisson model's goodness-of-fit tests are nonsignificant. It is assumed that h_i = exp($\in_{i,a}$) and has a one parameter gamma distribution, $\in(\theta, \theta)$. The greater $d_{i,a}$, the greater the overdispersion. $d_{i,a}$ = 0 reduces equation 18 to the standard Poisson model in equation 15.

Estimation strategy: Double hurdle model

Cragg 1971 proposed a two-stage regression model similar to a Tobit model where the presence of 0's (no adoption) can be controlled while using MLE and uses two equations to model the adoption decision (selection equation and intensity equation). Cragg's Double Hurdle Model (DH) allows for different RHS variables than the independent variables in the selection equation. However, for this work both equation's independent variables are the same. The latent variable for the first equation is left truncated at 1 ($y_{1,i,a} \leq 1$), while the intensity equation is right censored at 1 ($y_{2,i,a} \geq 1$). IPM adoption response variables that have an overwhelming presence of no adoption could use the DH model for two reasons. One, the DH model is tailored for response variables that have a high density of zeros, with respect to higher counts, which could improve accuracy of the DH estimates when compared to the Poisson model. Two, DH can improve understanding of the factors of IPM adoption because the DH model provides estimates for why farmers choose to participate in the market for IPM techniques (selection equation) and estimates for the factors that influence their intensity of adoption (intensity equation). The two sets of estimates are unique and can be used to tailor future IPM program strategies and objectives. These equations are shown in equations 19 and 20 respectively.

$$\check{y}_{1,i,a} = \beta_{1,i,a}X + \mu_{i,a} \qquad (19)$$

$$\check{y}_{2,i,a} = \beta_{2,i,a}X + \varepsilon_{i,a} \qquad (20)$$

Equation 19 represents the IPM market entrance equation (selection) and equation 20, the IPM intensity equation (level of IPM adoption). Where farmer *i* will participate in the market for IPM's, $y_{1,i,a} = 1$, if $\check{y}_{1,i,a} > 0$, or not participate (no IPM adoption), $y_{1,i,a} = 0$, if $\check{y}_{1,i,a} \leq 0$. Equation 19's *X* is a vector of variables that serve as proxies for mechanisms that influence farmers to participate in the market for IPM strategies. $\beta_{1,i,a}$ is the respective effects of X and $\mu_{i,a}$ is the error term where $\mu_{i,a} \sim N(0,1)$. Equation 20's $\check{y}_{2,i,a}$ is the response variable that estimates farmers IPM intensity (count of IPM techniques used last season) where *X* is a vector of determinants of IPM intensity IPM category *a* and the error term, $\varepsilon_{i,a} \sim N(0,\sigma^2)$. As noted before the same independent variables are used in both equations which is reflected in our notation but the estimates of *X's* are not equal, $\beta_{1,i,a} \neq \beta_{2,i,a}$.

3.11 Addressing endogeneity

Addressing endogeneity: *Training count*

Motivated farmers may be more likely to attend IPM training sessions than their less motivated counterparts. Therefore, including IPM training (*Training count*) in our models without accounting for endogeneity could lead to biased estimates and misleading results. An instrumental approach can be used to address this issue. The instruments considered for *Training count* are farmer *i's* distance to the nearest market (*D. Market*) in kilometers, and percentage of farmers trained on IPM at the sub county level (*% IPM*). *D. Market* is expected to have a negative relationship with the dependent variable as markets are typically located in the center of Kenyan villages. It is assumed that being closer to the community center increases the likelihood of social interaction, which would increase the chances of hearing about and attending IPM training sessions. *% IPM* is expected to have a positive relationship with *Training count* because

% IPM is believed to be a function of time and not constant from year to year, implying that more IPM training opportunities are available for farmers each year. As a result, as the number of opportunities increases so too does the likelihood of participating IPM training sessions, leading to higher *Training counts*. Furthermore, given the complexity of many of the IPM practices, *% IPM* is only expected to affect IPM adoption when a farmer is trained on IPM.

Addressing endogeneity: Testing the validity and necessity of instruments

This research uses three dependent variable specifications for IPM adoption (*IPM Count*, *Advanced IPM*, and *Basic IPM*). The instrumental variables previously mentioned are tested in 2SLS regressions to determine whether they are valid for each of the dependent variable specifications. The test consists of a test for weak instruments (Montiel Oleo-Pflueger 2013), presence of endogeneity using Wooldridge's (1995) robust score test and a robust regression-based test, and testing for overidentification if the endogenous variable has more than one instrument. (Wooldridge 1995).

Good instruments are highly correlated with the potential endogenous variable and not correlated with the error term in the second stage regression. If the first condition does not hold, instruments could be weak, which would result in biased estimates. An F statistic of the instrument(s) in the first stage regression is one way to test for a good instrument(s), following Cragg and Donald (1993) the H_o is that the instrument is weak in the first stage regression. If the F statistic is not significant, then the instruments used as proxies for the endogenous variable have no explanatory power and new instruments should be implemented or the presence of endogeneity assumed away, which is not advised. However, significance of the F statistic alone is not sufficient to determine a strong instrument. Stock, Wright, and Yogo (2002) show that the F statistic should exceed 10 for a consistent estimator. For further discussion on weak instruments see Pflueger, C. E., & Wang, S. (2015). The first stage F statistic used in this work use the Montiel Oleo-Pflueger (2013) test from the "ssc" package in STATA to correct for the shortcomings of the Kleibergen-Paap F statistic presented by Andrews and Stock 2018. If the F statistic does not exceed 10 and if there are more instruments than endogenous variables, Limited Information Maximum Likelihood (LIML) estimation will be used and results compared with 2SLS (Stock, Wright, and Yogo 2002; Mikusheva and Poi 2006). However, our instruments meet the condition for strong instruments and LIML estimation is not used.

Wooldridge 1995 proposed a method similar to the Durban-Wu-Hausman test that identifies the presence of endogeneity in a model by including the residuals of the endogenous variables with the exogenous variables in a regression of the original model. If we fail to reject the exogeneity of *Training count*, the most appropriate count model will be used given the distribution of the dependent variable (Poisson, Negative Binomial, or Double Hurdle). The Wooldridge tests are tailored for models with heteroskedasticity (i.e. allows for robust standard errors) whereas the Durban-Wu-Hausman is not. The tests evaluate the H_o that the potential endogenous variable is exogenous. There are two tests, a Chi^2 test and an F-statistic. If either one is significant, we fail to reject the null and the potential endogenous variable could be exogenous.

The test for overidentification is only performed when there are more instruments than endogenous variables. Similar to the test for endogeneity, the test for overidentification uses the first stage OLS estimation of the endogenous variable on all exogenous variables where the H_o is that our endogenous variable is not overidentified. If the Chi^2 is not significant and we fail to reject the null, we have support for the conclusion that endogenous variable is not overidentified.

Addressing endogeneity: model selection

As discussed in the previous section, IPM training count could be endogenous with the decision to adopt IPM techniques. As a result, the standard Poisson model would be insufficient in estimating the response variables because it cannot control for endogeneity. Further, 2SLS is inappropriate because the response variables are not continuous and can only take on non-negative values. Hence, if endogeneity is present, for IPM adoption category *a,* we will estimate IPM adoption following Mullahy 1997's generalized method of moments (GMM) using additive errors. Equation 15 then becomes:

$$\mathrm{E}\left(y_{1,i,a} \middle| x_1 + x_2, \ldots, x_{k_a}\right) = \exp\left(\beta_{1,i,a}X + \beta_{2,i,a}y_{2,i,a}\right) + \in_{i,a} \ldots\ldots\ldots (21)$$

Where the adoption decision for farmer *i* for IPM category *a* is represented by $y_{1,i,a}$, which is a function of the exogenous covariates X and endogenous variable $y_{2,i,a}$, and additive error term $\in_{i,a}$. The endogenous variable *Training count* takes the form:

$$y_{2,i,a} = \delta_{1,i,a}X + \delta_{2,i,a}Z_a + v_{i,a} \ldots\ldots\ldots (22)$$

Where $Z_a$is(are) the instrument(s) and $v_{i,a}$ are the residuals of the linear regression of *Training Count*. Substituting the estimates of the RHS of equation 22 into equation 21 for $y_{2,i,a}$ results in the second stage regression where the estimate of v_i controls for endogeneity in equation 21. Solving for $\in_i$ leads to the following error function, equation 23 and the population-moment condition, equation 24.

$$u(y_{1,i,a}, X, y_{2,i,a}, \beta_{1,i,a}, \beta_{2,i,a}) = y_{1,i,a} - \exp\left(\beta_{1,i,a}X + \beta_{2,i,a}y_{2,i,a}\right) \ldots\ldots\ldots (23)$$

$$E\left\{\tilde{Z}_i u\left(y_{1,i,a}, X, y_{2,i,a}\ \ \beta_{1,i,a}, \beta_{2,i,a}\right)\right\} = 0 \ldots\ldots\ldots (24)$$

The GMM estimator minimizes the sample-moment condition to make it as close to zero as possible.

3.12 Pesticide Applications and Expenditures

Total pesticide applications represents the total count of pesticide applications made last season across the three crops (*Pesticide applications*). Total pesticide expenditures last season is the sum of all pesticide expenditures (no labor nor pesticide application costs are included in its calculation) and is divided by the total acres farmed across the three crops and adjusted to 2019 USD (*Pesticide expenditures)*. The regressions for pesticide applications and expenditures use the same independent variables as the IPM adoption regressions with the exception of acres for the pesticide expenditure regression. *Advanced IPM* and *Basic IPM* adoption are also included in the regressions to evaluate the impact that IPM adoption has on the two pesticide related response variables. We include the individual IPM techniques instead of the aggregated variables in separate regressions in order to isolate the effects of specific techniques. We control for seasonal pest severity by including the variable *Severity*, which represents the average pest severity across the crops grown last season. Farmers were asked to rank their pest infestation last season for each of the three crops. *Severity* had four categories: 'none', 'low', 'medium', and 'high'. The *Severity* for each crop was converted to 0-3 with 0 being no pest infestation and 3 being high pest severity. The average severity for the three crops is used as the independent variable *Severity* in the two pesticide regressions.

The first regression represents *Pesticide applications* using the aggregated IPM adoption categories *Advanced IPM* adoption and *Basic IPM* adoption for farmer *i*, which can only take on positive values, and hence a Poisson regression is used. The regression takes the following form:

$$\mathrm{E}(y|x_1 + x_2, \dots, x_j) = \exp(\beta_1 X_i + \beta_3 Severity_i + \beta_4 Adopt_{i,a}) \quad (25)$$

Where X_i are the covariates used in the previous adoption regressions and β_1 their respective coefficients. Average pest severity last season for farmer i is represented by $Severity_i$ while $Adopt_{i,a}$ is farmer *i's* aggregated IPM adoption level *a* last season (changing $Adopt_{i,a}$ to $Adopt_{i,k}$ indicates that the individual IPM techniques, *k,* are used instead of the aggregated techniques. This will be done for regressions following the aggregated regressions).

Similarly, *Pesticide expenditure* is represented by equation 26 below using the same variables, but OLS is used to model the continuous variable (*Acres* is excluded from equation 26 because the dependent variable is specified per acre, hence X'_i).

$$y_i = \beta_0 + \beta_1 X'_i + \beta_2 Risk_i + \beta_3 Severe_i + \beta_4 Adopt_i) \qquad (26)$$

Chapter 4. Summary Statistics for 2016 and 2019 Surveys

4.1 Survey Comparison: 2016 to 2019

In 2016 a baseline survey was conducted in Kenya's major vegetable producing counties, which was followed by a survey three years later to gauge IPM adoption rates. The 2016 survey used a simple random sampling method using village lists provided by village elders and selected random households using a random number generator. The baseline survey included a sample of 402 farm households, 206 of them in two counties in the Rift Valley Province, Bomet and Nakuru counties, 96 collected from the Central Province, Nyeri county, and 100 taken from Tharaka-nithi county located in the Eastern Province. Three years later our follow up survey was conducted, and a total of 447 farmers were surveyed in June 2019 in three major horticulture producing counties in Kenya. Two of the counties, Kirinyaga and Nyeri, are located in the Central Province where 113 and 101 farmers were surveyed respectively, and 233 farmers were surveyed farther east in Tharaka-nithi. The survey used a simple sampling method designed to minimize bias. It involved a snowballing method because we were unable to acquire village lists of households in the study area. The method was performed using two teams made up of two enumerators, one manager, and a driver. The managers coordinated with the sub-counties' government extension workers so enumerators would not oversample any village. If the number of villages for the day was not a multiple of four, a village(s) would be selected at random where additional surveys were collected. Enumerators would be dropped off in their respective villages and walk seven houses and begin the survey at the seventh house. If the seventh house did not produce any of the crops of interest, the enumerator would go to the next house until a vegetable farmer was found. After finishing the interview, the enumerator would count another seven houses and the process would continue until they collected the predetermined number of interviews to be collected from that village. After the driver would pick them up and take them to the next village and the process would continue. The follow up study did not seek out the households that were interviewed in the baseline survey. The summary statistics for the two surveys are shown in tables 3-8.

The major difference in the results in table 3 is that the sample population in the second survey is more dependent on agriculture for income generation than is the population in the first survey. The 2019 sample shows that 96% of all households surveyed have agriculture as their main income source as compared to the 78% in the baseline survey. The difference between the primary income sources in the two samples could be due to the difference in counties sampled or to how the households were sampled. A relatively even distribution across counties' primary income sources is seen for the four employment types in the 2016 survey. Agriculture primary: Bomet 26%, Nakuru 25%, Nyeri 26%, and Tharaka-nithi 23%. Wage job: Nyeri 20%, Bomet

28%, Nakuru 22%, and Tharaka-nithi 30%. Households that claimed business as their primary source of income had even less variation across counties as all but Nyeri county, with 17%, showed 28% of households with business as their primary profession. The percentage of income that vegetable sales provide saw a large increase from 33% to 67% between the two surveys, while the percentage of vegetable production consumed by the household fell from 25.2% in 2016 to 7% in the 2019 sample. Hence, the 2019 sample suggests a population that has a higher dependence on their own agricultural production than the sample in 2016.

With regard to crop production, the follow up survey identified 14% more farmers who had access to irrigation for their crop production, rising from 57% to 71% in three years (table 3). The Mbogoni irrigation scheme that planned to begin in 2014 in Tharaka-nithi county is likely a major reason for this jump in access to irrigation, with over two thirds of the 2019 sample using irrigation being from Tharaka-nithi county. Surprisingly, only 1 household had access to irrigation in Nyeri county in the 2019 sample.

