Analyzing the Impacts of an IPM Vegetable Technology Transfer in Bangladesh

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ABSTRACT

This study evaluates the effectiveness and impacts of USAID's IPM IL vegetable technology transfer subproject in Bangladesh. The effectiveness of the technology transfer is evaluated in four ways: IPM adoption rates and determinants of IPM adoption, measuring the impact of IPM adoption on vegetable yields, pest management costs, and the number of pesticide applications used, estimation of the economic impacts of IPM adoption and the technology transfer, and analysis of the relative efficiency of the various technology transfer methods used to transfer the IPM practices to farmers. Adoption determinants were identified using traditional and ordered probit regression analysis. Difference-in-difference models were used to identify the impacts of IPM adoption on yields, pest management costs, and the number of pesticide applications applied. Economic impacts of IPM technology adoption were measured using economic surplus analysis. Finally, to compare the relative efficiency of different technology transfer methods, adoption rates were identified for each transfer method and combined with the training cost per farmer to identify the cost per farmer adopting IPM practices.

The results from the adoption analysis suggest the number of years of agricultural experience of the household head, the number of IPM adopters known by the household, and learning agricultural information from media sources and/or farm training events such as field days significantly increase the likelihood of IPM adoption. The impacts of IPM adoption on vegetable yields, pest management costs, and the number of pesticide applications were non-significant for vegetable crops. Analysis of the cost efficiency of the different IPM technology transfer methods suggests that media sources such as television, radio, and newspapers have the lowest cost per farmer.

Dedication

To my wife Heather, my best friend and greatest encourager. Knowing you will be with me, I look forward to many more wonderful years and enjoyable adventures together with you!

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Acronyms

AAEC	Agricultural and Applied Economics
BARI	Bangladesh Agricultural Research Institute
CAPI	Computer-Assisted Personal Interviewing
CIP	International Potato Center
.csv	Comma-Separated Values
DAE	Department of Agricultural Extension
DD	Difference-in-Difference Model
FtF	Feed-the-Future
GDP	Gross Domestic Product
HH	Household
HHH	Household Head
IPM CRSP	Integrated Pest Management Collaborative Research Support Program
IPM IL	Integrated Pest Management Innovation Lab
IRR	Internal Rate of Return
kg	Kilogram
NGO	Non-Governmental Organization
NPV	Net Present Value
RCT	Randomized Control Trial
SAAO	Sub-assistant Agricultural Officer
sq km	Square kilometer
US	United States
USAID	United States Agency for International Development
USD	United States Dollar
VA Tech	Virginia Polytechnic Institute and State University

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1. Introduction

Pest problems are major contributors to income loss in agriculture resulting from decreased crop yields and increased costs from pesticides. Further, the improper use of pesticides in controlling pests leads to farmer health problems and long-term environmental damage. Close to three-quarters of the poor population in developing countries live in rural areas and most of those rural poor depend on agriculture for survival and subsistence (World Bank, 2007). In developing countries, estimates place agricultural production and post-harvest losses due to pests at 25-50% of total production (IPM-IL, 2013). The cost of pesticides in developing countries can be as much as 35% of total agricultural production costs (Karim, 2009). Pesticide expenditures in vegetable production can be nearly seven times the agricultural average expenditure on pesticides (Fernandez-Cornejo, et al., 1994).

Pesticides cause environmental and health problems when farmers are unaware of best practices for pesticide use. Pesticide cost studies in the Philippines found that the average health expenditures for farmers using pesticides were 40% higher than for farmers not using pesticides (Pingali and Roger, 1995), with healthcare expenditures rising by 0.5% to 0.74% for every 1% increase in pesticide use above average levels (Rola and Pingali, 1993). Another study in Zimbabwe found that for every $1 a household spends on pesticides, the household will spend as much as $0.83 on pesticide-related healthcare costs (Maumbe and Swinton, 2003).

Pesticides impact all parts of the environment from microorganisms to birds, fish, and mammals. While microorganism populations in the soil are only negatively impacted a few days after pesticide application, larger organisms such as fish, birds, and assorted mammals are impacted in the long term as pesticides build to toxic levels as they are absorbed through the food chain and environment (van der Werf, 1996). Birds, mammals, and fish are all impacted by pesticides indirectly through contaminated food sources (van der Werf, 1996). In addition, fish are also directly affected by contaminated water (J.B.H.J. Linders, 1994). Environmental studies in the Philippines have also found negative pesticide impacts on fish, shrimp, frogs, chicken, and ducks as well as significant short-term decreases in algae populations as a result of pesticide applications in rice farming (Pingali and Roger, 1995).

With the growing costs to finances, health, and the sustainability of agricultural land, farmers in developing countries desperately need alternative, less costly, healthier, and more environmentally friendly methods for dealing with pests. To address this need, in 1993 United States Agency for International Development (USAID) initiated the Integrated Pest Management Collaborative Research Support Program (IPM CRSP, now called the Integrated Pest Management Innovation Lab or the IPM IL) to develop and disseminate alternative pest management approaches.

The three primary goals of the IPM IL are to reduce agricultural losses caused by pests, damage to local ecosystems and losses of biodiversity, and pollution and contamination of food and water supplies (IPM-IL, 2013). The IPM IL addresses these three goals by identifying pest problems and developing, testing, and transferring IPM technologies and practices to farmers. The IPM IL focuses on developing pest control strategies and practices that minimize the use of traditional pesticides that can be expensive and harmful to both the farmers and environment when used improperly (IPM-IL, 2013). Some of the approaches used by the IPM IL include monitoring pest populations, handpicking of evasive pests, amending the soil with organic material, and planting resistant varieties.

There have been several phases to the IPM IL. The early phases from 1993 to 2004, focused on developing IPM technologies within specific countries in six developing regions. The IPM approaches developed were specifically suited for the key crops and climates of the countries chosen. Starting in 2004 with the third phase of the IPM IL, the programs were regionalized and began extending existing technologies to other crops and other countries within each region (IPM-IL, 2013).[1]

One of the countries targeted in the South Asian IPM IL region since the second phase is Bangladesh. Bangladesh's ongoing dependence on agriculture and the persistent poverty levels faced by those in the agriculture industry make it an ideal country for the development of alternative pest control methods. Bangladesh has a total population of 156.6 million (The World Bank, 2014) or more than 25 million households (Mollah and Ibrahim, 2010), 76.5% of which are living below the poverty line of $2.00 a day (World Bank, 2014). Agriculture directly supports 8.8 million households (35% of all households) in Bangladesh and accounts for 15.75% of GDP (Mollah and Ibrahim, 2010). Within the agricultural industry, an estimated 37% of those supported by agriculture are living below Bangladesh's national poverty line (Mollah and Ibrahim, 2010).

The IPM IL first began its program in Bangladesh in 1998, and has gradually introduced IPM technologies and approaches to new areas of the country through collaboration with the Bangladesh Agricultural Research Institute (BARI), Bangladesh's Department of Agricultural Extension (DAE), the International Potato Center (CIP), and other organizations.[2] Initial IPM efforts in Bangladesh prior to the third phase aimed to develop new IPM technologies when needed and adapt existing IPM technologies wherever possible. The IPM IL in Bangladesh aims to spread IPM technology packages not only in major vegetable areas, but also to USAID

[1] There are currently six regions of the IPM IL: Latin America and the Caribbean, Central Asia, South Asia, Southeast Asia, East Africa, and West Africa
[2] Other organizations include: Cereal Systems Initiative for South Asia, Mennonite Central Committee, Grameen Krishok Sohayak Sangstha, Action Aid - Bangladesh, Practical Action – Bangladesh, Care – Bangladesh, Ispahani Biotech, Ltd., and Safe Agriculture Bangladesh Ltd.

designated Feed-the-Future (FtF) regions within Bangladesh. Feed the Future is focused on increasing and improving agricultural productivity, research, and resilience in developing countries around the world (Feed-the-Future, 2014).

BARI is currently spreading existing IPM technologies for crops to new FtF regions in Bangladesh, including the districts of Barisal, Magura, Jessore, and Jhalokati. One of the ongoing sub-projects is the "technology transfer of IPM packages developed for tomato, eggplant, cucumber, bitter gourd, sweet gourd, country bean, and cabbage" (Bertelsen, et al., 2013, p 10). Begun in 2012, this sub-project targets the adaption of existing IPM agricultural practices and technologies that decrease pesticide use, lower production costs, and increase crop yields among the aforementioned vegetables.

In addition to introducing new IPM technologies to the four districts in Bangladesh, expanding the IPM IL's programs geographically also provides an opportunity to evaluate the technology transfer methods and the impacts of the transferred IPM technologies. Evaluating the IPM technologies with a controlled experiment and longitudinal survey provides opportunities to evaluate both the impacts of the IPM technologies and the effectiveness of the extension methods used to transfer the IPM technologies to farmers. Since the program extended IPM vegetable technology to four new districts, the first year of the sub-project's rollout primarily involved the setup for the randomized control trial (RCT), a baseline survey of farmers in the new districts, and beginning the transfer of IPM technologies to farmers within selected treatment villages. The second year of the sub-project's rollout included the second round of the longitudinal survey and continued the transfer of IPM technologies to farmers. In the third year of the sub-project, the transfer of IPM technologies to farmers in the treatment villages will continue to remaining treatment villages and the third and final round of the longitudinal survey will be conducted.

The effectiveness of the IPM technology transfer can be evaluated in three ways: the overall adoption rate of the IPM technologies, the household-level impacts of the transferred technologies, and the overall economic impacts of the technology transfer. In addition to measuring the effectiveness of the technology transfer, the efficiency of the technology transfer can also be evaluated by comparing the technology transfer approaches.

1.1 Objectives

There are four objectives to this thesis. The first objective is to measure the IPM technology adoption rates and the determinants of IPM adoption. The second objective is to measure the impacts of the IPM technology transfer on vegetable yields, pest management costs, and pesticide use. The third objective is to estimate the total economic impacts of the IPM technology transfer. The fourth and final objective is to compare the relative effectiveness of the different technology transfer methods in terms of adoption rates and programmatic transfer costs per farmer.

1.2 Hypotheses

There are four sets of hypotheses, one for each of the objectives. Hypotheses for the first objective focus on the adoption of IPM technologies and how adoption rates are affected by different technology transfer methods:

H1a: Learning agricultural information from field days will not increase the likelihood of adopting IPM technologies.
H1b: Learning agricultural information from agricultural officers will not increase the likelihood of adopting IPM technologies.
H1c: Learning agricultural information from the newspaper and other media sources will not increase the likelihood of adopting IPM technologies.

Hypotheses for the second objective focus on the impacts of the technology transfer:

H2a: Adoption of IPM practices will not increase vegetable yields.

H2b: Adoption of IPM practices will not increase production costs per hectare.
H2c: Adoption of IPM practices will not decrease pesticide use.

The hypothesis for the third objective focus on the economic impacts of the technology transfer:

H3: This technology transfer will generate an economic rate of return higher than ten percent.

The hypothesis for the fourth objective focus on the relative efficiency and effectiveness of the various technology transfer methods on adoption and the cost per farmer adopting:

H4a: Field days have a higher cost per farmer adopting the technology than other technology transfer methods.

1.3 Approach

This thesis will use data collected in the first two rounds of the three-year longitudinal survey of vegetable farmers in selected villages in the Barisal, Magura, Jessore, and Jhalokati districts of Bangladesh. Use of a longitudinal survey allow for the control of time-invariant effects such as village and regional characteristics, and unobservable individual or household characteristics. When selecting farmers to participate in a survey it is important that the characteristics of the surveyed population are balanced between the treatment and control groups to prevent selection bias. To avoid the problem of selection bias, the survey was designed using a RCT approach that randomizes villages in the four districts into treatment or control groups. Using survey data to compare the treatment and control groups, the impacts of the IPM technology transfer will be assessed in four ways. First, adoption rates will be determined for the various IPM vegetable packages. Second, the adoption rates will then be used to assess the impacts of the IPM technology transfer in several ways including vegetable yield, pest management cost, and pesticide use changes. Third, adoption rates will then be combined with cost and yield data from BARI test plots and survey data to estimate the total economic impacts of the IPM technology transfer using economic surplus analysis. Finally, adoption rates and other survey information will be used to compare the relative cost efficiency of the different transfer methods used to train farmers in IPM technology.

1.4 Organization of Thesis

This thesis is organized into six chapters. Chapter Two gives context for this study by providing background information about Bangladesh, the IPM IL program, and the ongoing IPM IL vegetable sub-project. Chapter Three reviews literature and methods for the use of RCT in the econometric evaluation of adoption rates, impact analysis, economic surplus analysis, and analyzing the relative efficiency of different technology transfer methods. Chapter Four examines the source and general characteristics of the data in this study. Chapter Five presents and explains the results of the econometric and economic analyses. Finally, Chapter Six provides a summary of the results and questions for future study.

2. Background

2.1 Introduction

Chapter Two provides background information on Bangladesh as well as the IPM IL and the vegetable technology transfer subproject. First is a discussion of background information for Bangladesh, the IPM IL, the vegetable technology transfer subproject, and the selected districts. Next, is a description of the IPM methods transferred by the IPM IL. The IPM methods are followed by production information, and descriptions of pests and the recommended IPM packages for the vegetables in the study. Finally, the different transfer methods used by the IPM IL to transfer the IPM technology are discussed.

2.2 Bangladesh background

Bangladesh is a small South Asian country bordering India and Myanmar, with the Bay of Bengal to its south. Bangladesh has a total area of only 143,998 square kilometers (sq km). Despite being a relatively small country compared to neighboring India and Myanmar, Bangladesh is one of the most densely populated countries in the world with a total population of 158.5 million or 1,100 people/sq km (CIA, 2014).

Bangladesh has an annual gross domestic product (GDP) of $324.6 billion with one of the lowest GDP per capita worldwide at $2100. The manufacturing and export of garments is the largest single industry in Bangladesh (accounting for more than 18% of total GDP) (CIA, 2014). The second largest industry in the Bangladesh economy is the agricultural sector, accounting for approximately 17% of total GDP. Within the agricultural sector, crop farming alone is responsible for 11% of Bangladesh's GDP. An estimated 37% of those supported by the agricultural sector are living below the national poverty line (Mollah and Ibrahim, 2010).

2.3 IPM IL program background

The IPM IL, was originally founded by USAID in 1993 with three main goals to (1) reduce agricultural losses caused by pests, (2) raise farmers' incomes, and (3) reduce environmental damage due to pesticides. More specifically, its objectives are to reduce crop losses due to pests, increase farmer income, reduce pesticide use or promote the use of safe pesticides when non-pesticide alternatives are lacking, reduce pesticide residues in food and food products, improve IPM research and education program capabilities, improve pest monitoring, transfer IPM technologies to farmers, and increase the involvement of women in IPM decision-making and program design.

The first phase, from 1993-1998, and the second phase, from 1998-2004, focused on specific countries within the six regions. For each chosen country, the IPM IL would identify pests affecting the key crops within the country and develop IPM technologies and processes to reduce the losses due to those pests. The third and fourth phases of the IPM IL, from 2004 to the present, have expanded the emphasis of the IPM IL by creating IPM IL regional programs and extending and spreading packages of IPM technologies to additional crops and countries within each of the regions.

2.3.1 IPM IL in Bangladesh

In Bangladesh, the IPM IL has focused on a variety of crops including: okra, tomatoes, eggplant, cucumbers, bitter gourds, country beans, and cabbage. One of the current subprojects of the IPM IL program in Bangladesh is a vegetable IPM technology transfer program targeting six vegetables: tomatoes, eggplant, cucumbers, bitter gourds, country beans, and cabbage. Started in 2013, this vegetable IPM technology transfer program is extending existing IPM vegetable practices to new districts in Bangladesh. Focusing on four USAID designated FtF districts, this subproject involves a RCT, the transfer of IPM vegetable practices to farmers over multiple years, and a longitudinal survey of farmers within those districts to ascertain the impacts of the technology transfer.

2.3.2 District agricultural characteristics

The four FtF districts targeted as part of this vegetable IPM technology transfer subproject are: Barisal, Magura, Jessore, and Jhalokati. These districts were targeted as part of the FtF goals of "reducing poverty and hunger by improving the availability of food and by improving incomes among poor smallholder farmers" (Bertelsen, et al., 2013, p 7). With those goals in mind, the four targeted districts each have a significant population engaged in the agricultural industry or a significant rural poor population that can benefit from agricultural technology improvements.

In the Jessore district of Bangladesh there are approximately 809,000 people (close to 33% of the district's population) and more than 240,000 households (46% out of 524,000 total) relying on agricultural labor to support their families. More than 311,000 of Jessore's farm holdings are less than an acre (83% of the 374,000 total farm holdings). Approximately 370,000 acres or 58%, of Jessore's total area is sown at least once each year with a cropping intensity[3] of 182% (Ibrahim, 2011, Mollah and Ibrahim, 2010).

In the Magura district of Bangladesh there are more than 315,105 people (about 38% of the district's population) and more than 63,000 households (17% out of 380,000 total) relying on agricultural labor to support their families. More than 88,714 of Magura's farm holdings are less than one acre in size (63% of the 140,199 total farm holdings). Approximately 170,000 acres or

[3] Cropping intensity is the number of plantings in one year divided by the number of fields planted in a percent form, i.e. one field planted three times has a cropping intensity of three divided by one equals 300% cropping intensity.

66%, of Magura's total area is cropped or sown at least once each year with a cropping intensity of 209% (Ibrahim, 2011, Mollah and Ibrahim, 2010).

In the Barisal district of Bangladesh approximately 600,000 people (more than 25% of the district's population) and more than 137,000 households (29% out of 474,000 total) are supported by agricultural labor with over 322,000 separate farm holdings (and close to 47% or 224,000 holdings of less than 1 acre in size). Approximately 248,000 acres or 36%, of Barisal's total area is cropped or sown at least once each year with a cropping intensity of 171% (Ibrahim, 2011, Mollah and Ibrahim, 2010).

In the Jhalokati district of Bangladesh approximately 104,000 people (more than 15% of the district's population) or 21,000 households (14% out of 145,000 total) rely on agriculture to support their families. Approximately 70,000 of Jhalokati's farm holdings are less than an acre (72% of the 97,000 total farm holdings). Around 99,000 acres or 50%, of Jhalokati's total area is cropped or sown at least once each year with a cropping intensity of 133% (Ibrahim, 2011, Mollah and Ibrahim, 2010).

2.4 IPM Technologies

For each vegetable in the vegetable technology transfer subproject the IPM IL recommends a unique IPM package. Ricker-Gilbert (2005) classified the Bangladesh IPM technologies into three categories: simple, intermediate, and complex. This classification is based on the management skills and understanding needed for successful implementation of the IPM technology.

A separate classification for IPM technologies is product-based. A product-based technology is built-in to a product prior to reaching a farmer. Grafting is one example of a product technology. For a farmer to successfully graft a plant requires significant training and effort, but if the plants are grafted prior to the farmers purchasing them it is a simple technology (Ricker-Gilbert, 2005).

2.4.1 Simple IPM Technologies

A simple IPM technology requires little more than the farmer following simple directions for successful implementation (Ricker-Gilbert, 2005). The simple technologies used in the IPM vegetable technology transfer subproject include: pest-resistant plant varieties, handpicking pests from the plants, mulching, biopesticides, and neem cake.

A simple, product based technology, pest-resistant varieties are plant lines where resistance to insects, fungi, or viruses has been developed through either genetic modification or through gradual selection of more resistant offspring over time. The resistances developed depend on the particular pests the plant faces, but often focus on resistances to common plant viruses (Harris, 2011).

Some pests, particularly those affecting cabbages, can be reduced by hand picking pest eggs and caterpillars off of the plant's leaves or pruning the leaves themselves. A simple, but often labor-intensive IPM approach, handpicking of pests and pest eggs from vegetables is an IPM substitute to pesticides (Ricker-Gilbert, 2005). When handpicking is used, pests must be removed from the plant twice a week until the fruit of the vegetable has fully formed (Hoque and Uddin 2003 as cited in Harris, 2011).

The other simple IPM technologies are the use of mulching, biopesticides, and neem cake. A simple IPM technology, mulching involves using a material to cover the soil around a plant and suppress weeds (University of California 2014). A simple, product based technology, biopesticides are commercially produced pesticides and other pest control agents that use micro-organisms and other naturally occurring products to control pests (Chandler, et al., 2011). Neem, often used in the form of Neem cake or Neem oil, has natural occurring antimicrobial and insecticidal properties (Nandagopal and Ghewande, 2004). In the South Asia IPM region, Neem cake is a simple IPM technology used to control nematodes (Muniappan, 2014).

2.4.2 Intermediate IPM Technologies

The needs of intermediate IPM technologies fall somewhere in between simple and complex technologies with a little more effort needed than simple technologies, but not nearly as knowledge-intensive as complex technologies (Ricker-Gilbert, 2005). The intermediate technologies used in the IPM vegetable technology transfer subproject include: soil amendments, pheromone traps, tray-raised seedlings, and yellow sticky traps.

Soil amendments such as poultry refuse and *Trichoderma* are often used in Bangladesh to reduce the damage of soil-borne fungal pathogens on crops. By applying soil amendments to fields, the damage caused by diseases such as root rot and stem rot can be minimized (Harris, 2011). One of the simpler soil amendments is poultry refuse, which is simply the manure from chickens and other birds a household might raise. As it breaks down, poultry refuse releases organic acids that help to control soil-borne pathogens and improve the soil (Rahman, Miller, and Karim 2004 as cited inHarris, 2011). A simple, product-based technology or a more complex technology otherwise, Tricho-compost is composed of eight parts: cow manure, molasses, maize bran, sawdust, poultry refuse, water hyacinth, ash, and a suspension of fungal spores from *Trichoderma harzianum*. After the ingredients are all combined, the mixture is stored and left to decompose for 35-50 days before being dried in the sun and applied to fields. In addition, a beneficial liquid known as Tricho-leachate runs off of the compost during its decomposition which can then be used to produce additional Tricho-compost or sprayed directly on the fields by farmers (Harris, 2011).

An intermediate technology, pheromone traps are designed to attract fruit flies and other pests to prevent them from destroying crops. A basic pheromone trap consists of a container, soapy water, and an attractant which the farmer combines to form the pheromone trap. A variety of attractants can be used from synthetic hormones to mashed sweet gourd, but the synthetic sex hormone Cuelure is the most effective attractant for fruit flies (Harris, 2011).

The other intermediate IPM technologies are tray-raised seedlings and yellow sticky traps. An intermediate technology, raising plant seedlings in trays or seedbeds helps to control external effects and leads to healthy seedlings (Muniappan, 2014). Yellow sticky traps are used to measure the relative density of pests and changes from day-to-day. Pests measurable by yellow sticky traps include: whitefly, thrips, aphids and parasites (University of California 2009).

2.4.3 Complex IPM Technologies

A complex technology may require knowledge of the local ecosystem or some degree of management skill (Ricker-Gilbert, 2005). Some of the complex technologies used in the IPM vegetable technology transfer subproject include: grafting and biological controls such as natural predators.