Table 3. Characteristics of the respondents in the 2016 and 2019 Kenyan samples

Variable Description	2016	2019
	N = 402	N = 445
Age of Primary Decision Maker	48.87	47.59
Family members under same roof	2.73	3.91
Years in School of Primary Decision Maker	9.36	9.59*
Gender of Primary Decision Maker		
Male	51%	60%
Female	49%	32%
Male and Female Share Responsibility Equally	NA	9%
Married household head	82%	78%
Primary Income Source		
Agriculture	78%	96%
Business	9%	2%
Wage Job	12%	2%
Other	1%	0%
Acres Owned	3.09	2.79
Acres Farmed	2.69	1.81
Livestock Owned	7.47	5.93
Veg Sales % of Income	33%	67%
Consumption % of total vegetable production	25.2%	7%
Borrow to finance crop production	25%	24%
Were you able to borrow enough	56%	77%
Irrigation	57%	71%

Distance Market	3.89	5.16
Distance Extension	7.62	6.95
Distance Inputs	5.62	5.15

Notes: Years in school of the Primary Decision Maker for the 2019 survey asked which education category best represented the education of the primary decision maker (Did not attend school, Did not complete primary (less than 7 years), Completed Primary (7 or 8), Secondary (9-13), Some tertiary (greater than 13), and Completed a university program some primary, completed university program, These categories were used to generate the estimate shown for Years in School of Primary Decision Maker.

The summary statistics for tomato, cabbage, and French bean producers in the two samples are presented in table 3. For the baseline survey, Tharaka-nithi held the majority of tomato growers (40%) followed by Bomet (29%), Nyeri (17%), and Nakuru (14%). The largest number of cabbage growers in the 2016 were in Nyeri (38%) followed by Bomet (34%), Nakuru (21%), and Tharaka-nithi (7%). French bean growers in the initial survey were overwhelming in Nakuru (75%), followed by Nyeri (21%), and both Bomet and Tharaka-nithi at 2%. Similar to the baseline survey, in the 2019 survey the majority of tomato farmers were in Tharaka-nithi (61%), followed by Kirinyaga (31%), and Nyeri (8%). The majority of cabbage growers in the follow-up survey were from Nyeri (49%), with 40% in Tharaka-nithi growers and 11% in Kirinyaga. Similarly, Tharaka-nithi had the greatest change in quantity of French bean growers between the surveys and holds the majority of producers for the sample (40%) followed by Kirinyaga (34%), and Nyeri (26%). The clear changes in Tharaka-nithi vegetable production could be a direct result of the Mbogoni irrigation scheme.

The baseline survey did not ask how many years of experience each farmer had with the three crops respectively, but rather how many years the farmer had grown vegetables. The average was 14.8 years. The 2019 survey found that farmers in the sample had the most experience with cabbage and tomatoes, 9.48 and 8.14 years respectively, followed by roughly 6 years for French beans. The average plot size for tomatoes increased by 0.9 acres, decreased for cabbage by 0.13 acres, and decreased by 0.36 for French beans. Tomato growers in the 2019 reported on average $1009 in sales from their tomato crop for the past year. This is an increase of about $560 dollars from the 2016 sample average. Cabbage sales also increased by $143 between the two samples. Though the 2019 sample reported higher sales for tomatoes and cabbages, revenue per acre for both of these crops decreased by 25% and 16%, respectively. Not surprisingly, given the 70% decrease in average plot size, French bean sales decreased. However, the revenue per acre increased about 19%.

In order to understand the types of non-market factors that influenced the productivity of each sample's producers, the pest influence, pesticide use, and IPM use are presented below in tables 4-6.

Table 4. Crop producer summary statistics for Kenyan 2016 and 2019 samples

Variable Description	2016 N = 402		2019 N = 445	
Crop Producers				
Tomato Growers	141	35%	254	57%
Cabbage Growers	182	45%	186	42%
French Bean Growers	48	12%	96	22%
Years grown tomatoes	NA		8.14	
Year grown cabbages	NA		9.42	
Years grown French Beans	NA		6.01	
Acres Farmed				
Tomato	0.38		0.47	
Cabbage	0.53		0.4	
French Beans	0.51		0.15	
Value in 2019 adjusted currency for last year's crop production	KSh.	$	KSh.	$
Tomato	44990.36	447.36	101500.00	1009.27
Cabbage	37319.91	371.09	51769.73	514.77
French Beans	49972.98	496.91	43076.77	428.34
Value per acre in 2019 adjusted currency for last year's crop production	KSh.	$	KSh.	$
Tomato	199860.21	1987.32	151866	1510.09
Cabbage	115436.04	1147.84	96761	962.15
French Beans	74140.83	737.22	88114	876.17

Table 5 presents the pest severity and worst pest for tomatoes, cabbage, and French beans. Questions presented to respondents in both samples were asked in the same way, with farmers asked to rank the severity of diseases or insect pests for the past growing season for each of the three crops.

The comparison suggests that tomato producers in the 2016 sample had a worse growing season with respect to tomato pests. The worst pest changed from disease/viruses in the 2016 survey to insect/worms in the 2019 survey. Both Cabbage and French bean producers experienced similar pest severity in the two years, with the largest difference being French bean insect severity, with 10% higher "high severity" in 2016 than in 2019. However, given the small sample of French bean producers (47) for baseline survey, caution is needed when comparing the French bean samples. Similar to tomato producers' worst pest, cabbage and French bean producer's worst pest switched from disease/virus to insect/worms between the samples.

Table 5. Pest severity 2016 and 2019 samples

Variables		2016	2019
Severity of Tomato Diseases			
	High	50%	29%
	Medium	23%	33%
	Low	26%	38%
	None	0%	0%
Severity of Tomato Insect Pests			
	High	50%	34%
	Medium	13%	33%
	Low	35%	33%
	None	1%	0%
Worst Tomato Pest			
	Diseases/viruses	59%	44%
	Insects/Worms	40%	56%
	Weeds	1%	1%
Severity of Cabbage Diseases			
	High	25%	21%
	Medium	26%	31%
	Low	43%	47%
	None	5%	2%
Severity of Cabbage Insect Pests			
	High	23%	19%
	Medium	23%	44%
	Low	48%	36%
	None	6%	1%
Worst Cabbage Pest			
	Diseases/viruses	52%	46%
	Insects/Worms	45%	53%
	Weeds	3%	1%
Severity of French bean Diseases			
	High	23%	27%
	Medium	45%	49%
	Low	26%	21%
	None	6%	3%
Severity of French Bean Insect Pests			
	High	36%	25%
	Medium	32%	43%
	Low	28%	31%
	None	4%	1%
Worst French Bean Pest			
	Diseases/viruses	45%	41%
	Insects/Worms	53%	59%
	Weeds	2%	0%

Characteristics of pesticide applications for the two samples are presented in table 6. The average number of times tomato and cabbage producers applied pesticides in the last growing season remained similar between years, with about 8 and 4.5 applications respectively. The average number of applications on French beans decreased by nearly 2 across the two samples. Even though the number of applications remained similar across samples, 38% more farmers that applied pesticides last year exhibited health symptoms after applying pesticides on their vegetable crops. Pesticide expenditures per acre decreased across all crops from 2016 to 2019, by almost half for both cabbage and French bean producers and by about 14% for tomato producers. However, the 2016 survey did not explicitly ask for only the pesticide cost while the 2019 survey did, therefore this large difference could be due to labor costs included in the 2016 average.

In both samples, respondents were asked to state whether their pesticide applications were effective on their vegetable crops. This response changed little between the two years and in both samples more than 80% of the farmers stated that their pesticide applications were effective in fighting insect pests. Both samples of farmers were asked how they determine when to apply pesticides on their vegetable crops. The respondents were allowed multiple responses and the percentages are based on the number of respondents to the question for each sample respectively. In the 2016 survey, the top responses were: Based on visible damage to the plant 76%; Growth stage of plant 71%; Read label on pesticide container 70%; Spray at regular or fixed intervals 66%; Advice from pesticide dealer 62%. The 2019 sample had Based on visible damage 85%; Based on number of pests 81%; Spray at regular or fixed intervals 45%; Growth stage of the plant 43%; Read label on pesticide container 42%.

Table 6. Pesticide use for 2016 and 2019 Kenyan samples

Variable		2016		2019	
Tomato Pesticides		KSh.	$	KSh.	$
	Applications last season	7.87		8.11	
	Expenditure 2019 adjusted	4989.62	$49.61	6722.31	$66.84
	Expenditure 2019 adjusted per acre	21433.74	213.13	18447.4	183.43
Cabbage Pesticides				2019	
	Applications last season	4.52		4.63	
	Expenditure 2019 adjusted	2827.50	$28.12	2503.3	$24.89
	Expenditure 2019 adjusted per acre	13838.76	137.61	4905.7	48.78

French Beans Pesticides				
Applications last season	7.11		5.2	
Expenditure 2019 adjusted	4683.76	46.57	2768.26	27.53
Expenditure 2019 adjusted per acre	13068.80	129.95	6677.5	66.40
Health symptoms exhibited after applying pesticides	42%		80%	
Effectiveness of pesticides				
Pesticides were effective	83%		88%	
Pesticides were not effective	13%		11%	
Don’t know	1%		0%	
Did not apply pesticides	3%		1%	
How pesticide application timing is determined				
Read label on pesticide container	70%		42%	
Advice from pesticide dealer	62%		38%	
Advice from extension agent	35%		24%	
Advice from relative or friend	39%		30%	
Growth stage of plant	71%		43%	
Spray at regular or fixed intervals	66%		45%	
Based on number of pests	64%		81%	
Based on visible damage to the plant	76%		85%	
Other	12%		0%	

The following tables show the IPM training and adoption rates across the two samples and for the three crops, tomato, cabbage, and French beans. Table 7 shows that the 2019 sample had an additional 14% of the sample trained on IPM, 34%, compared to the 20% that had received IPM training in 2016. Additionally, the number of times an individual received IPM training, *Training count*, tripled from around 2 times in the baseline survey to around 6 times in 2019.

Table 7. Household Integrated Pest Management training for 2016 and 2019 samples

Variable	2016	2019
Received IPM Training	20%	34%
Training count	2.04	6.16

The largest difference in IPM adoption rates is the pest-resistant varieties (PRV) increasing from 34.8% to 80%, 29.1% to 71%, and decreasing from 38.8% to 33% for tomato, cabbage, and French beans, respectively. However, after comparing how the questions were presented to the farmer between surveys, a word of caution is in order. The 2016 survey asked farmers whether they adopted any pest resistant variety for a given crop, while the 2019 survey asked them whether they used specific PRV’s that were provided by KALRO scientists, a

Kenyan agriculture research organization. Selecting healthy seeds or providing a sanitizing seed treatment increased from 10.6% to 12%, decreased from 12.7% to 7.6%, and decreased from 25% to 7.6% for tomato, cabbage, and French beans. Use of trays to raise seedlings in sterilized soil, coco peat, or peat moss decreased for both tomatoes 12.8% to 4.4% and cabbage 7.1% to 1.1%. Use of nursery nets to exclude insects from seedlings decreased from 23.4% to 16.4% and from 21.4% to 7.6% for tomato and cabbage respectively. Trichoderma use on seeds, seedlings or soil saw the most consistent change in use across all crops. Increasing by 9% for tomato growers, 7.3% by French bean growers, and 4.3% for cabbage growers. Removing damaged plants is still a practice that the majority of farmers utilize. It Decreased by about 8% and 15% for tomato growers and French bean growers respectively, but increased for cabbage growers by 2%. Use of sticky traps increased in use for all growers. It increased by about 1%, 3.5%, and 6% for tomato, cabbage, and French bean growers respectively. Use of microbial pesticides showed mixed results, increasing by 6% for tomato growers, decreasing by 6% for cabbage growers, but was unchanged for French bean growers. Use of Bio-pesticides increased by 5% for tomato growers, saw little change for cabbage growers, and increased by 14% for French bean growers. Use of mulch and sowing seeds in solarized soil in seed beds were not asked in the 2016.

Table 8. IPM adoption for 2016 and 2019 samples

IPM Practices	2016			2019		
	Tomato	Cabbage	French bean	Tomato	Cabbage	French bean
Use of pest resistant varieties	34.8	29.1	38.8	80.0	71.0	33.0
Selecting healthy seeds or sanitizing seed treatment	10.6	13.7	25.5	12.0	7.6	7.6
Raise Tomato Seedlings in trays with sterilized soil, coco peat, or peat moss	12.8	7.1	NA	4.4	1.1	NA
Use of nursery nets to exclude insects	23.4	21.4	NA	16.4	7.6	NA
Apply Trichoderma on seeds, seedlings, or soil	1.4	4.4	6.4	10.4	8.7	13.7
Remove damaged plants	72	73.1	80.8	64.4	75.3	65.3
Use sticky traps	5.7	7.0	4.3	16.4	10.4	11.6
Use of microbial pesticide	2.1	9.0	6.4	8.0	2.7	6.3
Use of Bio-pesticides	5.7	9.0	2.1	11.2	7.7	15.8

Use of Mulch	NA	NA	NA	37.6	37.9	23.2
Sowing of seeds in solarized soil in seed beds	NA	NA	NA	10.0	5.4	8.4

Notes: The percentages represent the number of the farmers that adopted the individual IPM technique with respect to crop and IPM technique.

In conclusion, comparison of the 2016 and 2019 surveys showed a population that is more dependent now on agricultural production for income generation. The data also suggest that the growing season pest severity, number of pesticide applications, and pesticide effectiveness remained similar or decreased with respect to pest severity across years for tomato and cabbage farmers. Yet, revenue per acre for tomato and cabbage growers decreased by 25% and 16% respectively. French bean farmers showed a 19% increase in revenue per acre with a similar pest severity and a reduction of seasonal pesticide applications by about 2. However, sample size for French bean farmers in 2016 was small. Though the percentage of total farmers trained on IPM and the average amount of IPM training sessions attended increased by about 15% and 4 training sessions respectively, IPM adoption did not increase across all practices. The only two IPM practices that saw increases for all crops were Trichoderma and use of sticky traps. Ignoring comparison of the PRV results because of the difference in question framing, tomato farmers appear to have experienced the greatest increase in IPM utilization across specific practices. Table 8 shows that tomato growers are utilizing six of the eight IPM practices more than they did in 2016. With regard to cabbage, the data showed that adoption of only three of the eight IPM practices increased. For French beans, two of the six IPM practices increased and one practice remained roughly the same.

Chapter 5. Results

5.1 IPM Adoption Dependent Variables

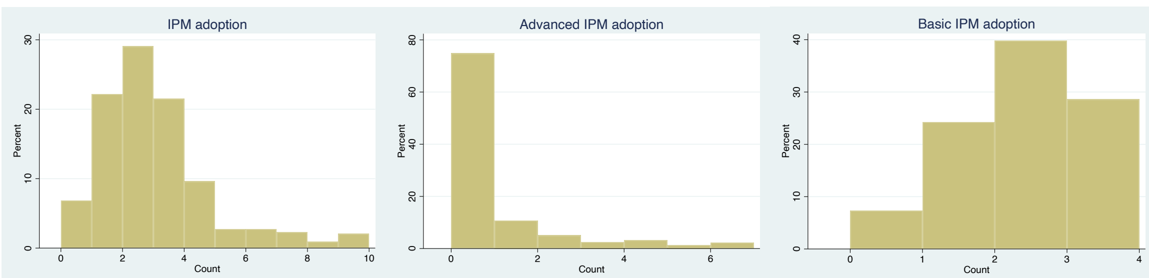
The following table presents summary statistics for the response variable categories in the 2019 sample. The average farmer uses 2.57 IPM practices (*IPM Count*) and on average tomato growers use the highest number of IPM practices in each category. Additionally, 2.5% of tomato growers and only 1% of cabbage growers do not use any IPM techniques while, 24% of French bean growers do not use any IPM techniques and only 23% use *Advanced IPM.* The average adoption rate for *Advanced IPM* for each specification is below 1, implying that most farmers do not utilize any *Advanced IPM* practice. The average farmer uses 0.62 *Advanced IPM* practices with cabbage farmers utilize the fewest. The average farmer in our sample uses around 2 *Basic Practices,* with French bean farmers adopting the least among the three crops.

Table 9. Dependent Variable Descriptive Statistics for Study Region

	Observations	Min	Max	Mean	Std.dev
IPM Count	**437**	**0**	**10**	**2.57**	**1.89**
Tomato Count	250	0	10	2.74	1.99
Cabbage Count	181	0	9	2.41	1.39
French bean Count	95	0	9	1.89	1.89
Advanced IPM	**437**	**0**	**7**	**0.62**	**1.38**
Tomato Advanced IPM	250	0	7	0.74	1.53
Cabbage Advanced IPM	181	0	6	0.45	1.03
French bean Advanced IPM	95	0	5	0.56	1.22
Basic Practices	**437**	**0**	**4**	**1.94**	**0.98**
Tomato Basic Practices	250	0	4	2	0.94
Cabbage Basic Practices	181	0	4	1.96	0.86
French bean Basic Practices	95	0	4	1.34	1.03

The distribution of the three IPM categories, *a,* is shown in figure 5.1. Both *IPM Count* and *Basic Practices* appear to follow the Poisson distribution. The distribution of *Advanced IPM* shows that nearly 75% of all farmers do not use any *Advanced IPM* practice. This result could cause a violation of the mean variance assumption of the Poisson model and lead to misleading results. Based on the results in table 9 and figure 5.1, the Poisson models appears to be the best choice for *IPM Count* and *Basic Practices,* while Negative Binomial and Double Hurdle are best for *Advanced IPM* which has limited adoption.

Figure 5.1. Distribution of IPM Adoption



5.2 Independent variables

Table 10 presents descriptive statistics for the sample and shows that the majority of farmers grew tomatoes (250), followed by cabbage (181), and French beans (91). Forty percent of the farmers interviewed had less than or equal to a primary education. The data indicate that roughly 60% of decision makers were male, 30% female, and for 10% of the sample, a male and a female share equal responsibility for farm decision making. The average years of horticulture experience for the sample is 9.38. Cabbage farmers on average are the most experienced, followed by tomato farmers, and French bean farmers. The lower French bean experience is expected given that the crop is not a common Kenyan food and has only recently been promoted as an export crop in the region. Similar to experience, cabbage farmers on average have the largest parcels, followed by tomato farmers, and French bean farmers. The average plot size is about an acre, but this result is skewed by a few outliers (50% of all farms in the sample are less than a half-acre and 25% are between a half-acre and one acre). Only 25% of farmers borrowed to finance last year's crop production and the average number of working age dependents is 2.54. The sample is highly dependent on vegetable sales for income, with 67% of all income on average being generated by vegetable production (*% income*). The trust variables, which indicate beliefs about whether most people, agricultural extension officers, and agricultural salespeople can be trusted, indicate farmers on average are trusting of sources within their social networks. Agricultural extension officers are the most trusted in the sample with 85% of all farmers surveyed indicating that they believe most agricultural extension workers can be trusted. About 35% of all farmers were trained on IPM, and for those that received IPM training the average number of times trained was six. The sample's average IPM training count was about 2 times (Table 10 notes).

Table 10: Sample Descriptive Statistics

Variable	Mean	Std.dev	Min	Max
Education	0.40		0	1
Male	0.60		0	1
Female	0.32		0	1
Both Male and Female	0.09		0	1
Experience	**9.38**	**7.81**	**1**	**40**
Experience tomatoes	8.14	7.21	1	40
Experience cabbage	9.42	8.22	1	40
Experience French beans	6.05	5.54	1	26
Acres	**1.01**	**1.68**	**0.01**	**25**
Acres Tomato	0.786	1.24	0.01	15
Acres Cabbage	0.956	2.01	0.062	25
Acres French bean	0.623	0.667	0.062	5

Borrow	0.25		0	1
Working Age	2.54	1.49	0	15
% Income	67.1	30.4	1	100
Trust Gen.	0.70		0	1
Trust Ext.	0.85		0	1
Trust Sales	0.79		0	1
IPM Train	0.34		0	1
Training count*	6.16	6.80	1	50

Notes: Training count is for those farmers that received IPM Training, not the entire sample. The average for the entire sample is 2.12 training sessions.

Table 11 shows farming characteristics for the three counties. Most of the tomato farmer observations are from Tharaka-Nithi (155), followed by Kirinyaga (78), and Nyeri (21). Kirinyaga had the smallest proportion of cabbage farmers, 21%, followed by 32% in Tharaka-nithi, and 90% in Nyeri. The number of French bean farmers are similarly dispersed across counties, but as a percentage of total county farmers there is a large difference. Roughly 30% of all farmers from Kirinyaga and Nyeri grow French beans, but only 16% of Tharaka-nithi farmers grow the crop. Kirinyaga has the largest tomato and French bean plots with 0.81 acres and 0.25 acres on average respectively. Nyeri has the largest cabbage plots by far, with an average plot size of 1.37 acres. The most experienced tomato farmers are in Kirinyaga, which is not surprising given the reputation the county has for producing tomatoes. Nyeri farmers have the most experience growing cabbages and French beans with over 13.5 and 9 years on average respectively. Tharaka-nithi has a slightly higher percentage of farmers trained in IPM, but those who have been trained have on average 2 more sessions than farmers in Nyeri, the county with the second highest IPM training count.

Table 11: County Descriptive Statistics

Variable	Tharaka-Nithi	Kirinyaga	Nyeri
Observations	233	113	101
Tomato Farmers	155	78	21
Cabbage Farmers	75	20	91
French B. Farmers	38	33	25
Acres Tomato	0.42	0.81	0.14
Acres Cabbage	0.17	0.11	1.4
Acres French B.	0.08	0.25	0.19
Experience Tom	6.35	11.24	9.9
Experience Cab	6.57	8.03	13.58
Experience French B.	3.7	6.6	9.09
Trained on IPM	39.48%	21.24%	37.62%
IPM Train Count*	7.28	3.75	4.95

Notes: IPM Train Count is for those farmers that received IPM Training not the entire sample.

With regard to CPT results, the risk parameters α and σ range 0-1.5 and for λ, 0-12. Twenty-one farmers did not pass the first test that evaluated their ability to interpret probabilities. These observations were excluded from the sample. The risk descriptive statistics are presented in table 12.

Table 12: Risk Parameters' Descriptive Statistics (n = 426)

Variable	Mean	Std.dev	Min	Max
α	0.73	0.38	0.05	1.5
σ	0.54	0.5	0.05	1.5
λ	4.08	4.31	0.1	12

An additional test checked whether their practice answers were consistent with their results in the actual behavioral experiment with the three series. A new sample was created for farmers who passed at least one of the practice questions. Forty-nine farmers did not pass the second test. The CPT results using the sub-sample that passed both tests are presented in table 13. We see little change in the weighting parameter, α, and the risk aversion parameter, σ, for the new sample compared to the original. The loss aversion parameter, λ, changed by 0.45, reflecting a sample that is less loss-averse on average. The regressions shown in the following sections use the sample that passed the first test that checked whether they understood probabilities. The regressions that use the sample that passed at least one of the practice examples are provided in the Appendix: Participant Comprehension: CPT table A1-A5. We find that not including these observations in the IPM adoption regressions has little impact on the non-CPT variable estimates and few changes were observed for the CPT estimates. The regressions presented below use the full sample and differences with sample CPT estimates are discussed in their respective sections.

Table 13: Risk Parameters Descriptive Statistics using sub sample (n = 377)

Variable	Mean	Std.dev	Min	Max
α	0.75	0.39	0.05	1.5
σ	0.55	0.48	0.05	1.5
λ	3.63	4.12	0.1	12

The sample average α and σ are 0.75 and 0.55 respectively, which implies that the sample overweights small probabilities and underweights large probabilities and that the average farmer is risk averse. The average loss aversion parameter of 3.63 implies that farmers are loss averse on average. Table 14 presents a comparison of average CPT parameter values for five studies. Notice that the parameters are similar across them.

Table 14: CPT parameter comparison

Studies	α	σ	λ
O'Reilly and Norton	0.75	0.55	3.63
Kahenman and Tversky	NA	NA	2.25
Tanaka	0.74	0.61	2.63
Liu	0.69	0.48	3.47
Bocqueho	0.65	0.51	3.76

5.3 Instrumental variables

Table 15 presents the IPM training percentages at the sub-county level (*% IPM)*, with results ranging from 20.41%-52.94%. The smallest *% IPM* is found in Kirinyaga West with roughly 20% of farmers in that sub-county identified as being trained on IPM. Chuka sub-county has the highest *% IPM* at about 53%.

Table 15: IPM training percentages on the sub-county level (% IPM) (n= 447)

Sub-County	% IPM	County
Kieni East	37.78	Nyeri
Kieni West	39.47	Nyeri
Mathira	26.32	Nyeri
Kirinyaga West	20.41	Kirinyaga
Miwea East	22.73	Kirinyaga
Miwea West	34.3	Kirinyaga
Maara	25.44	Tharaka-nithi
Chuka	52.94	Tharaka-nithi

The summary statistics for *D. Mrkt* are presented in table 16. The average distance from farmers to the nearest market is 5.16 kilometers. There is little difference between the famers from Kirinyaga and Tharaka-nithi with respect to *D. Mrkt*, however farmers from Nyeri on average are about 2 kilometers farther away from markets then farmers from the other two counties.

Table 16: Summary statistics of D. Mrkt (n=447)

	D. Mrkt

All Counties	**5.16**
Nyeri	6.54
Kirinyaga	4.68
Tharaka-nithi	4.76

Note: The average distance from county farmers to the nearest market is shown in kilometers.

Table 17 presents OLS results for training count, with robust standard errors provided in parentheses. Both instruments are highly correlated with the potential endogenous variable and significant (*D. Mrkt* $p < 0.05$; *% IPM* $p < 0.01$). Therefore, both *D. Market* and *% IPM* will be considered for instrumenting IPM training count.

Table 17: Testing for Instruments

	Training Count
Intercept	-0.61
	(0.75)
D. Mrkt	-0.12**
	(0.04)
% IPM	0.10***
	(0.02)
N	446
R-sq	0.07
adj. R-sq	0.07

5.4 IPM adoption instrumental variable tests

Table 18 presents the instrument/endogeneity results for the three IPM adoption specifications, *a*. *Training count* is instrumented using three variable specifications: *Both* (*% IPM* and *D. Mrkt*), *% IPM*, and *D. Mrkt*. When the potential endogenous variable is instrumented using two variables, an overidentification test is performed for the respective panel (*Both*; panels 1, 4, and 7). The Breusch-Pagan Cook-Weisberg test was used to test for heteroskedasticity for the three model specifications. The results indicate that heteroskedasticity is present in each IPM adoption specification and therefore robust standard errors were used in the 2SLS specification and Wooldridge's endogeneity and overidentification tests (Breusch-Pagan Cook-Weisberg chi^2 results: *IPM Count* chi^2 133.46 (prob > chi^2 0.00), *Advanced IPM* chi^2 218.72 (prob > chi^2 0.00), *Basic IPM* chi^2 29.70 (prob > chi^2 0.04)). For all specifications using *Both*, we find that the model is overidentified which could imply that one or more of our instruments is invalid. Instrumenting training count using *% IPM* and *D. Mrkt* separately shows that *D. Mrkt* is a better choice for an instrument (F stat >10). However, we reject the null of *Training count* being exogenous for *Count IPM* and *Basic Practices* but fail to reject for *Advanced IPM*. Hence, training count will be instrumented using *D. Mrkt* for *Count IPM* and *Basic Practices* and treated as exogenous for *Advanced IPM*.

Table 18: Results for Training count instrumental variables

	Count IPM			*Advanced IPM*			*Basic IPM*		
	Both (1)	% IPM (2)	D. Mrkt (3)	Both (4)	% IPM (5)	D.Mrkt (6)	Both (7)	% IPM (8)	D. Mrkt (9)
Weak Instrument									
F (1,217)	8.86	8.57	10.54	8.86	8.57	10.54	8.86	8.57	10.54
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Endogeneity									
Robust Sore Chi2(1)	9.98	24.03	4.60	32.22	45.57	0.00	7.89	0.74	16.23
	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(1.0)	(0.01)	(0.39)	(0.00)
Robust Regression F (1,216)	9.13	26.08	3.89	28.77	56.94	0.00	7.63	0.70	11.24
	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(1.0)	(0.01)	(0.40)	(0.00)
Overidentification									
Score Chi2(1)	14.82	NA	NA	8.14	NA	NA	3.83	NA	NA
	(0.00)	NA	NA	0.00	NA	NA	(0.05)	NA	NA
Observations	403	403	403	403	403	403	403	403	403

Notes: p values are presented in parenthesis.

5.5 IPM adoption regression results

IPM Count

Table 19 shows the results for *IPM Count* using training count as the endogenous variable instrumented by distance to market (*D. Mrkt*). With respect to the risk parameters, both

α and σ are not significant predictors of *IPM Count*. However, the loss aversion parameter, λ, is highly significant and positive ($p < 0.01$). Table A1 in the *Participant Comprehension: CPT* section of the appendix provides results of a robustness check for the estimates of the risk parameters. The table shows the same regressions performed in table 19 but for a sub-sample of farmers who passed at least one of the practice questions. The results are similar between the two samples. Thus, farmers who are loss averse on average adopt more practices than less loss-averse counterparts. The 2SLS results suggest that for each marginal increase in λ, the *IPM Count* increases by 0.08. Furthermore, using the IV Poisson specification and converting to IRR shows that each unit increase in λ increases the likelihood IPM adoption by 3% on average, ceteris paribus.

Gender impacts between 2SLS and IV Poisson are inconsistent across model specifications. *Females* are found to have a lower *IPM Count* than their male counterparts in the IV Poisson regression ($p < 0.10$), but the results are non-significant in the 2SLS regression. Farms where males and females share joint responsibility for farm management decisions with respect to farms run by males alone are found to have higher *IPM Counts* in the 2SLS regression ($p < 0.10$) but not in the IV Poisson regression. *Experience*, *# Crops*, *Borrow*, *Trust Ext*, and county variables show consistent results across panels. Ten years of experience increases the likelihood of adopting IPM practices by 20% (e^(0.02)*10 = 1.20) ($p < 0.01$), while each of the three crops of interest grown by the farmer increases the likelihood of IPM adoption by about 27% ($p < 0.01$), all else held constant. Borrowing to finance last year's production is found to be a strong positive influence on IPM adoption. If the farmer received financing to support their agricultural production, they were 19% more likely to adopt IPM techniques ($p < 0.05$). Given the low-income levels for farmers in the sample, this could reflect a liquidity constraint limiting

IPM adoption in the region. Farmers who indicated that they believe most agricultural extension workers can be trusted, *Trust Ext*., are 34% more likely to adopt IPM techniques on average than those that do not, ceteris paribus ($p < 0.05$). The county variables *Nyeri* and *Kirinyaga* use *Tharaka-nithi* as the reference category. The results show that Tharaka-nithi farmers are the most likely to adopt IPM techniques ($p < 0.01$). The endogenous variable, *Training Count*, though significant in the OLS specification, remained a non-significant factor in each regression that included *D. Mrkt* as its instrument.