A simple, product-based technology or a complex technology otherwise, grafting involves combining a highly-productive plant seedling with the rootstock of another variety that may not produce as much, but has beneficial characteristics that the highly-productive plant is missing such as a stronger root system or resistance to bacterial wilt and root-knot nematodes (Harris, 2011).

An intermediate to complex technology requires knowledge and understanding of pests and the timely release of natural predators. A biological control is an approach to managing pests by using natural predators of the pests (Ricker-Gilbert, 2005). Bio-control agents for insect pests often include natural insect predators and parasitoids. When releasing biological controls, the goal is to keep pest populations under certain thresholds for economic damage without the biological control itself becoming a pest. Beneficial insects often used by IPM in Bangladesh include *Trichogramma* (a small, parasitic wasp), *Bracon Hebetor*, green lacewing, and lady bug beetles. Biological controls are usually purchased by the farmer in the form of eggs, larvae, or fully grown insects and are then released or spread over the affected area to combat the pest (Harris, 2011).

2.5 The Vegetables

Of the six subproject vegetables, eggplant is the most commonly grown in Bangladesh, with two growing seasons and almost 350,000 tons produced each year, but cabbage is not too far behind at over 205,000 tons produced each year (Ibrahim, 2011). There are two growing seasons for vegetables in Bangladesh: the summer (kharif) season (June to October) and the winter (rabi) season (October to March).

2.5.1 Tomato

In the 2010 to 2011 winter growing season, 61,213 acres of tomatoes were grown in Bangladesh, producing 232,459 metric tons of tomatoes. Of those, 3,004 metric tons were grown in Barisal, 11,377 metric tons were grown in the Jessore region (including the Jessore and Magura districts), and 5,155 metric tons were grown in the Tangail region (including Jhalokati district) (Ibrahim, 2011).

Tomatoes in Bangladesh are susceptible to a variety of insects and mites as well as viral, nematodal, fungal, and bacterial diseases that can curtail plant growth and significantly reduce yields. Specifically, tomatoes are attacked by insects such as the tomato fruit worm, cutworm, leaf miner, spider mite, and broad mite, as well as infested by a number of diseases, including:

soil-borne bacterial wilt, Phytophthora late blight, tomato yellow leaf curl virus, root knot nematodes (Bertelsen, et al., 2013).

To combat local pests, IPM recommends a variety of methods, including: resistant varieties, Tricho-compost, grafting tomato plants onto eggplant stalks, and the application of non-toxic bio pesticides (Bertelsen, et al., 2013). Careful application of Tricho-compost can help reduce fungal, nematode, and viral diseases affecting tomatoes by up to 35% and increase yields by as much as 28.5%. Using grafting practices alongside other IPM practices can lead to as much as a 17.9% increase in yield (per plant) over non-grafted plants using comparable practices, as well as significantly decrease bacterial wilt and nematode infestations of the plants (Muniappan, et al., 2013).

2.5.2 Eggplant

Eggplant is grown in both the summer and winter growing seasons in Bangladesh, with 2010-2011 production yields of 215,490 and 124,384 metric tons respectively. In that same year, the Jessore (including the Jessore and Magura districts), Barisal, and Tangail (including Jhalokati district) regions accounted for around 26.4% of the total summer production and 17.4% of the total winter production for Bangladesh (Ibrahim, 2011).

Eggplants in Bangladesh are susceptible to a wide variety of insects including fruit and shoot borers, leaf-eating ladybeetles, melon aphids, thrips, whitefly, leaf hoppers, and even mites in some seasons. In addition to the insects, eggplants also struggle with two types of wilt: bacterial wilt and Fusarium wilt (Bertelsen, et al., 2013).

To combat these pests, the IPM IL recommends using a combination of IPM practices such as pheromone traps, Tricho-compost, grafting, raising seedlings in trays, and the use of parasitoids and natural predators like ladybird beetles and chrysopids to control pests (Bertelsen, et al., 2013). Trials for Tricho-compost on eggplant have shown that proper application can reduce fruit and shoot borer infestations by 29-61% and 42-55% respectively. Subsequent yields can also be increased by 37-55% as a result (Muniappan, et al., 2011).

2.5.3 Cucumber

A summer crop in Bangladesh, 48,448 metric tons (on 19,030 acres) of cucumbers were grown in Bangladesh during the 2010-11 growing season. Jessore (including the Jessore and Magura districts), Barisal, and Tangail accounted for 8016 metric tons or approximately 16.5% of the national production (Ibrahim, 2011).

Cucumbers in Bangladesh struggle with multiple insects including the melon fly, cucumber worm, melon aphid, cucumber beetles, and leaf-footed bug. In addition to insects, the cucumber is susceptible to the root-knot nematode, powdery mildew, downy mildew, southern blight, and diseases like the cucumber mosaic virus (Bertelsen, et al., 2013).

The IPM package for cucumbers includes the use of grafting onto pumpkin rootstock, yellow sticky traps for aphids and whiteflys, pheromone traps, Tricho-compost, and the release of natural pest enemies including ladybird beetles and chrysopids among others (Bertelsen, et al., 2013). Tests comparing the IPM package to standard Farmer’s practice in Nepal show anywhere from a 30-56% increase in yields when the IPM package is implemented (Muniappan, et al., 2013).

2.5.4 Country Bean

Grown during the winter season, there are no detailed production estimates available for the country bean. The country bean in Bangladesh suffers damage from a variety of pests including the pod borer, tomato fruit worm, aphids, root-knot nematode, the southern stink bug, broad mites, and several virus diseases (Bertelsen, et al., 2013).

To control for country bean pests, the recommended IPM package in Bangladesh includes hand-picking then destroying pod-borer infested flowers and pods, weekly releases of parasitoids, spraying soapy water to control aphids, and two applications of the bio pesticide Spinosad (Bertelsen, et al., 2013). Test plot comparisons of the recommended IPM treatment and the common farmer's practice treatments have shown a potential 65.68-82.80% decrease in pod infestations as well as a 34.6-43.8% increase in yields for the IPM package over the farmer's practice in trials (Muniappan, et al., 2013).

2.5.5 Bitter Gourd

Grown in the summer season in Bangladesh, 45,097 metric tons of bitter gourd were produced on 22,793 acres during the 2010-2011 growing season, including 7,566 metric tons (16.8%) produced in the Jessore (including Jessore and Magura districts), Barisal, and Tangail (including Jhalokati district) regions (Ibrahim, 2011).

The bitter gourd faces many of the same pests and diseases as cucumbers with the main difference between the two being that the melon fly prefers bitter gourd to cucumbers and other cucurbits. Bitter gourds in Bangladesh struggle with multiple insects including the melon fly, cucumber worm, melon aphid, cucumber beetles, and leaf-footed bug. In addition to insects, the bitter gourd is susceptible to the root-knot nematode, powdery mildew, downy mildew, southern blight, and diseases like the Cucumber mosaic virus (Bertelsen, et al., 2013).

The recommended IPM treatment package for the bitter gourd is similar to cucumbers, with slightly more emphasis on the use of pheromone traps to manage melon fly infestations (Bertelsen, et al., 2013). The IPM treatment package for reducing fruit fly and borer infestations of bitter gourd fruit can reduce infestations by as much as 63.2-85.2% and subsequently increase production yields by 26.4-29.9% when compared to farmer's practice plots in Bangladesh (Muniappan, et al., 2013).

2.5.6 Cabbage

During the winter 2010-2011 growing seasons, 206,851 metric tons of cabbage were produced on 39,015 acres of land across Bangladesh. Of this production, 44,079 tons (21.3%) were produced in the Jessore (including Jessore and Magura districts), Barisal, and Tangail (including Jhalokati) regions (Ibrahim, 2011).

Insect pests threatening cabbage production in Bangladesh include the diamondback moth, the tomato fruit worm, the cut worm, and the white fly. Cabbage is also susceptible to the root-knot nematode, and multiple soil-borne fungal pathogens (Bertelsen, et al., 2013).

IPM's treatment package for cabbage consists of using a recommended cabbage variety (Summer Warrior) planted in fields where Tricho-compost and poultry refuse have been incorporated. Pheromone traps are used to monitor pest populations, and parasitoids, ladybird beetles, and chrysopids are released to help control pests (Bertelsen, et al., 2013). IPM's recommended applications of Tricho-compost and poultry refuse on cabbage fields in Bogra have shown mortality reductions from 9.7-13.9% over the traditional farmer's practices (Muniappan, et al., 2013).

2.6 IPM Technology Transfer Methods

To transfer the IPM technology packages to farmers, the IPM IL has utilized a number of technology transfer methods including: training and lectures led by IPM field officers, small group discussions with the IPM field officers, introducing farmers to the IPM materials suppliers, dispersal of IPM related posters, and IPM field days. Training and lectures led by IPM field officers as well as small group discussions often take place in the fields with farmers and a demonstration plot where the IPM field officer can demonstrate IPM techniques and the benefits of using them. There are a few suppliers of IPM materials such as pheromone traps, yellow sticky traps, Tricho-compost, resistant plant varieties, and biopesticides. Part of the technology transfer process involves IPM field officers introducing farmers to the suppliers so the farmers can continue to use IPM methods in future growing seasons. A few handouts and IPM information posters were created to help remind farmers of the IPM methods and technologies available. Finally, field days involve IPM field officers and other IPM experts visiting a village and providing in-depth training and demonstrations of IPM technologies to as many as several hundred farmers at once (Ricker-Gilbert, 2005). According to the IPM field officers for Jessore and Barisal, training with the IPM field officers and IPM field days were the most used transfer methods by the IPM IL during the 2013 to 2014 growing season.

2.7 Conclusion

Agriculture is at the core of Bangladesh’s economy and even more so in the four districts specified for the IPM IL vegetable technology transfer subproject. Chapter Two covered IPM program history, goals, technologies, treatment packages, and the vegetables included in the technology transfer subproject. The IPM technologies and packages discussed in this chapter are used to define and construct the frameworks for evaluating the objectives in the upcoming chapters. The following chapter lays out the methodology used to evaluate IPM adoption, IPM impacts, and relative efficiency of IPM transfer methods.

3. Methods

Chapter Three presents the methodology used to design the survey and evaluate the four objectives as described in Chapter One. The first section introduces the RCT used to evaluate the changes and impacts of the IPM technology transfer at the household level. The next four sections discuss the four objectives outlined in Chapter One and the methodology used. Section Two addresses the first objective of measuring the IPM technology adoption rates as a result of the IPM vegetable technology transfer subproject's rollout. It describes the strategy used for estimating adoption and identifying its determinants as laid out in the first objective. Section Three focuses on the second objective of measuring the impacts of the technology transfer on vegetable yields, pest management costs, and pesticide use. It presents the empirical approaches used to evaluate the impacts of the technology transfer on yields, pest management costs, and pesticide usage. Section Four addresses the third objective of estimating the total economic impacts of the IPM technology transfer. It lays out the framework for estimating the economic impacts via economic surplus analysis as part of the third objective of the thesis. Finally, Section Five addresses the fourth objective of comparing the relative effectiveness and efficiency of the different technology transfer methods in terms of adoption rates and programmatic transfer costs per farmer. It presents the strategies used to compare the relative efficiency of different technology transfer methods.

3.1 Design of the Impact Evaluation

When evaluating the impacts of an agricultural technology transfer there are two potential problems: selection bias and spillover effects. The first potential problem, selection bias, is caused when farmers are either selected or self-select themselves into participating in the technology transfer program based on an unobserved attribute or trait that influences the measured outcome (Bauchet and Morduch, 2010, Khandker, 2010, Maffioli, et al., 2010). The second potential problem, spillover effects, occurs when the technology transfer is received by households not targeted by the experiment. When implementing the experiment and transferring the technology, care must be taken to insure the control group remains uncompromised by spillover effects from the treatment group. A compromised control group can lead to an inaccurate assessment of the impacts of the technology transfer (Maffioli, et al., 2010).

The primary difficulty in evaluating the impacts of the technology transfer is comparing the outcome for a group exposed to the IPM technology transfer to what the outcome for that exact same group would have been had the technology transfer never happened (Khandker, 2010, Maffioli, et al., 2010). Since it is impossible to know exactly what would have happened to those receiving the technology in the absence of the technology transfer, the two possible outcomes are compared using two groups: a control group never exposed to the technology transfer and a treatment group which was exposed to the technology transfer. When creating a control group to compare the treatment group to, it is important to insure that the control group is an accurate counterfactual, with similar demographic and agricultural characteristics as the treatment group in as many ways possible aside from exposure to the technology transfer. Two general approaches are used when creating a control group: experimental approaches where the control and treatment groups are randomly assigned prior to the technology transfer and non-experimental approaches where a control group is created or identified after the technology transfer (Maffioli, et al., 2010).

To minimize the likelihood of selection bias and spillover effects and create balanced counterfactual an RCT approach was used when designing the methodology to evaluate the impact of the IPM technology transfer on outcomes of interest (i.e. yield, pesticide costs, and pesticide use). The RCT approach involves randomly selecting members into the control and treatment groups (Bauchet and Morduch, 2010, Khandker, 2010, Maffioli, et al., 2010). In implementing the RCT an equal number of villages from Barisal, Jessore, Jhalakati, and Magura were randomly assigned to the treatment or control groups. Random assignment to the two groups eliminates the problem of selection bias, allowing for unbiased evaluation of technology adoption and its impacts. Randomizing treatment status at the village level minimizes the potential for spillovers from the treatment group to the control group by insuring treatment and control villages are sufficiently far enough apart to minimize the flow of direct agricultural information between the two groups.

3.2 Adoption

The first objective of this thesis is to measure the adoption rates of IPM technology and the determinants of adoption as a result of the IPM technology transfer. While the majority of adoption studies have evaluated the complete adoption of a technology package, a number of studies have shown that farmers frequently choose to adopt only part of a technology package rather than the whole package (Byerlee, 1986, Ersado, et al., 2004, Leathers and Smale, 1991, Ryan and Subrahmanyam, 1975). Cummings (as cited in Ryan and Subrahmanyam, 1975), working with the Puebla Project in Mexico from 1967 to 1974 found that farmers often experimented with adopting components in stages rather than adopting the complete package. A 1972 survey of 200 farmers in the Puebla Project found that while approximately 60% of the farmers adopted all of the recommended components, close to 50% adopted at least one of those components at a level well below the recommendations of the Puebla Project (Ryan and Subrahmanyam, 1975).

A variety of explanations have been suggested to explain farmers' incomplete adoption decisions including, profitability of components, risk of components, uncertainty of positive return, and investment cost (Byerlee, 1986, Ersado, et al., 2004, Ghadim and Pannell, 1999, Leathers and Smale, 1991, Ryan and Subrahmanyam, 1975). Ryan and Subrahmanyam (1975) and Byerlee and Polanco (1986) both found that farmers first adopt the technology components with the greatest expected economic returns and minimal additional risk. Ryan and Subrahmanyam (1975) suggest that when package components are more costly to adopt, it can be advantageous for farmers to adopt only the relatively less costly components. Leathers and Smale (1991) focused on sequential adoption of components as a risk management response from farmers. Their model shows that farmers combat missing and imperfect information by adopting one component first to test the technology in their own field and conditions prior to full adoption.

Since farmer adoption of new technologies often comes in steps and the second round of surveying for this study took place one year after the initial technology transfer, an evaluation of a stepwise or partial adoption approach provides more detailed information regarding farmer adoption trends than a whole package approach. Partial adoption is the implementation of one or more components of the recommended technology package. For example, the country bean's recommended IPM package includes handpicking and destroying pod borer infested flowers and pods, the release of egg and larval parasitoids, using soapy water to control aphids, and using the biopesticide Spinosad.[4] Partial adoption of the country bean package is adopting one or more of the components of the recommended package, such as, adopting just handpicking and destroying pod borer infested flowers and pods. Partial adoption also includes full adoption as a special instance of partial adoption where an individual adopts all components of a vegetable's

[4] See Chapter 2 for more information about the pests and IPM package for the Country bean

recommended IPM package.

Two of the more common approaches for modeling partial adoption are the probit model and the logit model. Both models produce similar marginal effects, but the primary difference between the two models is the assumed distribution of residuals. The probit model assumes residuals follow a standard normal distribution and the logit model assumes the residuals follow a logistic distribution. For this study, the residuals are assumed to be normally distributed and the probit model will be used. With the probit model, there are two potential approaches for estimating partial adoption: a regular probit model and an ordered probit model.

3.2.1 The Traditional Probit Model

First, using the traditional probit model, the dependent variable, Y_{it}, is binary and restricted to a value of 0 or 1, where Y_{it} represents the adoption (Y) of observation i in time t (Wooldridge, 2002, Wooldridge, 2013). In this case, 1 would represent adoption of the IPM package with 0 representing non-adoption of the IPM package. In this model, adoption of any components in the recommended IPM package counts as adoption. With the traditional probit model for partial adoption, the dependent variable, Y_{it}, is adoption of any of the recommended package of components and the independent variables X_i include a treatment dummy variable and other determinants of adoption.

The probit model is:

$$Y_{it}^{*} = \beta_0 + \beta_1 T_{it} + \beta_2 D_{it} + \beta_3 F_{it} + \beta_4 H_{it} + \beta_5 A_{it} + \beta_6 R_{it} + e_{it} \text{, where } Y_{it} = 1 \; if \; Y_{it}^{*} > 0 \tag{1}$$

where Y_{it} is the dependent variable in the model, with a value of 1 representing adoption of any components of the recommended IPM package for a vegetable, T_{it} is a binary variable representing the treatment status of the household with a value of 1 for a household in a treatment village and 0 otherwise, D_{it} represents the district the household is located in, F_{it} represents farm characteristic variables affecting adoption, H_{it} represents household and individual variables affecting adoption, A_{it} represents agricultural information source characteristics variables affecting adoption, R_{it} represents the survey round, e_{it} is the error term representing all unobserved factors and measurement errors. The

$$P(Y_{it} = 1|X) = P({Y_{it}}^{*} > 0|X) = 1 - G[-(\beta_0 + X_i\beta)] = G(\beta_0 + X_i\beta) \quad (2)$$

is the probability of a value for Y_{it} given X_i and G is the standard normal cumulative distribution function:

$$G(z) = \Phi(z) \equiv \int_{-\infty}^{z} \phi\,(v)dv \quad (3)$$

where

$$\phi(z) = (2\pi)^{-1/2}\exp(-\frac{z^2}{2}) \quad (4)$$

(Wooldridge, 2002, 2013).

To estimate a probit model with panel data in STATA version 13, the random effects model is used to preserve the binary variable T_{it}. A random effects model is used to ensure that farmer inclusion in the treatment group has no impact on farmers adoption of the technology.

3.2.2 The Ordered Probit Model

The second approach for estimating partial adoption is an ordered probit model. For an ordered probit model, instead of a binary result for adoption, the dependent adoption variable is an ordered response conveying different thresholds of adoption (Wooldridge, 2002, Wooldridge, 2013) . In this case the ordinal values represent the number of the recommended IPM package components that have been adopted.

$${Y_{it}}^{*} = \beta_0 + \beta_1 T_{it} + \beta_2 D_{it} + \beta_3 F_{it} + \beta_4 H_{it} + \beta_5 A_{it} + \beta_6 R_{it} + e_{it} \quad (5)$$

where Y_{it} is the dependent variable in the model, with a count value ranging from zero to the total number of components in the recommended IPM package, representing the number of components of the recommended IPM package adopted by the household, T_{it} is a binary variable representing the treatment status of the household with a value of 1 for a household in a treatment village and 0 otherwise, D_{it} represents the district the household is located in, F_{it} represents farm characteristic variables affecting adoption, H_{it} represents household and individual variables affecting adoption, A_{it} represents agricultural information source characteristics variables affecting adoption, R_{it} represents the survey round with values of 1 and 2, e_{it} is the error term representing all unobserved factors and measurement error (Wooldridge, 2002).

3.2.3 The Variables

The dependent variables are adoption. In the traditional probit model, the dependent variable is a binary value denoting the household's adoption of any of the recommended IPM package components (see Table 3.1). In the ordered probit model, the dependent is an integer value denoting the number of components of the recommended IPM package adopted (see Table 3.1).

Table 3.1 Dependent Variables used in Adoption Models

Variable	Description	Units	Model
Full Package Adoption	Binary, equals 1 if HH adopts any components from a recommended IPM package	Binary Integer	Traditional Probit
Component Adoption	Ordinal value representing the number of components a HH adopts from a recommended IPM package	Integer	Ordered Probit

The independent variables in both models are the determinants of adoption. The treatment variable is a binary variable with a value of 0 for households in the control group and a value of 1 for households in the treatment group (see Table 3.2). The round variable denotes which round of the survey the information was collected in. A value of 0 means the data was collected in the first round and a value of 1 means the data was collected in the second round (see Table 3.2).

There are three binary district variables representing which district a household is located in. A value of 1 means the household is located in Jessore, Jhalakati, or Magura and a value of 0 means the household is located in a different district (see Table 3.2). If all three district variables have a value of 0, the household is located in the district of Barisal. The district variables help to control for differences in climate and weather since the treatment and control villages were divided evenly amongst the districts.

Farm characteristics variables often examined in agricultural adoption include farm size, land tenure, and labor availability (Ersado, et al., 2004, Feder, et al., 1985, Feder and Slade, 1984, Ghadim and Pannell, 1999) with an occasional agricultural ecology variable such as soil type, quality, etc. (Ashby, 1982, Nowak, 1987). The first characteristic, farm size, is represented as the percentage of total land owned and rented that is devoted to vegetables (see Table 3.2). Since farmers are historically seen as risk averse and a higher level of specialization in one vegetable leads to higher levels of risk (Feder, et al., 1985), this variable is expected to have a negative impact on adoption.

Another farm characteristic that often impacts agricultural technology adoption is labor availability. Labor availability in this study is represented by the number of household members who can work (see Table 3.2). More labor-intensive technology requires more labor and less labor-intensive technologies require less labor (Feder, et al., 1985). While some of the IPM practices such as handpicking pests are more labor-intensive, the use of components such as pheromone traps are expected to greatly reduce the frequency of pesticide applications. The percentage of household members who can work should be positive since they can help with labor-intensive IPM practices.

Finally, a less used, but still relevant type of variable for farm characteristics is an ecological variable. A number of studies have shown that local ecological and topographical characteristics such as the soil type, quality, and elevation of a farm can impact the likelihood of adoption (Ashby, 1982, Nowak, 1987). Since the agricultural technology being transferred is for pest management, it makes sense to include an ecological variable indicative of pest pressure, capturing the average severity of the household's pest problems for a vegetable during the growing season (see Table 3.2). This is expected to have a positive sign.

Household characteristics include both general household characteristics and individual characteristics. Commonly examined household characteristics include: family size and wealth , and individual characteristics such as the Household Head's (HHH) gender, age, education level, the amount of agricultural experience the HHH has, and whether the HHH's primary occupation is farming (Baidu-Forson, 1999, Ersado, et al., 2004, Feder, et al., 1985, Ghadim and Pannell, 1999) (see Table 3.2).