Table 19: *IPM Count* regression

	OLS (1)	2SLS (2)	IV.Poisson (3)
education	-0.05	-0.04	-0.03
	(0.17)	(0.20)	(0.08)
female	-0.36*	-0.30	-0.13*
	(0.19)	(0.19)	(0.07)
both male and female	0.79**	0.97*	0.24
	(0.31)	(0.52)	(0.15)
experience	0.03**	0.04***	0.02***
	(0.01)	(0.01)	(0.00)
acres	0.14***	0.16	0.05
	(0.05)	(0.13)	(0.03)
# crops	0.91***	0.75***	0.24***
	(0.20)	(0.27)	(0.09)
borrow	0.48**	0.43*	0.17**
	(0.20)	(0.22)	(0.08)
workable age	-0.06	-0.02	-0.00
	(0.06)	(0.06)	(0.03)
% income	0.00	-0.00	-0.00
	(0.01)	(0.01)	(0.00)
trust Gen	-0.20	-0.13	-0.08
	(0.23)	(0.24)	(0.09)
trust Ext.	0.34	0.68**	0.29**
	(0.25)	(0.28)	(0.12)
trust Sales	-0.01	-0.18	-0.09
	(0.23)	(0.25)	(0.10)
α	-0.07	-0.15	-0.05
	(0.22)	(0.23)	(0.09)
σ	-0.31*	-0.23	-0.10
	(0.18)	(0.21)	(0.09)
λ	0.05**	0.08***	0.03***
	(0.02)	(0.03)	(0.01)

nyeri	-1.71***	-2.00***	-0.80***
	(0.26)	(0.31)	(0.13)
kirinyaga	-1.08***	-1.55***	-0.62***
	(0.23)	(0.29)	(0.11)
training count	0.08***	-0.10	-0.05
	(0.02)	(0.09)	(0.05)
Intercept	1.50***	1.78***	0.67***
	(0.45)	(0.48)	(0.18)
N	404	404	404
R2	0.29		

Note: robust standard errors are listed in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Advanced IPM

The results in table 18 are from the tests that evaluated the need and validity of the potential instruments for *Training count*. We concluded that endogeneity was not present when we specified the model using *Advanced IPM* adoption as the dependent variable, resulting in the regressions choices presented in table 20: Poisson, Negative Binomial, and Double Hurdle. As noted in the previous chapter, roughly 70% of all farmers did not adopt any *Advanced IPM* practices. The Pearson's chi^2 and deviance goodness of fit suggest that Poisson model is inappropriate given the distribution of the response variable (795.94 ($p < 0.001$) and 495.82 ($p < 0.001$) respectively). As a result, we have included negative binomial (regression 3) and double hurdle models (regression 4) for this regression. However, as table 20 shows, little difference is observed between Poisson and NegBin estimates. NegBin's estimate for *d,* the parameter that controls for over- or under-dispersion, indicates that our data are over-dispersed (exp(0.39)=1.48). Not only are the new models more appropriate for the response variable, but the double hurdle model provides further insight into the adoption process with its selection and intensity equations.

The estimates remain consistent across the first three model specifications with minor differences between the exponential and OLS regressions. The risk aversion parameter, σ, shows no significant effects in *Advanced IPM* adoption, while λ is a positive significant factor in the first three specifications and α a negative factor in regression 3 (NegBin). The results for α hold when we control for farmers who potentially did not understand the behavioral experiment, and λ becomes significant at the 1% level for the first three models and at the 5% level for the entrance equation for model 4 (Appendix, section Participant Comprehension: CPT, table A2). The estimates for λ are consistent with the results in the previous regression. A marginal increase in the loss aversion parameter is expected to increase the likelihood of adopting *Advanced IPM* by about 5-6%, ceteris paribus. The result for the weighting parameter α suggests that individuals who place more value on prospects with higher probabilities (certainty) are 50% less likely to adopt *Advanced IPM* techniques ($p < 0.10$). This result could reflect uncertainty in *Advanced IPM* which could be a shortcoming to address with future IPM training.

Gender impacts are not consistent across all models, but the Poisson and Negative Binomial regressions find that *Females* are about 70% less likely than males to adopt *Advanced IPM* ($p < 0.05$). Both *Experience* and *Acres* are found to be significant positive factors influencing *Advanced IPM* adoption in each of the model specifications. The results for experience are consistent with the previous results for IPM count. Total acres farmed appear to be a significant positive factor in the *Advanced IPM* intensity equation but not the entrance equation, in which each acre farmed increases the likelihood of *Advanced IPM* adoption by about 13%, ceteris paribus. Similar to the results for experience, *# Crops* is identified as a positive factor for *Advanced IPM* adoption. The Dbl. Hurdle model shows that *# Crops* is a factor influencing the intensity of adoption ($p < 0.01$) and not the selection equation. These results indicate that farmers who grow more than one of the three crops have different portfolios of IPM techniques across crops. This could imply that farmers are tailoring their IPM adoption based on the specific needs of their crops, which is one of the main tenets for successful IPM. Borrowing to finance crop production last year is found to be a highly significant positive factor in the *Advanced IPM* adoption, but the Dbl. Hurdle model shows that it only affects the probability of adopting at least one technique and not the intensity of adoption. This result could reflect a liquidity constraint limiting *Advanced IPM* adoption in the region and a preference towards conventional pest management methods. Dependence on vegetable production, *% Income*, has a positive relationship with *Advanced IPM* adoption, though only significant at the 10% level in most models. Farmers in Tharaka-nithi again are found to adopt more IPM techniques on average than those in the other two counties. Furthermore, not only are Tharaka-nithi farmers more likely to adopt any advanced technique, but they adopt with higher intensity on average, ceteris paribus ($p < 0.01$). IPM training count is highly significant in each regression ($p < 0.01$) and positively affects the likelihood of adopting at least one technique and adoption intensity. Each training session attended is expected to increase *Advanced IPM* adoption by about 5% ($p < 0.01$).

Table 20: ***Advanced IPM*** **regression**

	OLS (1)	Poisson (2)	NegBin (3)	Dbl. Hurdle (4)	
				Selection	Intensity
education	0.05	0.02	0.11	0.07	0.02
	(0.13)	(0.19)	(0.20)	(0.16)	(0.11)
female	-0.23	-0.51**	-0.54**	-0.16	-0.23**
	(0.14)	(0.22)	(0.23)	(0.17)	(0.11)
both male and female	0.40*	0.04	0.04	0.09	-0.06
	(0.23)	(0.23)	(0.27)	(0.24)	(0.17)
experience	0.02**	0.05***	0.05***	0.02*	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
acres	0.10***	0.17***	0.18***	0.05	0.13***
	(0.04)	(0.04)	(0.07)	(0.04)	(0.03)
# crops	0.41***	0.59***	0.56***	0.22	0.30***
	(0.15)	(0.18)	(0.20)	(0.17)	(0.10)
borrow	0.46***	0.57***	0.53***	0.45***	0.02
	(0.15)	(0.17)	(0.19)	(0.16)	(0.11)
workable age	-0.05	-0.05	-0.06	-0.01	-0.07**

	(0.04)	(0.07)	(0.06)	(0.05)	(0.03)
% income	0.01	0.01	0.01	0.01	0.00
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)
trust Gen	-0.09	-0.37	-0.35	-0.17	-0.12
	(0.17)	(0.26)	(0.25)	(0.21)	(0.12)
trust Ext.	0.03	0.23	0.51	0.22	0.34**
	(0.19)	(0.29)	(0.32)	(0.24)	(0.16)
trust Sales	0.03	-0.13	-0.23	-0.07	0.07
	(0.17)	(0.26)	(0.30)	(0.21)	(0.14)
α	-0.08	-0.35	-0.43*	-0.32	0.02
	(0.17)	(0.25)	(0.25)	(0.20)	(0.13)
σ	-0.03	0.05	0.11	-0.04	0.07
	(0.14)	(0.21)	(0.27)	(0.17)	(0.17)
λ	0.05***	0.07***	0.07**	0.03	0.02
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
nyeri	-1.47***	-3.89***	-3.50***	-1.60***	-1.00***
	(0.20)	(0.63)	(0.57)	(0.33)	(0.19)
kirinyaga	-0.98***	-2.29***	-2.35***	-1.11***	-0.98***
	(0.17)	(0.34)	(0.39)	(0.23)	(0.19)
Training count	0.06***	0.05***	0.05***	0.03**	0.02**
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
constant	0.15	-1.17**	-1.25**	-0.74*	-0.11
	(0.34)	(0.50)	(0.49)	(0.40)	(0.27)
d			.39*		
			(0.24)		
Ln(std.dev error term)				-0.70***	
				(0.06)	
std.dev error term				0.55	
				(-0.03)	
N	404	404	404	404	
R2	0.27				

Note: robust standard errors are listed in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Basic IPM

Table 21 presents the results for *Basic IPM* adoption using D. Mrkt. as the instrument for training count. λ, *Both male and female*, *Experience*, *# crops*, and *Trust Ext.* are positive factors influencing *Basic IPM* adoption across the three model specifications. The estimates for λ, *Experience*, and *# crops* are consistent with the previous results in the other two dependent variable specifications. λ again is identified as a positive factor affecting IPM adoption. The loss aversion parameter is significant at the 10% level in 2SLS and IV.Poisson. When we control for farmers who might not have understood our behavioral experiment, our estimates remain the same but their significance improves to 5% (Appendix table A3). Moreover, when we control for farmers who might not have understood our behavioral experiment, the estimates for σ for 2SLS and IV Poisson become significant at the 10% level. The two estimates for σ are -0.25 and -0.15 for the two models respectively. These results indicate that risk aversion decreases the likelihood of *Basic IPM* adoption by about 16% for the IV Poisson estimate, all else held constant.

Being from a farm where the male and females share equal decision-making responsibility increases the likelihood of *Basic IPM* adoption as compared to being from a farm with only a male decision maker. The number of crops grown increases the likelihood of *Basic IPM* adoption, which was also found in the previous regressions. Farmers who believe most government extension workers can be trusted adopt more *Basic IPM* practices than farmers that do not ($p < 0.01$). *Training count* is found to have a negative effect on *Basic IPM* adoption when specified as 2SLS. However, when re-specified using the IV. Poisson model, regression 3, *Training count* is non-significant. Perhaps the lack of effect of training reflects the fact that the topics covered in most training sessions are targeted at more *Advanced IPM.* Similar to the results found in the previous section, it appears that farmers in Tharaka-nithi adopt more *Basic IPM* practices than farmers in the other two counties, all else held constant.

Table 21: *Basic IPM* regression

	OLS (1)	2SLS (2)	IV.Poisson (3)
education	-0.10	-0.11	-0.06
	(0.09)	(0.14)	(0.06)
female	-0.13	-0.08	-0.06
	(0.10)	(0.14)	(0.06)

both male and female	0.39**	0.57*	0.21*
	(0.17)	(0.31)	(0.12)
experience	0.01	0.02***	0.01**
	(0.01)	(0.01)	(0.00)
acres	0.04	0.06	0.02
	(0.03)	(0.06)	(0.03)
# crops	0.50***	0.33**	0.14**
	(0.11)	(0.15)	(0.07)
borrow	0.02	-0.03	0.00
	(0.11)	(0.14)	(0.07)
workable age	-0.00	0.04	0.03
	(0.03)	(0.05)	(0.03)
% income	-0.00	-0.01*	-0.00
	(0.00)	(0.01)	(0.00)
trust Gen	-0.11	-0.02	-0.03
	(0.13)	(0.19)	(0.09)
trust Ext.	0.32**	0.62***	0.32***
	(0.14)	(0.18)	(0.10)
trust Sales	-0.05	-0.20	-0.10
	(0.13)	(0.19)	(0.08)
α	0.00	-0.08	-0.02
	(0.12)	(0.19)	(0.08)
σ	-0.28***	-0.18	-0.12
	(0.10)	(0.15)	(0.07)
λ	0.01	0.03*	0.02*
	(0.01)	(0.02)	(0.01)
nyeri	-0.25*	-0.54**	-0.28***
	(0.15)	(0.24)	(0.10)
kirinyaga	-0.09	-0.59***	-0.28***
	(0.13)	(0.21)	(0.10)
Training count	0.02**	-0.17**	-0.14
	(0.01)	(0.07)	(0.09)
Intercept	1.35***	1.66***	0.52***
	(0.25)	(0.31)	(0.16)
N	404	403	403
R2	0.16		

Note: robust standard errors are listed in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

5.6 Conclusion: IPM adoption

The results of the IPM adoption regressions above show clear differences in estimates which could shed some light on why different conclusions were made with respect to the presence of endogeneity. The estimate for *Training count* in every specification for *Advanced IPM* was found to be a positive factor while it does not appear to have an effect on *Basic IPM* adoption. The consistent positive effect of borrowing to financing last year's crop production and number of acres farmed in each of the *Advanced IPM* models is not found to affect the likelihood of *Basic IPM* adoption. Additionally, farms where male and female share equal responsibility, as compared to farms where males make decisions alone, and whether the farmer trusts most Ag. extension officers increase the likelihood of *Basic IPM* adoption, while the same variables are not significant factors influencing *Advanced IPM* adoption. These differences indicate the uniqueness of the respective IPM adoption categories, which may explain why different conclusions were found with respect to endogeneity for *Advanced IPM* and *Basic IPM*.

With regard to the influence of the CPT behavioral parameters, λ has a consistent positive effect on IPM adoption regardless of response variable specification and sample used. This implies that farmers who are more loss averse adopt more IPM technologies on average. This result could reflect farmers' attempts to reduce income losses due to pest infestations by increasing the diversity of their pest management practices. All CPT parameter effects on *Advanced IPM* adoption are not present in the selection or the intensity equation of the double hurdle model using the entire sample. However, when we use the subsample that controls for farmers' comprehension, the effect of the loss aversion parameter is identified in the selection equation ($p < 0.05$). Thus, loss aversion increases the likelihood of adopting any *Advanced IPM* technique rather than the intensity of adoption. The weighting parameter, α, for *Advanced IPM*, was found to be a significant negative factor. Though only significant at the 10% level in the

NegBin specification, the effect was the same across both samples. This result suggests that farmers who value prospects with higher certainty adopt fewer *Advanced IPM* than farmers who value prospects with lower probability. This could indicate the need to continue IPM training but shift towards educational methods best suited to reduce the uncertainty farmers have with *Advanced IPM* such as field demonstrations in which farmers can see with and without scenarios. This result could also reflect the inability of *Advanced IPM* techniques to remain consistent across seasons or that advanced techniques are not as consistent across seasons as their alternatives. The next section evaluates pesticide use and expenditures, but no evidence suggests that the weighting parameter is associated with higher pesticide application counts or expenditures. Thus, further research is needed to identify exactly why this trend occurs with *Advanced IPM* adoption in the region.

With regard to non-risk factors affecting IPM adoption, we find that women farmers adopt fewer *Advanced IPM* techniques than their male counterparts. The results of the intensity equation in table 20 regression 4 suggest that being female only affects the intensity of adoption and not the choice to adopt initially. After further review of *Training count* by gender of the farmer, we identify that females attended more IPM training sessions on average (1.19 more IPM training sessions) and are trained on IPM at about the same percentage as their male counterparts in our sample (about 34% of all females in the sample were trained on IPM). The *Female Advanced IPM* result is concerning, especially since some *Advanced IPM* techniques decrease the likelihood of pesticide applications, which could reduce female exposure to toxins during their child rearing years. Further research is needed to understand why being female decreases the likelihood of higher counts of *Advanced IPM* adoption. Similarly, for *Basic IPM* adoption, farms run by males and females who share equal responsibility adopt more *Basic IPM* practices than farms run by males alone, all else held constant. *Training count* showed mixed results with regard to the IPM adoption. *Training count* is associated with higher *Advanced IPM* adoption, but reduces the likelihood of *Basic IPM* adoption. This result could suggest pest management topics at IPM training sessions should focus more on non-*Basic IPM.* With regard to differences between counties, farmers in Tharaka-nithi were found to adopt IPM practices at higher rates than farmers in the other counties. This could reflect the improved markets for *Advanced IPM* technologies or spillovers from the higher counts of IPM training that are seen in Tharaka-nithi as compared to the other counties. Though this work did not focus on farmer groups, KALRO helped to establish farmer groups in Tharaka-nithi between 2016 and 2019, which could have helped disseminate technologies in the region. The number of acres farmed and borrowing to finance crop production were found to increase the likelihood of *Advanced IPM* adoption, while years of horticulture experience plays a pivotal role in determining IPM adoption for all specifications. We believe that these results reflect a challenge for the next generation of farmers who are farming on smaller parcels of land. Not only will they need to increase their productivity to meet their own financial needs, but as a whole, the next generation needs to produce using less pesticides so Kenya's horticulture production can meet global markets where higher profits can be generated.

5.7 Pesticide Applications and Pesticide Expenditures summary statistics

The average number of *Pesticide applications* for the three crops is about 7.5 applications. Tomato growers have the most pesticide applications, roughly 8, followed by French bean growers with 5 and cabbage growers with 4.5. Pesticide expenditures follow a similar pattern with tomato growers spending the most with $100, followed by French bean growers with $42 and cabbage growers with $36.5. The average across the three crops is roughly $82.

Table 22. Pesticide Applications and Pesticide Expenditures per acre (USD) descriptive statistics

	Observations	Min	Max	Mean	Std.dev
Pesticide Applications	**440**	**0**	**96**	**7.67**	**7.40**
Tomato Pesticide Applications	249	0	96	8.11	8.06
Cabbage Pesticide Applications	185	0	24	4.63	3.67
French bean Pesticide Applications	96	0	20	5.20	2.99
Pesticide Expenditure	**428**	**0**	**1119.28**	**82.54**	**119.73**
Tomato Pesticide Expenditure	250	0	1119.38	101.11	144.85
Cabbage Pesticide Expenditure	171	0	261.19	36.54	41.20
French bean Pesticide Expenditure	93	0	223.88	41.98	45.68

Figure 6.1 shows the distribution of the pesticide response variables, and both show a high density of observations for low pesticide application counts and expenditures per acre followed by a gradual decline.

Figure 5.2 Distribution of pesticide response variables

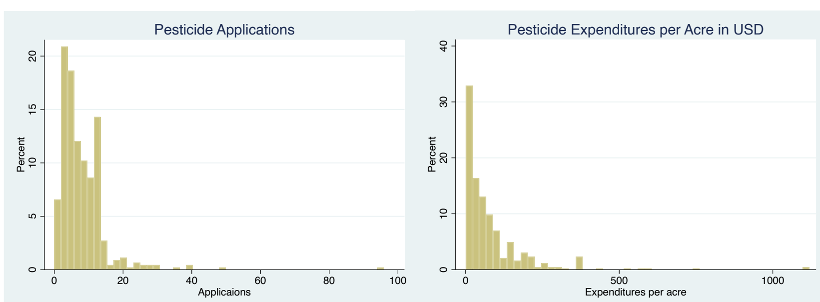


Table 23 shows the pest severity for the last growing season. The averages for all specifications indicate that pest severity was around 'medium' for the last growing season.

Table 23. Pest severity last season

	Observations	Min	Max	Mean	Std.dev

Severity	**441**	**0**	**3**	**1.93**	**0.78**
Tomato severity	254	1	3	2.02	0.82
Cabbage severity	182	0	3	1.81	0.75
French bean severity	95	0	3	1.93	0.78

5.8 Pesticide Application and Expenditure IV tests

The same process that was used to determine the need to instrument *Training count* and the validity of instruments for IPM adoption models was followed for the two variables that evaluate the impact of IPM adoption on *Pesticide applications* and *Pesticide expenditures*. In both specifications we found heteroskedasticity present and thus robust standard errors were used and Wooldridge's endogeneity and overidentification tests. Panels 1 and 4 of table 24 represent regressions that used *Both* as an instrument for training count. Though we fail to reject exogeneity and overidentification in the models, both of the first stage F statistics are considerably under the 10 "rule of thumb", reflecting their inability to provide consistent estimates. Re-specifying the instruments using *% IPM* and *D. Mrkt* in separate 2SLS regressions show that *D. Mrkt* is the most consistent predictor of *Training count,* but we fail to reject that *Training count* is exogenous. Thus, both models will treat *Training count* as exogenous. Similar results are found when we re-specify $Adopt_{ia}$ as $Adopt_{ik}$, representing a vector of the adoption decision for each individual IPM technique.

Table 24: Instrumental variable tests for pesticide response variables

	Total Pesticide Applications			Total Pesticide Expenditures per Acre		
	Both (1)	% IPM (2)	D. Mrkt (3)	Both (4)	% IPM (5)	D. Mrkt (6)
Weak Instrument						
F (1,217)	5.29	2.89	9.5	5.41	2.67	10.02
		(0.03)	(0.00)		(0.10)	(0.00)
Endogeneity						
Robust Sore Chi2(1)	1.82	4.27	0.05	0.56	0.24	0.25

	(0.18)	(0.04)	(0.83)	(0.46)	(0.62)	(0.63)
Robust Regression F (1,216)	1.75	4.14	0.04	0.55	0.23	0.23
	(0.19)	(0.04)	(0.83)	(0.46)	(0.63)	(0.63
Overidentification						
Score Chi2(1)	1.66	NA	NA	0.06	NA	NA
	(0.20)	NA	NA	0.81	NA	NA
Observations	394	394	394	394	394	394

5.9 Pesticide applications and Pesticide expenditures regression results

Pesticide applications

Table 25 shows the factors affecting *Pesticide applications*. The model is specified as OLS and Poisson in panels 1 and 2 respectively. All the results are similar between model specifications except for *Trust Sales*, which is not significant in OLS and significant using the Poisson model. With respect to the risk parameters, the results in this section are the same when using the sub-sample of farmers that passed at least one of the comprehension tests (Table A4 of the *Participant Comprehension: CPT* section of the Appendix). A and λ are not found to be significant factors in determining the number of pesticide applications. However, the risk aversion parameter, σ, is positive and significant (Poisson $p < 0.05$). The direction of its effect was expected and suggests that farmers who are more risk averse apply pesticides more times per season than their less risk averse counterparts, ceteris paribus. This result is consistent with the results found in Liu and Huang (2013). However, we did not find a positive relationship with the loss aversion parameter with pesticide use as the Liu and Huang study did.

Holding all else constant, the Poisson model finds that male and females who share equal responsibility for farm decisions, compared to males who make farm decisions alone, have 23% more *Pesticide applications* on average ($p < 0.10$). The number of crops has a strong positive relationship with the dependent variable ($p < 0.01$). Specifically, each additional crop grown increases the likelihood of higher seasonal *Pesticide applications* by 72%. *Trust Gen.* and *Trust Sales* are both significant factors affecting pesticide applications ($p < 0.10$ and $p < 0.05$ respectively), but trusting most people increases *Pesticide applications* by 31%, while trusting salespeople reduces *Pesticide applications* by 32%. The first result coincides with our expectations. However, the second is surprising because agricultural input salespeople's salaries are likely tied directly to use of pesticides. No differences are found between farmers from Nyeri and Tharaka-nithi, but farmers from Kirinyaga are expected to make 54% more pesticide applications that their Tharaka-nithi counterparts. Unexpectedly, both *Severity* and *Training count* did not significantly affect pesticide applications in either model. Furthermore, neither *Advanced IPM* nor *Basic IPM* appear to affect farmers' *Pesticide applications*. This result is problematic for IPM programs in the region that hope to improve the health of the communities and open up the country's horticulture sector to exports by reducing exposure to pesticides. However, without being able to isolate the effects of individual programs in the region, we cannot say that all IPM programs are not being effective at making an impact in this regard.

Table 25: *Pesticide applications*

	OLS (1)	Poisson (2)
education	-0.07	-0.01
	(0.81)	(0.09)
female	-0.48	-0.06
	(0.66)	(0.09)
both male and female	-1.46*	-0.21*
	(0.79)	(0.12)
experience	-0.01	0.00
	(0.04)	(0.00)
acres	-0.16	-0.04
	(0.11)	(0.03)
# crops	5.20***	0.54***
	(1.12)	(0.10)

borrow	-0.33	-0.04
	(0.79)	(0.09)
workable age	-0.18	-0.03
	(0.21)	(0.03)
% income	0.01	0.00
	(0.04)	(0.00)
trust Gen	2.01*	0.27*
	(1.19)	(0.14)
trust Ext.	0.70	0.08
	(1.35)	(0.15)
trust Sales	-2.26	-0.28**
	(1.49)	(0.14)
α	0.62	0.08
	(0.96)	(0.11)
σ	2.14*	0.24**
	(1.13)	(0.10)
λ	-0.07	-0.01
	(0.11)	(0.01)
nyeri	0.97	0.11
	(0.85)	(0.11)
kirinyaga	3.49***	0.43***
	(1.33)	(0.15)
training count	-0.08	-0.01
	(0.08)	(0.01)
severe	0.73	0.07
	(0.73)	(0.08)
advanced IPM	0.46	0.06
	(0.54)	(0.06)
Basic IPM	0.33	0.04
	(0.62)	(0.07)
Intercept	-2.42	0.90***
	(2.61)	(0.29)
N	395	395
R2	0.21	

Note: robust standard errors are listed in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 26 shows the same regression presented in table 25, but the individual IPM techniques, *k,* are used instead of the aggregated IPM categories, *a*. In order to keep the table concise, only the individual IPM techniques are shown and all the farmer and farm characteristics, county fixed effects, and risk variables are suppressed from the table. We find that *PRV*, *Select*, *Trays*, and *None* are all associated with increased seasonal pesticide applications. Specifically, farmers who use *PRVs* and select healthy seedlings/sanitizing seed treatment apply 46% and 63% more *Pesticides applications* than farmers that do not use those practices respectively ($p < 0.01$). Furthermore, farmers who do not use any IPM techniques apply pesticides 48% more times than farmers who use IPM techniques, all else held constant ($p < 0.05$). Farmers who use *Trichoderma*, *Microbial*, and *Remove* apply 51%, 65%, and 23% less pesticides than farmers who do not utilize those IPM techniques ($p < 0.10$, $p < 0.01$, and $p < 0.05$ respectively), all else held constant.

Table 26: *Pesticide applications* using individual IPM techniques

	OLS (1)	Poisson (2)
PRV	2.16**	0.38***
	(0.89)	(0.12)
select	5.34**	0.49***
	(2.50)	(0.13)
trichoderma	-4.13	-0.41*
	(2.56)	(0.23)
trays	10.98	0.95***
	(7.00)	(0.27)
solar	1.08	0.04
	(1.97)	(0.14)
sticky	1.58	0.11
	(1.56)	(0.12)
microbial	-4.10**	-0.50***
	(1.85)	(0.19)
bio	-2.68	-0.20
	(1.89)	(0.15)
nets	1.93	0.15
	(1.52)	(0.16)
mulch	0.44	-0.03
	(1.44)	(0.10)
remove	-1.80**	-0.21**
	(0.79)	(0.09)
none	2.74*	0.39**
	(1.61)	(0.18)
Intercept	-3.68	0.78***
	(2.73)	(0.27)

N	354	354
R2	0.33	

Note: robust standard errors are listed in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Pesticide expenditures

Table 27 shows the results for total pesticide expenditures in 2019 USD per acre last season, regressed on the independent variables previously used but the RHS variable *X* is transformed to *X'* which removes *Acres* from the vector of explanatory variables. For the reasons addressed in the discussion about *Training count* in table 23, the dependent variable is treated as exogenous. All else held constant, we see that both the weighting and loss aversion parameters do not appear to have affected per acre pesticide expenditures last season. The risk aversion parameter however, σ, has a strong positive relationship with the dependent variable ($p < 0.01$). The coefficient on σ of 56.46 implies that if the farmer is one standard deviation more risk averse than the average farmer, and they will spend $28.23 more per acre on pesticides than the average farmer. We find that farmers who have more education than completed primary school spend on average $31.71 per acre less than farmers with lower education levels ($p < 0.05$). Similar to what was found with total pesticide applications, farms that are managed by male and female partners who make farm decisions jointly spend less on pesticides per acre than farms run by males alone. ($p < 0.05$). Specifically, they spend $33.51 less than male farmers, all else held constant. Pest severity has a strong positive relationship with the dependent variable ($p < 0.05$). A marginal increase in average pest severity for the crops farmed increases per acre pesticide expenditures by $15.61 per acre, ceteris paribus. Though no differences were found between the number of pesticide applications for Nyeri and Tharaka-nithi farmers, farmers in Nyeri spend $30.56 less per acre on pesticides than farmers from Tharaka-nithi ($p < 0.10$).

Table 27: ***Pesticide expenditures***

	OLS (1)
education	31.71** (12.62)
female	-13.30 (14.61)
both male and female	-33.51** (15.06)
experience	-0.25 (0.84)
# crops	5.51 (10.27)
borrow	-8.74 (11.75)
workable age	-0.22 (3.86)
% income	-0.22 (0.27)
trust Gen	5.83 (18.87)
trust Ext.	-1.43 (18.43)
trust Sales	-19.49 (16.55)
α	-19.29 (16.00)
σ	56.46*** (15.80)
λ	-1.50 (1.71)
nyeri	-30.56* (18.45)
kirinyaga	19.17 (21.25)
training count	2.36 (2.23)
severe	15.61** (7.89)
advanced IPM	-5.17 (4.29)
Basic IPM	-0.84 (6.58)
Intercept	49.56 (32.82)

N	395
R2	0.15

Note: robust standard errors are listed in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

Similar to table 26, table 28 shows only the effects of individual IPM techniques on pesticide expenditures per acre and suppresses farm characteristics, county fixed effects, and risk parameter effects. We find that farmers who used PRV's last season had higher pesticide expenditures than those who did not ($p < 0.05$). Farmers who used microbial pesticides and removed damaged plants were found to have lower pesticide expenditures per acre, all else held constant. Specifically, farmers who used microbial pesticides spent $70.53 less than farmers who did not, ceteris paribus ($p < 0.01$). Removing damaged plants is associated with a pesticide cost savings of $33.70 per acre ($p < 0.10$).