The number of household members per room in the house is used here as an indicator of wealth and the economic wellbeing of the household (see Table 3.2). With this variable, a lower number of household members per room indicates the household has either more wealth to support the household's size or a smaller household to support. Previous studies have found that better off households are often more likely to adopt a new technology (Feder, et al., 1985) so a higher value for this variable is expected to have a negative impact on adoption. A second wellbeing indicator often used in adoption studies is access to off-farm income. While having off-farm work is traditionally believed to increase credit availability, credit is not expected to be a constraint with IPM agricultural practices often less costly than traditional agricultural approaches (Feder, et al., 1985). Since practices such as the pheromone traps require consistent monitoring, having farming as the HHH's primary occupation (measured as a binary variable where 1 means he or she is primarily a farmer) will likely have a positive effect on adoption (see Table 3.2).

Age, education, and experience are three variables for which increasing levels of the variable are often expected to denote a certain attitude in adopting farmers. Age in this study will be measured by the age of the HHH (see Table 3.2). Though some, such as Baidu-Forson (1999), have found no relationship between age and adoption, a farmer's age is traditionally believed to influence a farmer's attitude towards risk and can be expected to have a negative sign (Ghadim and Pannell, 1999). A farmer's level of education has historically been found to have a positive effect on adoption rates with better educated farmers adopting new technologies earlier and more easily (Feder, et al., 1985, Ram, 1980). Education is denoted here by a binary variable representing completion of at least primary school with a value of 1indicating completion of a primary level of education and a value of 0 indicating no formal education (see Table 3.2). A farmer's agricultural experience (measured in years) can have a positive or negative effect on adoption depending on whether they have had good experiences with other innovations (Ghadim and Pannell, 1999) (see Table 3.2).

Agricultural information source characteristics can include a variety of variables impacting adoption such as access to different sources of agricultural information and proximity to others who have already adopted a technology (Feder, et al., 1985, Feder and Slade, 1984, Ghadim and Pannell, 1999, Nowak, 1987). Agricultural information source characteristics variables include: the number of times the farmer has received IPM training in the last 12 months, the total number of IPM adopters the farmer knows both in and outside of the village, and four composite variables for where the farmer learns agricultural information (see Table 3.2). The four composite variables for agricultural information sources are social networks (including learning agricultural information from relatives, neighboring farmers, farmers' groups, and IPM Clubs), agricultural authorities (including learning agricultural information from agricultural officers and seed/pesticide/fertilizer salespersons), agricultural training events (including learning agricultural information from farmers' fairs, field days, and farmer's field schools), and media (including learning agricultural information from radio, television, newspapers/leaflets, and mobile phone providers).

The number of times a farmer receives training can positively affect adoption by improving the farmer's efficiency in using the technology and by helping the farmer more rapidly accumulate the information needed for adoption (Feder, et al., 1985, Feder and Slade, 1984). The number of IPM adopters the farmer knows should have a positive effect on adoption since more IPM adopters offers the farmer more opportunities to observe and collect more relevant information regarding yields and profits from adopting a new agricultural practice (Feder, et al., 1985, Feder and Slade, 1984, Ghadim and Pannell, 1999).

Where the farmer learns agricultural information can be a key factor in whether the farmer chooses to adopt a technology. Information factors such as who is providing the agricultural information and their credibility can both positively and negatively affect a farmer's decision to adopt a technology (Nowak, 1987). Agricultural information source variables will be binary variables where the variable is a 1 if the farmer said he learned agricultural information from at least one of the sources compiled under the variable (see Table 3.2). While there are many sources for agricultural information available to the farmers, the ones primarily used by the IPM IL to transfer new agricultural practices are field days, training by IPM agricultural officers, demonstration plots with village farmers, and small group discussions such as farmer groups, and IPM clubs. Of the four agricultural information source variables, the agricultural training events variable should definitely have a positive effect, the social networks variable will likely have a positive effect, agricultural authorities will may be negative since the majority of salesmen work for pesticide and seed companies which are well established, and media will likely be insignificant.

Table 3.2 Independent Variables used in Adoption Models

Variable	Description	Units
Treatment	Binary, equals 1 if household is located in a treatment village	Binary Integer
Round	The round of the survey. 1 if round one, 2 if round two	Integer
Jessore District	Binary, equals 1 if household is located in Jessore, 0 if household is located in one of the other districts	Binary Integer
Jhalakati District	Binary, equals 1 if household is located in Jhalakati, 0 if household is located in one of the other districts	Binary Integer
Magura District	Binary, equals 1 if household is located in Magura, 0 if household is located in one of the other districts	Binary Integer
Farm Characteristics		
Farm Size	Area of the vegetable grown divided by total area of land owned and rented	Percentage
Household members working	The number of household members who can work.	Integer
Pest Severity	The average severity of pest problems. 0 if there were no pest problems.	Ordinal
Household Characteristics		
Household members per room	Number of household members divided by the number of rooms in the house	Rational number
Farming is Primary Occupation	Binary, equals 1 if the HHH’s primary occupation is farming	Binary Integer
HHH Age	The age of the HHH in years	Integer
HHH Primary Education	1 if the HHH has completed at least primary school, 0 otherwise	Binary Integer
HHH Experience	The agricultural experience of the HHH in years	Integer
Agricultural Information Source Characteristics		

Times Trained in IPM	The number of times the farmer has received IPM training in the last 12 months	Integer
IPM adopters known	The total number of IPM adopters the farmer knows.	Integer
Social Network	Binary, equals 1 if the HHH learned agricultural information from relatives, neighboring farmers, farmers' groups, or IPM clubs in the past year. Equals 0 if the HHH did not learn agricultural information from one of these sources.	Binary Integer
Agricultural Authorities	Binary, equals 1 if HHH learned agricultural information from agricultural officers or seed/pesticide/fertilizer salespersons in the past year. Equals 0 if the HHH did not learn agricultural information from one of these sources.	Binary Integer
Agricultural t Events	Binary, equals 1 if HHH learned agricultural information from farmers' fairs, field days, or farmer's field schools in the past year. Equals 0 if the HHH did not learn agricultural information from one of these sources.	Binary Integer
Media	Binary, equals 1 if HHH learned agricultural information from radio, television, newspapers/leaflets, or mobile phone providers in the past year. Equals 0 if the HHH did not learn agricultural information from one of these sources.	Binary Integer

3.3 Impacts

The second objective of the thesis is to measure the impacts of the technology transfer in three areas: vegetable yields, pest management costs, and pesticide use. Since the survey was set up using a RCT, the impacts of the technology transfer can be evaluated without selection bias. Basic impacts measured are changes in yield, pest management costs, and pesticide usage.

3.3.1 Yield Changes

The first impact to be evaluated is yield in kilograms per decimal[5] where yield is the total kilograms sold of a vegetable divided by the area dedicated to growing the vegetable.

A difference-in-differences or double difference (DD) model will be used to evaluate the impact of the IPM technology transfer on vegetable yields. The DD approach involves evaluating

[5] A decimal is a unit of area equal to 1/100th of an acre.

two differences in a dependent variable indicator: the difference over time and the difference between the treatment and control groups. If the treatment groups shows a statistically significant greater impact, then the technology transfer had an impact. There are three important assumptions behind the DD model: the control group is a valid and accurate counterfactual to the treatment group (Khandker, 2010, Maffioli, et al., 2010), no selection bias impacts the technology transfer (Khandker, 2010), and any unobserved heterogeneity is time-invariant and be removed by differencing (Khandker, 2010). While justifying the first two assumptions can be a weaknesses of the DD model (Khandker, 2010), in this case both assumptions are validated by the RCT.

In the model the dependent variable, yield, is measured as the total number of kilograms sold per decimal of the vegetable. The independent variables include the treatment variable, a variable indicating the survey round, district variables, a pest severity variable, and binary variables representing adoption of different components of the recommended IPM package for the vegetable.

$$Y_{it} = \beta_0 + \beta_1 R_{it} + \beta_2 T_{it} + \beta_3 R_{it} * T_{it} + \beta_4 D_{it} + \beta_5 S_{it} + \beta_6 C_{it} + e_{it} \quad (6)$$

where Y_{it}, the dependent variable, represents the yield (per decimal) for the vegetable between the two rounds, β_3 is the impact of the technology transfer as measured by the model, $R_{it}, T_{it}, D_{it}, S_{it}$ and e_{it} are the same as previously specified (see Table 3.2), and C_{it} represents use of the different components of the vegetable's recommended IPM package with binary variables representing use of each component in the recommended IPM package (with a value of 1 representing use of the component and a value of 0 representing non-use of the component) (Khandker, 2010, Maffioli, et al., 2010, Villa, 2012).

The round, treatment status, and district variables are all expected to take the same form previously described in Table 3.2. Increases in pest severity are expected to have a negative impact on yield. The component variables will be binary variables representing adoption of the individual components of the recommended IPM package. These variables are all expected to positively affect vegetable yields.

3.3.2 Pest Management Cost Changes

The second impact to be evaluated is pest management costs (in taka) per decimal. Pest management costs include expenditures on both pesticide and IPM pest management pest control methods. The pest management costs per decimal can be estimated from both the farmer's estimated total pest management costs for all vegetables (in taka) divided by the amount of land (in decimals) dedicated to the vegetables. The change in pest management costs per decimal stemming from the technology transfer will be identified using a DD model with a dependent variable representing the pest management costs (per decimal) and independent variables representing the survey round, treatment status, district location, changes in pest severity, and adoption of individual IPM package components.

Equation 6 will be used as the model for estimating changes in pest management costs where Y_{it}, the dependent variable, is the change in pest management costs (per decimal) for the vegetable between the two rounds and $R_{it}, T_{it}, \beta_3, D_{it}, S_{it}, C_{it}$, and e_{it} are all the same as previously specified. An increase in the average pest severity is expected to have increase the overall cost of pest management for farmers. Adoption of individual components of different IPM approaches is expected to decrease the overall cost of pest management for farmers.

3.3.3 Pesticide Application Changes

The third impact to be measured is changes in number of pesticide applications resulting from the technology transfer. The change in pesticide applications can be estimated using a DD model where the dependent variable is the number of applications (per decimal) of the pesticides applied during the growing season and the independent variables include treatment status, survey round, the district the household is located in, the change in pest severity, and adoption of the individual components of the IPM package.

Equation 6 will be used as the model for estimating changes where Y_{it}, the dependent variable, is the difference in the number of applications (per decimal) for the vegetable between the two rounds and $\beta_0, R_{it}, T_{it}, \beta_3, D_{it}, S_{it}, C_{it}$, and e_{it} are all the same as previously specified. An increase in the average severity of pest problems is expected to increase the number of applications of pesticides. Adoption of the IPM package components is expected to decrease the number of applications of pesticides.

3.4 Economic Surplus Analysis

The third objective of this thesis is to estimate the total economic impacts of the technology transfer. One of the main goals in analyzing the impact of new technology is to assess its impact on economic wellbeing at both household and regional levels in the area being surveyed. This study will use yield and cost data gathered from surveyed farmers in the Jessore, Magura, Jhalakati, and Barisal districts of Bangladesh to create before and after estimates of income stemming from the crops affected by the new technologies. To do this, economic surplus analysis will be used to identify the economic surplus changes stemming from the technology transfer where economic surplus is defined as the economic benefits accruing from a supply shift due to changes in productivity (Alston, et al., 1995).