Table 28: Total pesticide expenditures using individual IPM techniques

	OLS (1)
PRV	29.04** (12.48)
select	17.33 (18.95)
trichoderma	-12.42 (31.35)
trays	24.50 (23.76)
solar	-24.87 (28.51)
sticky	-11.30 (17.34)
microbial	-70.53*** (22.59)
bio	23.10 (44.23)
nets	4.47 (16.49)
mulch	4.62 (19.19)
remove	-33.70* (18.23)

none	-11.80
	(22.15)
Intercept	40.57
	(37.22)
N	335
R2	0.15

Note: robust standard errors are listed in parentheses. * significant at 10%; ** significant at 5%; *** significant at 1%.

5.10 Conclusion: Pesticide applications and Pesticide expenditures

Similar to the results found by Liu and Huang (2013), we find that more risk averse individuals apply more pesticides and spend more money on pesticides, and the weighting parameter does not influence pesticide applications or expenditures (Liu and Huang 2013 measured pesticides in Kg/hectare). Conversely, we find that loss aversion does not play a significant role in determining pesticide applications or expenditures for Kenyan horticulturalists. Kenyan farmers who are one standard deviation more risk averse than the average farmer are expected to spend \$28.23 more per acre on pesticides than the average farmer.

Gender impacts identified by the pesticide models show males and females who make farm decisions jointly make fewer seasonal pesticide applications and spend less per acre than males who make farm decisions alone, all else held constant. Further analysis of perceptions of pesticide risk with respect to gender of the primary decision maker could offer insight into this result but is beyond the scope of this project. *Trust Gen*., *Trust Ext*., and *Trust Sales* do not appear to have significant effects on per acre pesticide expenditures. However, *Trust Gen.* ($p < 0.10$) and *Trust Sales* ($p < 0.05$) are found to increase and decrease the number of pesticide applications respectively. The first result could reflect the connectivity of horticulture farmers in the community who communicate pesticide decisions to their neighbors and friends, which influences their pest management decisions. The latter result is unexpected given the fact that salaries of agricultural input suppliers are directly tied to the number of pesticide applications. Though IPM offers alternatives to pesticides, neither IPM training count nor the aggregated IPM adoption categories were found to have significant effects on either of the response variable specifications. However, when separating the aggregated IPM adoption categories into their respective activities we found that certain IPM techniques within the aggregated categories had opposite effects on the latent variables. Furthermore, we identified that farmers who used no IPM techniques had higher levels of pesticide applications per season than IPM adopters. Within the *Advanced IPM* technique category we found that selecting healthy seedlings/sanitizing seed treatment and using nursery trays had significant positive effects, while use of Trichoderma and microbial pesticides had significant negative effects on the count of seasonal pesticide applications. Additionally, with respect to *Basic IPM* adoption, use of a PRV was identified as a significant positive factor while removing damaged plants reduced the number of pesticide applications on average, all else held constant. A similar pattern was found for pesticide expenditures per acre with respect to *Basic IPM* adoption for *PRV* and *Remove*. These conflicting relationships with regard to the estimated effects within IPM category *a* could explain why the model that used the aggregated IPM categories did not identify a significant effect.

In conclusion, it appears that IPM adoption has a stronger effect on pesticide applications then it does on pesticide expenditures, and that the relationship that individual IPM techniques have with the latent variables are unique to the respective IPM techniques. Some techniques appear to be used in conjunction with pesticides, while others are used instead of conventional pest management methods. However, the methods that have a positive effect on the response variable appear to be IPM techniques used at the beginning of the season *PRV*, *Select*, and *Trays* where the need for pesticides are limited. Conversely, the IPM techniques *Trichoderma*, *Microbial*, and *Removed* are pest management practices that can be used throughout the growing season which are associated with lower pesticide use. Farmers who did not adopt any IPM techniques across the three crops were found to apply pesticides more than farmers who practice IPM.

Chapter 6 Conclusion

Our study investigated the factors that affect IPM adoption, seasonal pesticide applications, and seasonal pesticide expenditures for Kenyan vegetable farmers. Comparison between the results of the 2016 and 2019 surveys showed a population that is more dependent on their vegetable production as an income source in 2019. Our findings show that IPM adoption and impacts of IPM adoption on pesticide applications and expenditures per acre were mixed. Tomato farmers saw an increase in IPM adoption of six of the eight IPM practices and a reduction in adoption of two. Cabbage farmers' IPM adoption increased for three practices and decreased fort five. French bean farmers' IPM adoption increased for three practices, stayed the same for one, and decreased for two of the six IPM practices. The pesticide impact variables, *Pesticide applications and Pesticide expenditures*, also indicated mixed results with respect to the effects of IPM techniques within IPM category *a.* We found that IPM practices primarily used at the beginning of the season were associated with increases in pesticide applications and conversely a decrease in pesticide applications for IPM techniques that can be used throughout the season. Moreover, we found that farmers who did not use any IPM practice are expected to have 48% more pesticide applications than farmers who practice IPM.

With respect to the CPT parameters in the preceding regressions, a comparison of the results between the full sample and the sample that passed the second comprehension test show minor differences. α saw no change, σ became a significant factor in *Basic IPM* ($p < 0.10$; Table 21), and λ's significance increased between samples (table 20 and 21). Specifically, λ increased in significance in the *Advanced IPM and Basic IPM* regressions and became significant in the selection equation for the Double Hurdle model (*Advanced IPM* table 20). We believe that these results suggest that the marginal effects of CPT parameters can be estimated accurately without rigorous participant training, which can decrease participant's time burden and monetary program costs when collecting participant's risk preferences.

The loss aversion parameter's positive effect in each regression unambiguously shows that farmers who are loss averse adopt more IPM practices than their less loss averse counterparts, while the parameter was nonsignificant in the pesticide response variable regressions. One explanation of this result is that loss averse farmers are utilizing IPM techniques in each category to mitigate the risk of losses in income due to pest infestations. Because the aggregated IPM categories did not show a negative relationship with the pesticide impact response variables, this result does not suggest a preference for IPM over conventional pesticides. What this result could suggest is vegetable growers' preference for a diverse pest management portfolio, with IPM practices being a component of the entire pest management portfolio. If our previous assumption is true, and given the fact that *# crops* was found to have a strong positive relationship with the likelihood of IPM adoption, this suggests that vegetable farmers are taking a holistic approach to pest management and utilizing IPM practices based on the specific needs of their crops. This is a good sign for IPM in Kenya as this is a central tenet to successful IPM.

Farmers who place higher value on prospects with certainty were found to adopt fewer *Advanced IPM* practices than farmers who place more value on prospects with lower probability.

This result may reflect uncertainty with the expected benefits of *Advanced IPM* practices. One way to reduce uncertainty is through IPM training, but this result may imply a need to apply new methods to farmer training to reduce uncertainty. Perhaps more hands-on opportunities through farmer field days and using government extension workers to help with the training sessions would be beneficial in reducing uncertainty of the expected benefits of *Advanced practices*. The weighting parameter was not a significant factor of either pesticide response variable regression.

The risk aversion parameter is a significant factor in determining *Pesticide applications* and *Pesticide expenditures.* More risk averse farmers apply more pesticide applications and spend more on pesticides per acre. These results suggest that the income risk effect from pest infestations are greater than the health risk effects associated with applying pesticides for Kenyan vegetable growers on average. This result should influence future IPM efforts to tailor training to account for this market preference. Therefore, if Kenyan vegetable growers are not motivated by health risk reduction, marketing IPM as a way to reduce the risks of pesticide poisoning may not be an effective marketing strategy to increase the expected benefits of an IPM practice, $B_{i,k}$, over the needed threshold for that practice's adoption, $T_{i,k}$. We are not saying that pesticide poisoning is not a problem affecting Kenyan vegetable farmers. The 38% increase in pesticide poisoning between the 2016 and 2019 survey shows that the risks and externalities of pesticide poisoning are present and increasing on vegetable farms in Kenya.

The social network variables regarding farmer's trust of agricultural information suggest that government extension workers are a positive influence on IPM adoption. Specifically, for all IPM categories farmers who trust government extension workers adopt more IPM practices than those who do not. Trusting most people in general (*Trust Gen.*) and trusting most agricultural input suppliers (*Trust Sales*) are not significant factors that determine IPM adoption levels.

However, *Trust Gen.* increases the likelihood of higher seasonal pesticide applications, which suggests that Kenyan vegetable growers are influenced by farmers within their social network to apply more pesticides. Farmers who indicated they trust agricultural input suppliers apply fewer pesticides than farmers who do not. This last result does not coincide with our previous expectations and suggests a need for further investigations into Kenyan vegetable farmers' interactions with agricultural salespeople to understand why this relationship is found.

Future IPM research efforts should focus on understanding why females are less likely to adopt *Advanced IPM* practices then their male counterparts and work to tailor the next generation of Kenyan horticulturalists to produce using every tool in their arsenal. We understand the financial limitations of both research groups and Kenyan farmers that could limit both IPM dissemination and adoption but believe IPM could be a valuable tool to get Kenyan products in global markets. The results of the behavioral experiment suggest tailoring IPM programs to promote IPM as a method to reduce seasonal crop losses could be a method to enhance IPM adoption. Because the average farmer who receives any IPM training was trained about 6 times, and each training session increased the likelihood of using *Advanced IPM* practices by about 5%, if 100 farmers attended six training sessions, we would expect about 30% of the farmers to use at least one *Advanced IPM* practice on their farm. If IPM adoption is the only goal of IPM training, this could suggest the need to change dissemination strategy or make adjustments to IPM training sessions. However, this is not to say all IPM programs operate at the same efficiency, and that IPM adoption is the only goal of training sessions. In reality, IPM training offers a great opportunity for farmers to present farming issues in their community, ask questions about challenges they are facing, and offers a platform to teach holistic pest management methods that encompass both IPM use and conventional pest methods.

In conclusion, it appears that IPM adoption has a positive and negative impact on pesticide decisions, which depends on the IPM practice being used. However, we are unable to quantify the net environmental and health benefits without knowing more precisely the pesticide quantity used during the season. Additional impact assessment of IPM programs in the region would be helpful in assessing the benefits of the various IPM programs operating in Kenya.

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Appendix

Kahneman and Tversky Behavioral Experiment 1979

For problems 1 through 9 Kahneman and Tversky (1979) asked participants to select between participating in the gamble represented in column A or B. Where the outcome represents the value of the respective winning or loss for that gamble. N represents the number of participants and the bracketed value represents the percent of respondents that selected that gamble.

Even though he expected value of Gamble A is greater than the expected value for column B participants consistently selected Gamble B. Thus, suggesting editing the prospect in terms of the its outcomes weights and not their respective probabilities.

Problem 1: Select between			
A		B	
Outcome	Probability	Outcome	Probability
2,500	0.33		
2,400	0.66	2,400	1
0	0.01		
N=72	[18]		[82]

In problem 2 is derived by taking out a .66 chance of winning 2,400 from both gamble A and B. The change in preference from Gamble B to A with this removal is further evidence to support the need of a weighting function.

Problem 2: Select between			
A		B	
Outcome	Probability	Outcome	Probability
2,500	0.33	2,400	0.34
0	0.67	0	0.66
0	0.01		
N=72	[83]		[17]

Problem 3 we see that even though the expected value of both prospects are the same the preference of Gamble A identifies the empirical evidence to support overweighting small probabilities.

Problem 3: Select between			
A		B	
Outcome	Probability	Outcome	Probability
6,000	0.001	3,000	0.002
N=66	[73]		[27]

Even though the expected values of the two gambles are the same 84% of participants select Gamble B after they have theoretically been given 1,000. This suggest the framing presented in EU is not consistent with empirical evidence that implies that the reference for the decision is based off of the values of the prospects and not the individuals final asset or wealth.

Problem 4: In addition to whatever you own, you have been given 1,000. You are now asked to choose between			
A		B	
Outcome	Probability	Outcome	Probability
1,000	0.5	500	1
N = 70	[16]		[84]

Similar to Problem 4 this provides further evidence for CPT framing and evidence to support the risk loving preference in the domain of losses.

Problem 5: In addition to whatever you own, you have been given 2,000. You are now asked to choose between			
A		B	
Outcome	Probability	Outcome	Probability
-1,000	0.5	-500	1
N = 68	[69]		[31]

Notice in Table 1 the negative prospects are just the positive prospects multiplied by -1, ceteris paribus. The table provides empirical evidence that suggests that individuals are characterized as risk averse in the domain of gains and conversely in the domain of loss.

Table 1

Positive Prospects						Negative Prospects				
	Outcome	Probability	Outcome	Probability			Outcome	Probability	Outcome	Probability
Problem 6	4,000	0.8	3,000	1		Problem 6'	-4,000	0.8	-3,000	1
N = 95		[20]		[80]		N = 95		[92]		[8]
Problem 7	4,000	0.2	3,000	0.25		Problem 7'	-4,000	0.2	-3,000	0.25
N = 95		[65]		[35]		N = 95		[42]		[58]
Problem 8	3,000	0.9	6,000	0.45		Problem 8'	-3,000	0.9	-6,000	0.45
N=66		[86]		[14]		N=66		[8]		[92]
Problem 9	3,000	0.002	6,000	0.001		Problem 9'	-3,000	0.002	-6,000	0.001
N = 66		[27]		[73]		N = 66		[70]		[30]

Behavioral Experiment

Enumerator script for Behavioral experiment

"Thank you for your time your responses will be used to improve vegetable production in the region and thus accurate responses are important. Please respond to the following questions as accurately as possible. If you don't understand a question, please inform the enumerator and he/she will aid you in understanding."

"There are 3 series of questions that involve hypothetical amounts of money. Series 1 contains 14 question, Series 2 contains 14 questions, and Series 3 contains 7 questions. Please take as much time as you need to answer each question. Would you like to proceed?"

Practice 1

Take out the bag with the 9 white stones and 1 black stone. Let the farmer study the bag and let them know that there are 10 stones total with 9 white and 1 black stone. Ask the farmer, "Which color stone has the highest likelihood of being selected if one stone was to be selected at random?"

Practice 2

Take out the bag with the 3 green stones and 7 orange stones. Let the farmer study the bag and let them know that there are 10 stones total with 3 green and 7 orange stones. Ask the farmer, "Which color stone has the highest likelihood of being selected if one stone was to be selected at random?"

"For this part of the survey you will be given 80KSH. Additionally, in this section we will play a game where your final earnings will depend partly on your decisions and partly on chance. There are 3 series of questions that involve a decision to participate in the gamble presented in Option A or Option B. The gamble that will cost you nothing and will not pay out the Shilling values that you see. However, I (the enumerator) have a piece of paper that has a percentage written on it that will be used to determine the true values of each gamble, your final earnings could be more or less than 80 Kshs we will give you. Your final payment will be determined by your responses. It is important to note that you will not have to pay more than the 80 Kshs that we will give you for this part of the survey. The percentage will be revealed at the end of the experiment and a number between 1 and 35 will be drawn at random. The numbers 1-35 represent the number of rows in series 1-3 [Please show/explain this to the farmer]. The number that is drawn will identify the row that will be played for real money using the percentage value to determine the final values of the Options. Please imagine that you are playing for the Shilling values indicated in the series and make your decision based on the Shilling values and the mix of colored stones. Let's start with an example."

Example 1

	Option A		Option B	
	10 Stones: 3 Green and 7 Orange		10 Stones: 1 Black and 9 White	
1	300Ksh	70Ksh	500 Ksh	35 Ksh

"[Please show the individual the first example and its respective bags.]   Before you are two options: Option A and Option B. Each option uses 10 stones with a different mix of colored stones. Notice that options A and B have different Shilling values for each color stones. Row 1 represents a question asking you to choose between participating in the gamble using the mix of stones and respective Shilling values in Option A or Option B. If you choose to participate in the hypothetical gamble using the stones in Option A for example, the colors will correspond to the Shilling value presented in that option. The stones will then be placed in a different bag and one stone will be drawn at random. The color of stone drawn represents the value in Shillings that you would receive. It is important to note that there is no right or wrong answer. If you choose to participate using the gamble presented in Option A which uses 3 green stones and 7 orange stones. [Pull out green stone] If a green stone was selected at random you would receive 300 Ksh [Replace green stone and pull out an orange stone] If an orange stone was selected, you would receive 70 Ksh. ~~repeat process for Option B~~ Option B uses 1 black stone and 9 white stones. If a black stone was selected at random you would receive 500 Ksh and if a white stone was selected, you would receive 35 Ksh. It is important to note that there is no right or wrong answer. If a stone is to be selected at random from one of the options which option would you select? Option A or B?"

Series 1

"Now we will proceed with the experiment. Series 1 and Series 2 contain 14 rows, and Series 3 contains 7 rows. Each row is to be considered as a question like the ones previously practiced. The question being "Based on the shilling values presented in each row and the mix of colored stones and each option. If one stone was to be pulled randomly from a bag would you prefer to gamble using the stones in Option A or Option B? Please take as much time as you need to answer each question and know that there is no right or wrong answer."

Take out series 1 and proceed

"Series one has 14 questions like the ones we just practiced. Please take a second to look over the series. Notice that Option A uses 3 green and 7 orange stones and their respective Shilling values for each question in the series. Now look at Option B. It uses 1 black stone and 9 white stones. Please study the questions in the series and notice the changes in shilling values for each question in the series. When you have finished studying the series let the me know (enumerator). It is important to note that there is no right or wrong answer. Please answer the question to the best of your ability based on the number colored stones and the Shilling values for each option. Please identify the FIRST question number where you would switch participating in the gamble presented in Option A to Option B. However, you do not have to switch to Option B if you do not want to. Take a moment to review the series and when you are ready identify your decision."

Example 2. [Please show the individual the second practice series with their respective bags.]

"Let's do another example   Once again you see there are two options: Option A and Option B. However, the values that each color stone represents has changed from the previous gamble. Both options use 10 stones total but a different mix of stones. Option A uses 9 white stones and 1 black stone. If you selected to participate in the gamble in Option A and a white stone was selected at random you would receive 300 Ksh and if black stone was selected, you would receive 200 Ksh. Option B uses 7 orange stones and 3 green stones. If an orange stone was selected at random you would receive 560 Ksh and if a green stone was selected, you would receive 35 Ksh. If a stone is to be selected at random from one of the options which option would you select? Option A or B?"

Series 2

"Series 2 has 14 questions like the previous section. Please take a second to look over the series. Notice that Option A uses 9 white stones and 1 black stone and their respective Shilling values for each question in the series. Now look at Option B. It uses 7 orange stones and 3 green stones. Please study the questions in the series and notice the changes in shilling values for each question in the series. When you have finished studying the series let the enumerator know. It is important to note that there is no right or wrong answer. Please answer the question to the best of your ability based on the number colored stones and the Shilling values for each option. Please identify the question number where you would switch participating in the gamble presented in Option A to Option B. However, you do not have to switch to Option B if you do not want to. Take a moment to review the series and when you are ready identify your decision."

Series 3

"Again, remember this is a gamble that will cost you nothing and will not pay out the exact Shilling values that you see. However, please imagine that you are playing for the money presented and make your decision based on the Shilling values presented in each gamble. Series 3 has 7 questions. Notice that both Option A and B both use the same bag of stones 5 white stones and 5 orange stones. In this series you have the possibility to lose money as indicated by the negative values in the orange columns. Please study the questions in the series and notice the changes in shilling values for each question in the series. When you have finished studying the series let the enumerator know.   It is important to note that there is no right or wrong answer. Please answer the question to the best of your ability based on the number colored stones and the Shilling values for each option. Please identify the question number where you would switch participating in the gamble presented in Option A to Option B. However, you do not have to switch to Option B if you do not want to. Take a moment to review the series and when you are ready identify your decision."

Final Payment

Please ask the farmer to draw a number between 1-35. Identify which number has been drawn.

Reveal the 2% percentage value. Proceed with the gamble that the farmer prefers and the row that was drawn at random. Issue and record payment.

Participant Comprehension: CPT

Results: IPM Adoption

Table A1 below shows the regression for *IPM Count* using the sample that passed both comprehension tests. No change is seen with respect to the CPT parameters. Alpha and sigma remain nonsignificant predictors of *IPM Count*, while lambda remains highly significant and its respective estimates do not change for the panels that control for endogeneity.

Table A1: IPM Count using Training Count as the endogenous variable instrumented by distance market. CPT Pass subsample

	OLS (1)	2SLS (2)	IV.Poisson (3)
education	0.12	0.21	0.08
	(0.18)	(0.20)	(0.08)
female	-0.27	-0.24	-0.12
	(0.20)	(0.19)	(0.07)
both male and female	0.44	0.37	0.05
	(0.32)	(0.40)	(0.12)
experience	0.03***	0.04***	0.02***
	(0.01)	(0.01)	(0.00)
acres	0.38***	0.41***	0.13***
	(0.08)	(0.08)	(0.02)
# crops	0.86***	0.76***	0.25***
	(0.21)	(0.27)	(0.08)
borrow	0.38*	0.34	0.11
	(0.21)	(0.21)	(0.07)
workable age	-0.10	-0.09	-0.03
	(0.07)	(0.07)	(0.03)
% income	0.00	0.00	-0.00
	(0.01)	(0.01)	(0.00)
trust Gen	-0.38	-0.41*	-0.19**
	(0.24)	(0.22)	(0.08)
trust Ext.	0.38	0.61**	0.29**
	(0.25)	(0.27)	(0.11)
trust Sales	0.07	-0.05	-0.02
	(0.23)	(0.23)	(0.09)
alpha	-0.02	-0.02	-0.00
	(0.23)	(0.21)	(0.09)
sigma	-0.23	-0.22	-0.10
	(0.20)	(0.19)	(0.08)
lambda	0.07***	0.08***	0.03***

	(0.02)	(0.03)	(0.01)
nyeri	-1.90***	-2.06***	-0.79***
	(0.29)	(0.29)	(0.11)
kirinyaga	-1.41***	-1.72***	-0.71***
	(0.24)	(0.30)	(0.13)
training count	0.06***	-0.05	-0.02
	(0.02)	(0.08)	(0.03)
Intercept	1.43***	1.61***	0.58***
	(0.46)	(0.46)	(0.16)
N	359	358	358
R2	0.31	0.24	
* p<0.10	** p<0.05	*** p<0.01	

Table A2 shows the *Advanced IPM* regressions using the subsample that passed the CPT comprehension tests. The regression on the subsample shows no change in sigma, which remains nonsignificant. The weighting parameter alpha remains significant at 10% and decreases marginally from -0.43 to -0.42. Lambda increases in significance in regression 3 from 5% to 1% and is identified as a significant positive factor in the selection equation of the Dbl. Hurdle model ($p<0.05$).

Table A2: *Advanced IPM* Practices using training count

	OLS	Poisson	NegBin	Dbl. Hurdle	
	(1)	(2)	(3)	(4)	
				Selection	Intensity
education	0.17	0.11	0.18	0.13	0.05
	(0.16)	(0.19)	(0.19)	(0.16)	(0.11)
female	-0.21	-0.35*	-0.39*	-0.17	-0.08
	(0.17)	(0.20)	(0.22)	(0.18)	(0.11)
both male and female	0.13	-0.09	-0.05	-0.01	-0.05
	(0.28)	(0.25)	(0.26)	(0.25)	(0.19)
experience	0.03***	0.05***	0.05***	0.03**	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
acres	0.25***	0.23***	0.21***	0.06	0.15***
	(0.07)	(0.03)	(0.05)	(0.07)	(0.03)
# crops	0.44**	0.49***	0.44**	0.29	0.14
	(0.18)	(0.17)	(0.19)	(0.18)	(0.13)
borrow	0.38**	0.38**	0.36**	0.34**	0.04
	(0.18)	(0.17)	(0.18)	(0.17)	(0.12)
workable age	-0.03	-0.01	-0.01	0.04	-0.05*

	(0.06)	(0.06)	(0.06)	(0.06)	(0.03)
% income	0.01*	0.01*	0.01	0.01	0.01*
	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
trust Gen	-0.22	-0.38*	-0.32	-0.51**	0.20
	(0.20)	(0.21)	(0.22)	(0.20)	(0.13)
trust Ext.	0.05	0.28	0.42	0.13	0.25
	(0.22)	(0.29)	(0.29)	(0.24)	(0.16)
trust Sales	0.07	-0.01	-0.11	0.04	0.03
	(0.20)	(0.26)	(0.28)	(0.21)	(0.16)
alpha	-0.14	-0.35	-0.42*	-0.25	-0.09
	(0.20)	(0.22)	(0.24)	(0.21)	(0.12)
sigma	0.05	0.14	0.19	-0.09	0.15
	(0.17)	(0.19)	(0.27)	(0.18)	(0.18)
lambda	0.05***	0.07***	0.08***	0.05**	0.02
	(0.02)	(0.02)	(0.03)	(0.02)	(0.02)
nyeri	-1.96***	-3.36***	-3.38***	-1.95***	-0.91***
	(0.25)	(0.50)	(0.61)	(0.37)	(0.29)
kirinyaga	-1.39***	-2.33***	-2.32***	-1.22***	-0.87***
	(0.21)	(0.35)	(0.35)	(0.24)	(0.15)
Training count	0.05***	0.04***	0.04**	0.04***	0.00
	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)
constant	0.20	-1.04**	-1.06**	-0.65*	-0.01
	(0.40)	(0.44)	(0.44)	(0.39)	(0.25)
d			0.22		
			(0.23)		
Lnsigma				-0.60***	
				(0.06)	
sigma				0.55	
				(-0.03)	
N	359	359	359	359	359
R2	0.27				
* p<0.10	** p<0.05	*** p<0.01			

Table A3 shows the factors of *Basic IPM* using the subsample that passed both comprehension tests for the behavioral experiment. The weighting parameter alpha remains a nonsignificant factor while sigma and lambda do see some change using the sample that controlled for participant comprehension. Sigma which was not identified as a significant factor in the previous regression for *Basic IPM* becomes a negative factor (p<0.10). Sigma's estimate in regression 3 suggest that more risk averse farmers are less likely to adopt *Basic IPM* than less risk averse farmers, all else held constant. Lambda which was only significant at the 10% level in the regression presented in table 20 increases to the 5% level while the estimate for 2SLS increases by 0.01.

Table A3: *Basic IPM* Count using training count as the endogenous variable instrumented by D. Mrkt.

	OLS (1)	2SLS (2)	IV.Poisson (3)
education	-0.04 (0.09)	0.06 (0.12)	0.03 (0.06)
female	-0.06 (0.10)	-0.04 (0.13)	-0.05 (0.07)
both male and female	0.31* (0.16)	0.21 (0.20)	0.08 (0.10)
experience	0.00 (0.01)	0.01* (0.01)	0.01** (0.00)
acres	0.13*** (0.04)	0.17*** (0.05)	0.09*** (0.02)
# crops	0.43*** (0.11)	0.28** (0.11)	0.14** (0.06)
borrow	-0.01 (0.10)	-0.07 (0.12)	-0.01 (0.06)
workable age	-0.07** (0.03)	-0.06 (0.04)	-0.03 (0.03)
% income	-0.01** (0.00)	-0.01*** (0.00)	-0.01** (0.00)
trust Gen	-0.16 (0.12)	-0.17 (0.15)	-0.12 (0.08)
trust Ext.	0.32** (0.13)	0.59*** (0.17)	0.34*** (0.09)
trust Sales	0.00 (0.12)	-0.15 (0.18)	-0.10 (0.09)
alpha	0.12 (0.12)	0.11 (0.16)	0.09 (0.08)
sigma	-0.28*** (0.10)	-0.25* (0.13)	-0.15* (0.08)
lambda	0.02 (0.01)	0.04** (0.02)	0.02** (0.01)
nyeri	0.05	-0.16	-0.14

	(0.15)	(0.23)	(0.11)
kirinyaga	-0.02	-0.46**	-0.27**
	(0.12)	(0.20)	(0.12)
Training	0.01	-0.14**	-0.12*
	(0.01)	(0.06)	(0.07)
Intercept	1.23***	1.50***	0.43***
	(0.23)	(0.26)	(0.15)
N	358	358	358
R2	0.16		
* p<0.10	** p<0.05	*** p<0.01	

Results: Pesticide Applications and Expenditures per Acre

Table A4 presents the total pesticide applications being regressed on covariates using the subsample that passed both participant comprehension tests. No change is observed for alpha and lambda, while sigma decreases by 0.01 but remains at the 5% significance level.

Table A4: Total number of pesticide applications last season

	OLS	Poisson
	(1)	(2)
education	-0.24	-0.01
	(0.93)	(0.10)
female	-0.91	-0.10
	(0.76)	(0.10)
both male and female	-1.42*	-0.20*
	(0.86)	(0.12)
experience	-0.03	-0.00
	(0.05)	(0.01)
acres	-0.19	-0.02
	(0.29)	(0.03)
# crops	5.17***	0.52***
	(1.23)	(0.11)
borrow	-0.23	-0.03
	(0.85)	(0.10)
workable age	-0.09	-0.02
	(0.24)	(0.03)
% income	0.01	0.00
	(0.04)	(0.00)
trust Gen	2.15	0.28*
	(1.37)	(0.15)
trust Ext.	0.77	0.09
	(1.45)	(0.16)
trust Sales	-2.30	-0.27*
	(1.60)	(0.15)
alpha	0.83	0.10
	(1.01)	(0.12)
sigma	2.16	0.23**
	(1.34)	(0.11)
lambda	-0.02	-0.00
	(0.13)	(0.01)
nyeri	1.58	0.19
	(1.02)	(0.13)
kirinyaga	3.82**	0.46***

	(1.58)	(0.16)
training count	-0.08	-0.02
	(0.08)	(0.01)
severe	0.69	0.06
	(0.83)	(0.09)
advanced IPM	0.60	0.07
	(0.63)	(0.06)
Basic IPM	0.13	0.01
	(0.62)	(0.07)
Intercept	-2.48	0.92***
	(2.88)	(0.31)
N	350	350
R2	0.33	
* p<0.10	** p<0.05	*** p<0.01

Pesticide Expenditures per Acre

Table A5 shows the regressions for total pesticide expenditures per acre in 2019 USD using the subsample that passed both participant comprehension tests. The estimate for sigma decreases by 1.12 and still remains highly significant (p<0.01).