There are three basic models commonly used for economic surplus analysis: a closed economy model, a small open economy model, and a large open economy model (Alston, et al., 1995). The large open economy model is used when there is a high rate of extra-regional trade and the country produces enough to affect the price beyond the region after introducing the technology. The small open economy model is used when supply changes in a region do not affect prices. A closed economy model is used when there is little trade and price will be affected after the technology is introduced. Due to the perishability of the vegetables included in this study, a closed economy model will be used. Since perishable vegetables are unlikely to generate much trade outside of Bangladesh, it can be assumed that the market is self-contained within the country and will affect prices in the targeted regions.

Economic surplus impacts will be calculated using the closed economy model laid out in Alston, Norton, and Pardey (1995). To conduct economic surplus analysis using the closed economy model, the changes in total surplus and consumer surplus are calculated first. Total surplus is the overall economic benefit an economy accrues from shifts in supply stemming from productivity changes. The change (Δ) in total surplus (*TS*) is:

$$\Delta TS_t = K_t P_0 Q_0 (1 + .5 z_t \eta) \quad (7)$$

Consumer surplus is the economic benefit accrued by consumers from shifts in supply stemming from productivity changes. The change in consumer surplus (*CS*) is:

$$\Delta CS_t = Z_t P_0 Q_0 (1 + .5 Z_t \eta) \quad (8)$$

Producer surplus is the economic benefit accrued by producers from shifts in supply stemming from productivity changes. The change in producer surplus is the difference between the total change in surplus and the change in consumer surplus. The change in producer surplus (*PS*) is:

$$\Delta PS_t = \Delta TS_t - \Delta CS_t \quad (9)$$

where K_t is the vertical shift in the supply function as a proportion of the initial price:

$$K_t = \left[\frac{E(Y)}{\varepsilon} - \frac{E(C)}{1+E(Y)}\right] p A_t (1 - \delta_t) \quad (10)$$

Z_t is the decrease in price from the change in supply relative to its initial value:

$$Z_t = K_t \frac{\varepsilon}{(\varepsilon+\eta)} \quad (11)$$

and where, P_0 is the initial price, Q_0 is the initial quantity, η is the price elasticity of demand, ε is the supply elasticity, $E(Y)$ is the change in yields, $E(C)$ is the change in the cost of pest management, p is the probability of research successfully leading to a new technology where $p = 1$ since the technology has already been developed, A_t is the fraction of the region adopting the technology in year t. δ_t is the rate of depreciation of the technology in year t (see Table 3.3).

Table 3.3 Economic Surplus Analysis Variables

Variable	Definition	Source
P_0	Initial price of vegetables	Bangladesh Bureau of Statistics 2011 Agricultural Yearbook, Statistical Pocketbook of Bangladesh 2013
Q_0	Initial quantity of vegetables	Bangladesh Bureau of Statistics Yearbook of Agricultural Statistics 2011, Yearbook of Agricultural Statistics 2012, Statistical Pocketbook of Bangladesh 2013
ε	Supply elasticity	Rahman 1986
η	Price elasticity of demand	Rahman 1986 Ahmed and Shams 1994 Awal, Sabur, and Mia 2008 Anwarul Huq and Arshad 2010
$E(Y)$	Proportionate change in yield per hectare	BARI Field Survey 2013 Muniappan, et al. 2009 Muniappan, et al. 2010
$E(C)$	Proportionate change in cost per hectare	Muniappan, et al. 2009 Muniappan, et al. 2010 BARI Field Survey in Harris 2011 Akter, Islam, and Rahman 2011 BARI Field Survey 2013
A_t	Adoption rate in year *t*	Survey data
δ_t	Rate of depreciation for the new technology in year *t*	

The initial prices (P_0) and quantities (Q_0) of the vegetables are available from data published by the Bangladesh Bureau of Statistics. The initial prices (P_0) use a three year average of previous national average market prices across Bangladesh to control for annual variation (see Table 3.4). The 2009 to 2012 harvest time vegetable prices per 100 kilograms are available from the *2011 Yearbook of Agricultural Statistics of Bangladesh* and the *Statistical Pocketbook of Bangladesh – 2013*. The 2013 values were projected using the Food Index inflation rates available from the Bangladesh Bureau of Statistics and then the price/metric ton was calculated using a three year averaged value for each vegetable.

Table 3.4 Initial Crop Prices (taka/100kg)

Vegetable	2009	2010	2011	2012	2013	3 Year Average	Taka / 1 kg	Taka / metric ton	USD / metric ton
Bitter gourd	1480	1760	2385	1729	1819.25	1977.75	19.8	18399	235.57
Cabbage	552	754	552	2031	2137.02	1573.34	15.7	15733	201.44
Cucumber	1229	1338	1385	2287	2406.38	2026.13	20.3	20261	259.42
Eggplant	1458	1767	1775	1918	2018.12	1903.71	19.0	19037	243.74
Tomato	944	1912	1592	1259	1324.72	1391.91	13.9	13919	178.21
Country Bean	1171	1744	1487	1698	1786.64	1657.21	16.6	16572	212.18
Data Source:	(Ibrahim, 2011)		(Rahman, 2014)		Projected using (BBS 2015)				Converted using (World Bank, 2014)

The initial quantities (Q_0) for the vegetables use a three year average of district vegetable yields as the initial quantities. The most recent yield information available for all vegetables was from the *2011 Yearbook of Agricultural Statistics of Bangladesh*, but the values available were based on regional combinations of districts rather than the districts themselves. Since the net cultivated area and the cropping intensity were available for each of the regions and the districts within, the effective agricultural area for each region and district was calculated by multiplying the net cultivated area by the cropping intensity divided by 100 (see Table 3.5). Next the percentage of regional production for each district was calculated by dividing the effective agricultural area for each district by the effective agricultural area for the region as a whole (see Table 3.5). Once the percentage of regional production was known, that could be used to break down the regional quantity produced into district quantities produced by multiplying the regional quantity by the district percentage of regional production for each of the four districts. Those values were then averaged using 2009-2011 production information to create the initial quantities (Q_0) (see Table 3.6).

Table 3.5 District Effective Agriculture Area as % of Region (2014)

Region/District	Net Cultivated Area	Cropping Intensity	Effective Agricultural Area	% of Regional Production
Jessore region	**1115541**	**187.25**	**2088850.523**	**1.0000**
Jessore	431466	182	785268.12	0.3759
Magura	188747	209	394481.23	0.1889
Jhenaidah	342988	187	641387.56	0.3071
Narail	152340	171	260501.4	0.1247
Barisal region	**852739**	**172.75**	**1473106.623**	**1.0000**
Barisal	296837	171	507591.27	0.3446
Jhalakathi	99282	169	167786.58	0.1139
Perojpur	185827	143	265732.61	0.1804
Bhola	270793	208	563249.44	0.3824

(Rahman, 2014)

Table 3.6 Initial Quantities (metric tons)

Region/District	3 Year Average Production (2009-2011)						
	Eggplant	Bitter Gourd	Cucumber	Cabbage	Tomato	Country Bean	All Vegetables
Jessore Region	**50409**	**4822**	**4311**	**22577**	**11056**	**14969**	**108144**
Jessore	18951	1813	1621	8487	4156	5627	40655
Magura	9520	911	814	4264	2088	2827	20424
Barisal Region	**4127**	**1356**	**1163**	**4122**	**4280**	**1378**	**16426**
Barisal	1422	467	401	1420	1475	475	5660
Jhalakathi	470	154	133	469	488	157	1871
Initial quantity used:	30362	3345	2968	14641	8206	9086	68608
% of Total	44%	5%	4%	21%	12%	13%	100%

(Ibrahim, 2011)

Both the supply ($\mathcal{E}$) and price elasticity of demand (η) elasticities for vegetables in Bangladesh are available from previous studies by (Ahmed and Shams, 1994, Anwarul Huq and Arshad, 2010, Awal, et al., 2008, Rahman, 1986, Yaseen, et al., 2011) (see Table 3.7). For the price elasticity of demand, a relatively inelastic value of -0.50 was used since that is approximately the average of the price elasticities of demand for vegetables from the two most recently conducted studies (Anwarul Huq and Arshad, 2010, Awal, et al., 2008). For the supply elasticity, an elastic value of 2.00 was used since that is the approximate value of previous supply elasticities for vegetables.

Table 3.7 Price Elasticities of Demand and Supply Elasticities From Previous Studies

Vegetable	**Uncomp. Price Elasticity**	**Comp. Price Elasticity**	**Short Run Price Elasticity**	**Long Run Price Elasticity**	**Short Run Supply Elasticity**	**Long Run Supply Elasticity**	**Source**
Eggplant			0.07*	0.10			Rahman (1986)
Tomato			0.13	0.26			
Tomato			0.34*				
Cabbage			0.08	0.18			
Cabbage			0.08	0.17			
Cabbage			0.09	0.51			
Vegetable			0.20**	0.58	2.28**	6.78	
Vegetable			0.11*	0.24	2.08**	4.37	
Fruits & Vegetables	-0.77**	-0.72					Ahmed and Shams (1994)
Vegetables	-0.69674	-0.57137					Awal, Sabur, and Mia (2008)
Vegetables	-0.31425**	-0.26430					Anwarul Huq and Arshad (2010)

The proportionate changes in yields, *E(Y)*, for the vegetables can be calculated using yield data from the survey and the results of the DD impact analysis on yields. To calculate the proportionate yield change, the DD impact for each vegetable is divided by the average yield rate for the treatment group in round one.

The proportionate change in cost, *E(C)*, for the vegetables can be calculated using pest management cost data from the survey and the results of the DD impact analysis on pest management costs. To calculate the proportionate change in cost, the DD impact for pest management costs is divided by the average pest management cost per decimal for the treatment group in round one.

The rates of IPM use from 2013 and 2014, the first two years of the survey, will be used as the adoption rates (A_t) for this analysis because they provide a representative sample of the four districts. Since the IPM agricultural technologies are expected to remain relevant until either new low cost technologies are developed or higher end technologies become more affordable, a depreciation rate of 0 is assumed in this study. Once adoption rates are identified they can be plugged in to the closed economy model using the spreadsheet found in Alston, Norton, and Pardey (1995).

3.5 Relative Effectiveness of Technology Transfer Methods

The final objective of this thesis is to compare the relative effectiveness of the different technology transfer methods by examining the corresponding adoption rates and accompanying transfer costs per farmer. The cost effectiveness of the transfer methods can be evaluated in two parts: the adoption rates of the transfer methods and the costs to the IPM IL of using the transfer methods. Once the adoption rates and transfer costs are known, the cost effectiveness of the transfer methods can be derived using both the adoption rates and the transfer costs.

3.5.1 Effectiveness of Technology Transfer Methods

The first part of evaluating transfer method effectiveness is to examine adoption rates as they correspond to the different transfer methods used by the IPM IL. The effectiveness of technology transfer methods can be inferred from the determinants of adoption using a model similar to the traditional probit model in Equation 1, but with the agricultural information source variable broken down further to include individual binary variables for all of the agricultural information sources. Using this information, adoption rates by transfer method can then be determined for the 13 different agricultural information sources included in the survey. Using the percentage of farmers receiving agricultural information from a transfer method and the percentage of farmers who adopt the IPM technology after receiving agricultural information from a transfer method, the probability of a farmer adopting can then be determined.

3.5.2 Cost of IPM Technology Transfer Methods

The second part of evaluating transfer method efficiency and effectiveness is to examine the cost to the IPM IL of using the different transfer methods. The cost measurements will focus only on the transfer methods with a public cost such as public television, radio, agricultural officers, and field days. The transfer method costs previously calculated in Ricker-Gilbert (2005) and Harris (2011) are shown in Table 3.9. Ricker-Gilbert (2005) used cost information from BARI and IPM CRSP to analyze costs and Harris used DAE cost information for cost analysis. Harris (2011) postulates that the cost analysis is lower in the later study since the transfer costs in Ricker-Gilbert (2005) failed to account for how much of the information transferred was relevant to pest management. Harris (2011) found that only around 27% of the information conveyed in a DAE farmer field school was related to pest management with the other 73% of the information focusing on agricultural production and marketing. Since Harris' cost study more accurately aligns with the cost of IPM technology transfers, the results from Harris' study will be used here. While the dissemination costs for farmer's groups and IPM clubs were not included in either study, IPM clubs and farmer's groups are often targeted by extension agents since they offer an opportunity to share agricultural information with multiple farmers at once. Assuming there are at least five farmers in a farmer's group or IPM club, the dissemination costs will be one-fifth of the cost of an agricultural agent's visit, or approximately $0.21. After identifying the IPM technology transfer costs, the values were converted into 2013 dollars using the World Bank's inflation data for the conversion (2007).

Table 3.8 Public Transfer Method Cost Per Farmer (USD/household)

Transfer Method	Ricker-Gilbert (2005)	Harris (2011)	Cost Used	Converted to 2013[a]
Paper Media		$0.10	$0.10	$0.13
Electronic Media (radio/television)		$0.02	$0.02	$0.03
Field Day	$5.12	$0.21	$0.21	$0.27
Agricultural Officers	$0.50	$1.07	$1.07	$1.35
Farmer Field School	$10.00	$6.59	$6.59	$8.33
Farmers' Group			$0.21	$0.27
IPM Club			$0.21	$0.27

a: Converted using consumer price index and inflation information from The World Bank (2014)

3.5.3 Cost Effectiveness of Technology Transfer Methods

Finally, once adoption rates and costs are known for all of the public cost technology transfer methods, the probability of a farmer adopting for each transfer method can be converted to the number of farmers needing to be trained in IPM practices for one farmer to adopt IPM practices by dividing the probability of a farmer adopting out of one for each transfer method. Once the number of farmers needing to receive training for one farmer to adopt IPM practices is known, that value can be multiplied by the costs per farmer trained to provide the cost per farmer adopting the technology by transfer method. Once the cost per farmer adopting is known for each transfer methods, those values can be compared to find the transfer methods with the lowest transfer cost per adopting farmer.

3.6 Conclusion

Chapter Three covered the methods and approaches that will be used to evaluate the impacts of the IPM vegetable technology transfer subproject including: analysis of adoption rates and determinants, impact analyses of vegetable yields, pesticide applications, and pest management costs, economic surplus analysis, and analysis of the relative efficiency of different technology transfer methods. The following chapter will introduce the data used in these analyses.

4. Data

4.1 Introduction

Chapter Four discusses the source and composition of the data used to evaluate the objectives described in Chapter One. The first section explains the surveying and data collection process. The second section provides descriptive statistics for basic household information as well as descriptive statistics for all the dependent and independent variables described in Chapter Three.

4.2 Survey Design and Administration

The data for this thesis were gathered in the first two years of a three-year longitudinal survey. Data were collected from 104 selected villages divided evenly across four districts: Barisal, Jessore, Jhalakati, and Magura.[6] The four districts for the survey were chosen by the project to correspond with the USAID FtF program districts that are areas with low income and high malnutrition. Both Jessore and Magura have been the focus of previous IPM efforts with non-vegetable crops while the districts of Barisal and Jhalakati are both new to IPM practices and trainings.

This experiment was initially set up in the summer of 2013 as a RCT with 104 villages. Villages were randomly assigned to either the treatment or control groups with care to insure that spillover from treatment villages would not affect the control villages. The RCT divided the villages into 52 control villages and 52 treatment villages. To select farmers for the sample, a list of vegetable farmers was collected for each village and eight farmers were randomly selected to participate in the survey. The sample contained a total of 838 farmers with an average of 8.06 farmers per village in the full group, 8.10 farmers per village in the treatment group, and 8.02 farmers per village in the control group (see Table 4.1). While eight farmers were initially

[6] See Appendix A for a complete list of villages included in the survey

selected from each village, in some villages an additional farmer insisted on being surveyed increasing the number of farmers in those villages to nine.

Table 4.1 Experiment Design Information

	Full Group	Treatment Group	Control Group
Number of Villages	104	52	52
Average number of farmers per village	8.06	8.10	8.02

The first round of the survey was conducted in summer 2013 by Ahsanuzzaman, a PhD student from the Department of Agricultural and Applied Economics (AAEC) at Virginia Polytechnic Institute and State University (VA Tech), and three enumerators who traveled to all four of the districts with him. The first survey was conducted using a paper instrument written in English with questions asked in Bangla by the enumerators and the farmers' answers written in English by the enumerators. The original survey included 15 modules of questions (see Table 4.2).

Table 4.2 First Round Survey Modules

	Module	Contents
1.	Farmer's Identification	Farmer name, village, upazila, mobile #, etc.
2.	Demographic Information	Age, gender, occupation, education, agricultural experience, distance from market, etc.
3.	Housing Condition	House material, roof material, electricity
4.	Financial Information	Bank account, recent loan information
5.	Land Usage	Land owned, rented, sharecropped, land area conversion rate
6.	Participation in Organizations	Member of village society, farmer's group, school committee, mosque committee, IPM club, etc.
7.	Agricultural Knowledge	Learn agricultural knowledge from: Ag. Officer, neighbor, field days, farmer's fair, etc.
8.	Village Characteristics	Number of schools/madrash, mosques, college degrees, paved/brick roads
9.	Vegetable Cultivation	Area planted of each vegetable: last two growing seasons
10.	Pesticide Usage	# of applications, total cost, # of types, person days of application
11.	Pest Management	Pest damage, severity of damage, IPM practices used, non-IPM practices used
12.	Crop Sales Information	Total Kg sold, sales price, total income, sales location, buyer
13.	IPM Training	# of times trained in IPM, training organization, opinions on IPM use
14.	Other Crop Information	# of other crops grown, IPM practice used, non-IPM practices used
15.	Social Network Information	# of IPM users known, who farmer talks to about pest management, neighboring farmers using IPM, etc.

After the first round of data was collected, survey responses were manually entered into an Excel spreadsheet that was imported into STATA 13 for comprehensive data checks and cleaning. Conflicts were then manually checked on the paper surveys and then subsequently corrected using a STATA cleaning do-file for round one.

The second round of the survey was conducted in summer 2014 by the author of this thesis, as well as a supervisor, Md. Sadique Rahman,[7] with four enumerators for the districts of

[7] Md. Sadique Rahman is an Assistant Professor Department of Management and Finance, Faculty of Agribusiness management, at Sher-e Bangla Agricultural University in Dhaka, BD.

Jessore and Magura, and four enumerators for the districts of Barisal and Jhalakati. It was more cost effective to use different groups of enumerators for the Jessore and Magura districts and the Barisal and Jhalakati districts. Prior to beginning the second round of the survey, the questionnaire was updated. The second round of the survey included only 14 modules, excluding the village characteristics module from the first survey (See Table 4.3). The village characteristics module was dropped because these variables were unlikely to change from the previous year. For the second round, the survey was conducted in the Surveybe Computer-Assisted Personal Interviewing (CAPI) electronic surveying program[8] and the entire survey was conducted using tablet computers. The benefits of using Surveybe included having the survey administered in Bangla with responses easily converted into English, the ability to control for extreme responses, and to quickly and easily check for survey completeness in the field using checks built into the Surveybe program.

[8] Surveybe Implementer and Designer versions used were both 4.0.5254.

Table 4.3 Second Round Survey Modules

	Module	Contents
1.	Farmer's Identification	Farmer name, village, upazila, mobile #, GPS coordinates
2.	Demographic Information	Age, gender, occupation, education, agricultural experience, etc.
3.	Housing Condition	House material, roof material, number of rooms, electricity
4.	Financial Information	Bank account, recent loan information
5.	Land Usage	Land owned, rented, sharecropped, decimal-bigha conversion rate
6.	Participation in Organizations	Member of village society, farmer's group, school committee, mosque committee, IPM club, etc.
7.	Agricultural Knowledge	Learn agricultural knowledge from: Ag. Officer, neighbor, field days, farmer's fair, etc.
9.	Vegetable Cultivation	Bighas planted of each vegetable: last two growing seasons
10.	Pesticide Usage	# of applications, total cost, # of types, person days of application
11.	Pest Management	Pest damage, severity of damage, IPM practices used, non-IPM practices used
12.	Crop Sales & Consumption Information	Total Kg sold, sales price, total income, sales location, buyer, Kg consumed by household
13.	IPM Training	# of times trained in IPM, training organization, opinions on IPM use
14.	Other Crop Information	# of other crops grown, IPM practice used, non-IPM practices used
15.	Social Network Information	# of IPM users known in village and outside village, number of neighboring farmers adopting IPM

The Jessore and Magura enumerators in 2014 were undergraduate students from Jessore University of Science and Technology. Training took place at the BARI's Jessore location, followed by a pilot of the survey conducted in Churamon Kathi, a local village also used as the pilot village for round one. Conducting the surveys in Jessore and Magura took place over 14 days, visiting three to four villages each day. Sometimes the local sub-assistant agricultural officers (SAAO) helped locate and organize the farmers, the rest of the time GPS coordinates and local farmers were used to identify and find farmers. Upon arriving at each village, the four enumerators and supervisor would start interviewing farmers. After completing each interview, the surveys were checked for completeness prior to leaving the village. At the end of each day, surveys were offloaded from the tablets, checked by the supervisor, and then uploaded into Dropbox[9] to back up the data.

The Barisal and Jhalakati enumerators were all local graduate students in varying agricultural fields at Patuakhali Science and Technology University in Barisal. Training took place at a local hotel in Barisal, followed by the careful surveying of a single village. Conducting the surveys in Barisal and Jhalakati also took 14 days. In Jhalakati, local SAAOs were used for most of the region with varying cost and results while in Barisal local farmers were used to find the households. Surveying in each village followed the same process as in Jessore and Magura. There were three distinct issues while surveying in Barisal and Jhalakati. First, the Jhalakati district proved difficult to survey since villages were often spread out around and across local canals and rivers making farmers difficult to find. Second, while surveying Barisal and Jhalakati, Md. Sadique Rahman returned to Dhaka early and the local IPM Field Officer took over the logistics of finding the villages and farmers. Third, Ramadan began halfway through the surveying of the Barisal and Jhalakati districts during which business hours and daily life were altered to accommodate the Ramadan fast.

After the surveys were completed, Surveybe files from round two were exported to a comma-separated values file (.csv) and then imported into STATA and labeled using a do-file produced by the Surveybe program. Data cleaning for the second round of data was performed using normal data cleaning techniques and checks in STATA 13 with errors addressed via the STATA cleaning do-file for round two. After completing data checks and cleaning, data from

[9] Dropbox is a free, online file sharing and data backup program.

rounds one and two were appended in STATA to form a panel data set to be used for analysis.

4.3 Summary Statistics

This section includes descriptive and summary statistics for attrition rates, basic household information, farm size and vegetables, pests and pest management, adoption rates, impacts, and agricultural information sources.

4.3.1 Attrition Rates

The overall attrition rate for the second round of the survey was 55 households or 6.6% of households with 0.7% of the households rejecting the survey and 5.9% of the households were not found (see Table 4.4). Attrition rates for the control and treatment groups were similar with overall attrition rates of 6.5% for the control group and 6.7% for the treatment group. By district, Barisal had an attrition rate of 6.3%, Jessore had an attrition rate of 2.9%, Jhalakati had an attrition rate of 14.8%, and Magura had an attrition rate of 2.4%. Jhalakati in particular accounted for 56.4% of the overall attrition rate with the 31 households not found in Jhalakati accounting for 63.3% of all of the households not found.