Table A5: Total pesticide expenditures per acre last season in 2019 USD dollars

	OLS (1)
education	30.16**
	(13.89)
female	-12.41
	(15.73)
both male and female	-30.95*
	(15.94)
experience	-0.32
	(0.85)
# crops	3.78
	(11.39)
borrow	-3.76
	(12.23)
workable age	-3.55
	(4.16)
% income	-0.07
	(0.25)
trust Gen	-1.17

	(19.94)
trust Ext.	-4.47
	(18.15)
trust Sales	-16.55
	(16.41)
alpha	-16.82
	(16.78)
sigma	55.34***
	(18.73)
lambda	-0.38
	(1.88)
nyeri	-38.24*
	(21.27)
kirinyaga	4.40
	(22.10)
training count	2.23
	(2.55)
severe	11.57
	(7.60)
advanced IPM	-4.59
	(3.65)
Basic IPM	-1.49
	(7.74)
Intercept	73.54**
	(32.31)
	30.16**
N	352
R2	0.12
* p<0.10	** p<0.05

Results for IPM adoption regressions using *IPM Trained*

With regard to IPM training, there is the possibility that motivated farmers would be more likely to attend training sessions than their less motivated counterparts. Including this variable in the model without accounting for endogeneity could bias our estimates and lead to misleading result. Whether the farmer received IPM training (*IPM Trained*) could be correlated with the error term in our models, motivating the research to instrument the variable. The instruments considered are distance to the nearest market *D. Market*, and percentage of IPM at the sub county level, *% IPM*. Both of these potential instruments are assumed to meet both of the requirements for a valid instrument, i.e. highly correlated with the endogenous variable and not correlated with the error term in the adoption equation. Table A6 uses a linear probability model for the dummy variable Trained (1 = farmer has been trained on IPM) with robust standard errors provided in parenthesis.

The percentage of IPM Training at the subcounty level has a significant postive relationship with the potential endogenous variables (p=0.01). However, distance from the farmers house to the nearest market is not significant, therefore, only *% IPM* will be considered as a valid instrument for the regressions with the *IPM Trained*.

Table A6: Testing for Instruments

	(1) Trained
_Intercept	0.03
	(0.07)
D. Mrkt	-0.01
	(0.01)
% IPM	0.01***
	(0.00)
N	445
R-sq	0.075
adj. R-sq	0.070

Table A7 presents the instrument/endogeneity tests for the three different dependent variable specifications that instrumented Trained with *% IPM*. The Breusch-Pagan Cook-Weisberg chi^2 test was used to determine if heteroskedasticity was present in the regressions (H_o is that there is constant variance). We reject the null for all response variable specifications. Therefore, robust standard errors are used for each specification. With respect to the first stage endogeneity test we followed Wooldridge 1995. The results show that *% IPM* is a suitable instrument for *IPM Trained* (F stat >10). However, we fail to reject exogeneity using *Basic IPM* while we reject exogeneity of *Trained IPM* for *Count IPM and Advanced IPM*. Therefore, *IPM Trained* will be instrumented using *% IPM* for the first two specifications and treated as exogenous for *Basic IPM.*

ALL Breusch-Pagan Cook-Weisberg chi^2 (18) 143.81 (prob > chi^2 0.00)
ADV Breusch-Pagan Cook-Weisberg chi^2 (18) 226.73 (prob > chi^2 0.00)
BAS Breusch-Pagan Cook-Weisberg chi^2 (18) 33.12 (prob > chi^2 0.02)

Table A7: Results for endogeneity and validity tests using % IPM as instrument for trained.

		Count IPM (1)	Advanced IPM (2)	Basic IPM (3)
Weak Instrument				
	F (1,217)	18.14	18.14	18.14
Endogeneity		(0.00)	(0.00)	(0.00)
	Robust Sore Chi2(1)	25.2	48.31	0.17
		(0.00)	(0.00)	(0.68)
	Robust Regression F (1,216)	26.64	58.13	0.16
		(0.00)	(0.00)	(0.69)
Observations	404			

Results: *IPM Count*

Table A8 presents the regression results for IPM Count using *IPM %* as an instrument for trained. Using the IV.Pois specification,we find that sigma as a strong negative effect on adoption which could implies that risk averse farmers adopt fewer IPM techniques than less risk averse farmers, all else held constant ($p<0.10$). The other CPT parameters are nonsignificant predictors of *IPM Count*.

With respect to non-CPT parameters, farms that are run jointly by a male and female adopt more IPM practices than farms run by males alone. The results for acres (total number of acres farmed between the three crops) show that as the total number of acres increases so too does the likelihood of higher *IPM Count* ($p<0.05$). The highly significant and positive results for *# Crops* suggest that as farmers cultivate more of the three crops of interest, they are more likely to adopt IPM practices in general ($p<0.01$). We believe this suggests that Kenyan farmers are tailoring pest management strategies to the specific needs of each crop which is a good sign for IPM in the region. The highly significant negative values on Nyeri indicate that being a farmer from Tharaka-nithi makes you about 80% more more likely to adopt IPM practices than if that same farmer was from Nyeri, ceteris paribus. Whether or not the farmer was trained on IPM, *IPM Trained*, shows that receiving IPM training does make an impact on IPM adoption. Specifically, 2SLS shows that on average being trained on IPM increases IPM adoption by 4.9 practices ($p<0.01$). Similarly, transforming the result of regression 3 to IRR shows that being trained makes farmers four times more likely to adopt any of the IPM practices that farmers that have not been trained ($p<0.01$), ceteris paribus.

Table A8: IPM Count using Trained as the endogenous variable instrumented by % IPM

	OLS	2SLS	IV.Pois
	(1)	(2)	(3)

education	-0.03	0.12	0.04
	(0.17)	(0.28)	(0.09)
female	-0.32*	-0.26	-0.11
	(0.19)	(0.28)	(0.09)
both male and female	0.87***	0.90**	0.25**
	(0.31)	(0.41)	(0.11)
experience	0.03**	-0.02	-0.00
	(0.01)	(0.02)	(0.01)
acres	0.14***	0.10*	0.03**
	(0.05)	(0.06)	(0.02)
# crops	0.87***	1.08***	0.40***
	(0.20)	(0.32)	(0.09)
borrow	0.46**	0.47*	0.13
	(0.20)	(0.27)	(0.08)
workable age	-0.05	-0.13	-0.04
	(0.06)	(0.09)	(0.03)
% income	0.00	0.00	0.00
	(0.01)	(0.01)	(0.00)
trust Gen	-0.19	-0.34	-0.10
	(0.23)	(0.31)	(0.09)
trust Ext.	0.31	-0.58	-0.11
	(0.26)	(0.44)	(0.16)
trust Sales	-0.01	0.38	0.03
	(0.23)	(0.37)	(0.12)
alpha	-0.08	0.11	-0.06
	(0.22)	(0.35)	(0.11)
sigma	-0.29	-0.37	-0.16*
	(0.18)	(0.30)	(0.10)
lambda	0.06**	0.02	0.01
	(0.02)	(0.04)	(0.01)
nyeri	-1.76***	-1.35***	-0.60***
	(0.26)	(0.45)	(0.13)
kirinyaga	-1.11***	-0.09	-0.10
	(0.23)	(0.46)	(0.17)
trained	0.76***	4.90***	1.40***
	(0.18)	(1.28)	(0.37)
Intercept	1.47***	0.55	0.15
	(0.45)	(0.69)	(0.28)
IPM %			
Control			
N	404	404	404
R2	0.28		
* p<0.10	** p<0.05	*** p<0.01	

Advanced IPM

Table A9 shows the results for Advanced IPM Count using *IPM %*. IV.Pois is not shown because it did not converge. This could be due to the distribution of the response variable violating the assumptions of the model (70% of farmers that did not adopt any *Advanced Practice* causing). The 2SLS are presented but might not be the best model given the nature of the dependent variable. The 2SLS results suggest that the CPT parameters are nonsignificant factors of *Advanced IPM.* With respect to non-CPT covariates, *# Crops*, *Borrow*, and *IPM Trained* are positive factors of *Advanced IPM* while *Trust Ext.*, and *Nyeri* are negative. Again, the estimate on *# Crops* suggests that farmers are using IPM techniques based on the specific needs of a crop and not using the same techniques across crops ($p<0.05$). Similar to the results identified in table 19, borrowing to finance crop production last year increases the likelihood of *Advanced IPM* adoption. *IPM Trained* is identified as a positive factor of *Advanced IPM* like result of *Training Count* in table 19. Further, the result for *Nyeri* is also consistent with previous results that found that Tharaka-nithi farmers adopt more *Advanced IPM* than farmers from *Nyeri.* A result that conflicts with the estimates provided in Table 19 that used *Training Count* instead of *IPM Trained* is the negative relationship *Trust Ext.* has with the response variable.

Table A9: *Advanced IPM* results using *IPM Trained* as the endogenous variable instrumented by % IPM

	OLS (1)	2SLS (2)
education	0.07 (0.13)	0.23 (0.25)
female	-0.20 (0.14)	-0.13 (0.26)
both male and female	0.46** (0.23)	0.48 (0.39)

experience	0.02*	-0.03
	(0.01)	(0.02)
acres	0.10**	0.06
	(0.04)	(0.05)
# crops	0.39***	0.60**
	(0.15)	(0.30)
borrow	0.44***	0.45*
	(0.15)	(0.26)
workable age	-0.05	-0.13
	(0.04)	(0.09)
% income	0.01	0.01
	(0.00)	(0.01)
trust Gen	-0.09	-0.25
	(0.17)	(0.30)
trust Ext.	-0.04	-0.97**
	(0.19)	(0.39)
trust Sales	0.05	0.46
	(0.17)	(0.33)
alpha	-0.07	0.13
	(0.17)	(0.32)
sigma	-0.02	-0.11
	(0.14)	(0.26)
lambda	0.05***	0.01
	(0.02)	(0.04)
nyeri	-1.48***	-1.05***
	(0.20)	(0.41)
kirinyaga	-0.96***	0.10
	(0.17)	(0.41)
IPM trained	0.74***	5.06***
	(0.13)	(1.20)
Intercept	0.09	-0.88
	(0.33)	(0.63)
N	404	404
R2	0.28	
* p<0.10	** p<0.05	*** p<0.01

Basic Practices

Table A10 presents the results for the dependent variable Basic IPM Practices using *IPM Trained*. *Sigma*, *Both Male and Female*, *# crops*, *Trust Ext.*, and *Nyeri* estimates remain consistent across model specifications. The goodness of fit test for the Poisson regression identifies that the model is appropriate for the data (deviance GOF 208.78 ($p>0.10$) Pearson's GOF 166.56 ($p>0.10$))

The risk aversion parameter, sigma, is found to have a strong negative relationship with Basic IPM adoption. Hence, risk averse farmers are adopting fewer *Basic IPM* practices on average than their less risk averse counterparts ($p<0.05$). This could reflect a preference towards other pest management practices where they believe higher incomes can be generated. The weighting parameter, alpha, and loss aversion parameter do not appear to be a factor of *Basic IPM* when using the dummy variable for *IPM Trained.* Farms where male and females share equal responsibility for farm making decisions wrt. male run farms (*Both Male and Female)* adopt more basic practices on average ($p<0.05$). Specifically, *Both Male and Female* is expected to increase the likelihood of *Basic IPM* adoption by about 19%. The positive significance of # *Crops* suggests that farmers use a different mix of *Basic IPM* techniques across the crops of interest and growing one more of the three crops increases the likelihood of *Basic IPM* adoption by 23% on average, ceteris paribus. Farmer's trusts towards government extension officers makes a large positive impact on the probability of *Basic IPM* adoption. Specifically, it increases the likelihood of *Basic IPM* adoption by about 21% ($p<0.01$). With respect to county differences, Tharaka-nithi farmers adopt 15% more *Basic Practices* than farmers from Nyeri, however no differences are found between Tharaka-nithi and Kirinyagan farmers. With respect to the results presented in Table 20: *Basic IPM* Count using training count as the endogenous variable instrumented by D. Mrkt, a comparison shows the relationship *Both Male and Female*, # *Crops*, *Trust Ext.*, and *Nyeri* have with the response variable between models are the same. Conversely, *Experience*, *Lambda*, and *Kirinyaga* are not found as significant factors of *Basic IPM* adoption in the regression used in table A10 while they are when *Training Count* is used instead *of IPM Train* (Table 20). Similarly, sigma was not identified as a significant factor in Table 20 but is a significant factor in table A10.

Table A10: *Basic IPM* using *IPM Trained*

	OLS (1)	Poisson (2)	NB.Reg (3)
education	-0.10	-0.05	-0.05
	(0.09)	(0.05)	(0.05)
female	-0.12	-0.07	-0.07
	(0.10)	(0.05)	(0.05)
both male and female	0.41**	0.17**	0.17**
	(0.17)	(0.07)	(0.07)
experience	0.01	0.00	0.00
	(0.01)	(0.00)	(0.00)
acres	0.04	0.02	0.02
	(0.03)	(0.02)	(0.02)
# crops	0.48***	0.21***	0.21***
	(0.11)	(0.05)	(0.05)
borrow	0.01	0.01	0.01
	(0.11)	(0.05)	(0.05)
workable age	0.00	0.00	0.00
	(0.03)	(0.02)	(0.02)
% income	-0.00	-0.00	-0.00
	(0.00)	(0.00)	(0.00)
trust Gen	-0.10	-0.05	-0.05
	(0.13)	(0.07)	(0.07)
trust Ext.	0.35**	0.19***	0.19***
	(0.14)	(0.07)	(0.07)
trust Sales	-0.06	-0.04	-0.04
	(0.13)	(0.06)	(0.06)
alpha	-0.01	-0.00	-0.00
	(0.12)	(0.06)	(0.06)
sigma	-0.27***	-0.14***	-0.14***
	(0.10)	(0.05)	(0.05)
lambda	0.01	0.01	0.01
	(0.01)	(0.01)	(0.01)
nyeri	-0.28*	-0.14**	-0.14**
	(0.15)	(0.07)	(0.07)
kirinyaga	-0.15	-0.08	-0.08
	(0.13)	(0.07)	(0.07)
Training	0.02	0.01	0.01
	(0.10)	(0.05)	(0.05)

Intercept	1.38*** (0.25)	0.40*** (0.12)	0.40*** (0.12)
N	404	403	403