Table 4.4 Attrition Rate in the Second Round of the Survey

	All Four Districts			Barisal			Jessore			Jhalakati			Magura		
	Full Group	Control	Treatment	Full Group	Control	Treatment	Full Group	Control	Treatment	Full Group	Control	Treatment	Full Group	Control	Treatment
Sample size	838	417	421	208	104	104	211	104	107	209	104	105	210	105	105
Survey Completed (%)	93.4	93.5	93.3	93.8	93.3	94.2	97.2	98.1	96.3	85.2	86.5	83.8	97.6	96.2	99.0
Survey Rejected (%)	0.7	0.7	0.7	1.4	1.0	1.9	1.0	1.0	0.9	0.0	0.0	0.0	0.5	1.0	0.0
HH not located (%)	5.9	5.8	5.9	4.8	5.8	3.8	1.9	1.0	2.8	14.8	13.5	16.2	1.9	2.9	1.0

4.3.2 Basic Household Information

In round one of the survey, the household head (HHH) was predominately male, between 42 and 43 years of age, completed at least a primary level of education and had 16.7 years of agricultural experience (see Table 4.5). On average households in the sample had 5.4 family members, of which 1.6 were able to work.

In the second round of the survey, the HHH was predominately male, between 44 and 45 years old, completed at least a primary level of education and had 20.1 years of agricultural experience (see Table 4.5). On average households in the sample had 5.5 family members, 1.6 of which were able to work. In the second round, data was collected on the number of rooms each house had. On average a house had 3.2 rooms or less than 1 room per household member.

Using t-tests to compare the treatment and control groups within each round, there are significant differences in the gender of the HHH between the control and treatment groups with around 5% more male HHHs than female HHHs (see Table 4.5). Education rates are comparable between rounds for those with no education or a primary education. Comparing the two rounds, the HHH age significantly increased as expected as did the HHH years of agricultural experience. Only the percentage of HHHs who have farming as their primary occupation significantly decreased between rounds.

Table 4.5 Basic Household Information [a]

	Round 1			Round 2		
	Full Group	Control	Treatment	Full Group	Control	Treatment
Sample Size	838	417	421	783	390	393
Gender- Male (%)	96.9	94.7	99.0*	96.9	94.9	99.0*
Age (yrs)[b]	42.7 ± 12.8	42.8 ± 12.6	42.6 ± 13.1	44.1 ± 12.5°	44.2 ± 12.2	43.9 ± 12.8
No education (%)	20.3	19.4	21.2	19.3	19.7	18.8
At least a primary education (%)	79.7	80.6	78.6	80.7	80.3	81.2
Farming is primary occupation (%)	99.6	99.8	99.5	95.4°	95.4	95.4
Agriculture experience (yrs)[b]	16.7 ± 9.2	16.9 ± 9.2	16.6 ± 9.3	20.1 ± 11.2°	19.9 ± 11.2	20.3 ± 11.3
Average household size (#)	5.4 ± 2.2	5.4 ± 2.3	5.4 ± 2.0	5.5 ± 2.8	5.5 ± 3.2	5.4 ± 2.3
Average number of household members in workforce[bc]	1.6 ± 0.9	1.6 ± 1.1	1.5 ± 0.8	1.6 ± 1.2	1.6 ± 1.2	1.6 ± 1.0
Rooms in house	-	-	-	3.2 ± 1.3	3.2 ± 1.3	3.2 ± 1.2
Rooms/household size[d]	-	-	-	0.6 ± 0.3	0.6 ± 0.3	0.7 ± 0.3

a: When data was available for both rounds or both control groups, t-tests were performed comparing the rounds (denoted by °**)** as well as comparing the treatment and control groups within the rounds (denoted by *). ° and * denote significance at the 5% significance level.

b: Values are mean ± standard deviation

c: Number of persons in household divided by number of household members in the workforce

d: Number of rooms in the house divided by household size

4.3.3 Farm Size and Vegetables

In round one, on average, a household grew vegetables on 25.5 decimals[10] of land with 212.4 total decimals of land owned and operated (see Table 4.6). On average, a household owned 125.5 decimals of land, rented 52.7 decimals, and sharecropped 33.3 decimals. In round one, on average, a household grew 1.08 of the vegetables with 93.4% of farmers only growing one vegetable and 6% growing two or more vegetables. Out of 838 households surveyed, 98.6% grew at least one of the six vegetables in the most recent growing season. Of those, 48.9% grew eggplant, 30.5% of the households grew tomatoes, 15.9% grew bitter gourd, 4.5% grew country beans, 4.1% grew cucumbers, and 3.9% grew cabbage.

In round two, on average, a household grew vegetables on 37.1 decimals of land with 222.1 total decimals of land owned and operated (see Table 4.6). On average, a household owned 144.5 decimals of land, rented 47.1 decimals, and sharecropped 36.8 decimals. In round two, on average, a household grew 1.36 of the vegetables with 45.8% of farmers only growing one vegetable and 36.4% of farmers growing two or more vegetables. Out of 784 households surveyed, 87.9% grew one of the six vegetables. Of those, 27.6% of the households grew tomatoes, 48.2% grew eggplant, 14.9% grew cucumbers, 26.9% grew bitter gourd, 13.8% grew cabbage, and 13.8% grew country beans.

In round one there was a significant difference in the area of land farmed with vegetables between the treatment and control groups with significantly more land farmed in the control group (see Table 4.6). The average number of vegetables grown by the households increased significantly between rounds. Comparing the two rounds, there is a significant increase in the

[10]A decimal is 1/100th of an acre, see footnote 5

quantity of land farmed with vegetables between the two rounds which is also reflected in vegetable area farmed as a percentage of total land area which increased significantly between rounds (see Table 4.7). For the percentage of farmers growing any of the six vegetables, there was a significant decrease in farmers growing the vegetables in the second round of surveying. Examining the individual vegetables, cabbage, cucumbers, bitter gourd, and country bean all increased significantly in the percentage of households growing them with insignificant changes for eggplant and tomatoes.

There is a possibility that farmers surveyed in the first round overstated their involvement in vegetable farming to insure participation in the survey, especially if the farmers thought there might be compensation for participation. Since each round also asked about vegetables grown in the previous year, round two responses for the previous year were reviewed and compared to the round one responses for the current year. Round two responses for the previous year show that around 3.5% fewer farmers grew vegetables in round one than the round one responses for the current year. When comparing the previous year and current year responses within round two the percentage of farmers who grew vegetables decreases from the first year to the second year, but by a lesser amount than when the current year responses are compared between rounds.

Table 4.6 Farm Characteristics[a]

	Round 1			Round 2		
	Full Group	Control	Treatment	Full Group	Control	Treatment
Sample Size	838	417	420	784	390	394
Total Land farmed with the six vegetables (decimals)[b]	25.5 ± 29.1	27.6 ± 33.0	23.4 ± 24.4*	37.1 ± 46.8°	36.0 ± 42.7	38.3 ± 50.6
Total Land Owned & Operated (decimals)[b]	212.4 ± 220.5	214.1 ± 239.4	210.7 ± 200.2	222.1 ± 387.7	232.3 ± 511.0	212.1 ± 205.9
Land owned (decimals)[b]	125.5 ± 168.6	128.9 ± 190.7	122.2 ± 143.5	144.5 ± 297.6	151.4 ± 390.1	137.6 ± 160.3
Land rented (decimals)[b]	52.7 ± 120.2	55.0 ± 136.0	50.4 ± 102.1	47.1 ± 113.3	46.4 ± 107.1	47.7 ± 119.2
Land sharecropped (decimals)[b]	33.3 ± 88.6	29.5 ± 70.7	37.0 ± 103.3	36.8 ± 119.8	39.4 ± 149.5	34.3 ± 80.3
Number of vegetables grown (out of the six)[b]	1.08 ± 0.40	1.07 ± 0.41	1.09 ± 0.38	1.36 ± 1.02°	1.37 ± 1.00	1.34 ± 1.05
% of farmers growing:						
Any of the six vegetables in prior year	85.8	85.9	85.7	95.0°	95.4	94.7
Any of the six vegetables in survey year	98.6	98.3	98.8	87.9°	90.3	85.5*
Tomatoes in survey year	30.5	29.0	32.1	27.6	29.2	25.9
Eggplant in survey year	48.9	57.8	40.1*	48.2	50.8	45.7
Cucumbers in survey year	4.1	3.4	4.8	14.9°	14.4	15.5
Bitter gourd in survey year	15.9	10.8	20.9*	26.9°	25.4	28.4
Cabbage in survey year	3.9	2.2	5.7*	13.8°	12.3	15.2
Country bean in survey year	4.5	3.8	5.2	13.8°	14.9	12.7

a: When data was available for both rounds or both control groups, t-tests were performed comparing the rounds (denoted by °) as well as comparing the treatment and control groups within the rounds (denoted by *). ° and * denote significance at the 5% significance level.

b: Mean ± standard deviation

In round one, on average, a household utilized 20.1% of their total land to grow vegetables. Of the household's total land, 21.4% of their land was utilized for bitter gourd, 19.2% for eggplant, 17.7% for cucumbers, 17.6% for tomatoes, 15.7% for cabbage, and 11.5% for country bean. Of the land a household farmed with vegetables, on average, 95.1% of the land was utilized for eggplant, 94.7% for tomatoes, 91.6% for bitter gourd, 80.2% for cabbage, 78.0% for country bean, and 77.2% of the land for cucumbers (see Table 4.7). On average, a household in round two utilized 27.8% of their total land to grow at least one of the six vegetables. Of the household's total land, 16.8% was utilized for tomatoes, 20.0% for eggplant, 12.8% for cucumbers, 15.6% for bitter gourd, 14.8 % for cabbage, and 13.2% country bean. Of all the land a household farmed with vegetables, on average, 61.3% of was utilized for tomatoes, 72.3% for eggplant, 42.7% for cucumbers, 57.0% for bitter gourd, 52.0% for cabbage, and 52.6% of the land for country bean.

Comparing the two rounds, there was a significant increase in the area used for all six vegetables combined as a percentage of the total land owned and operated by the households. Examining vegetable area as the percentage of area farmed with all six of the vegetables, the individual values for all six of the vegetables significantly decreased between rounds. The significant increase in the percentage of total area used for the six vegetables and the significant decrease in the percentage of the vegetable area used for individual vegetables combined with the increase in the number of vegetables grown, suggests that farmers in round two of the survey were more diversified in vegetables than they were in round one.

Table 4.7 Land Used for Vegetable as % of Total Land & Total Land of All Six Vegetables[a]

	Round 1			Round 2		
	Full Group	Control	Treatment	Full Group	Control	Treatment
Sample Size	838	417	420	784	390	394
Land used for vegetable as % of total land owned and operated						
All six vegetables	20.1	22.0	18.3	27.8°	27.9	27.6
Cabbage	15.7	12.6	16.9	15.3	14.1	16.2
Tomatoes	17.6	20.2	15.2	16.8	19.5	13.8*
Cucumbers	17.7	12.8	21.2	12.8°	12.5	13.2
Bitter Gourd	21.4	23.2	20.5	15.7°	15.2	16.2
Country Bean	11.5	14.4	9.6	13.2°	12.9	13.6
Eggplant	19.2	21.0	16.5*	20.0	19.8	20.3
Land used for vegetable as % of total land used for all six vegetables						
Tomato	94.7	94.7	92.5	61.3°	64.1	58.1
Eggplant	95.1	96.5	93.1*	72.3°	74.4	70.0
Cucumbers	77.2	63.5	86.8*	42.7°	41.4	43.8
Bitter gourd	91.6	91.1	91.8	57.0°	54.3	59.4
Cabbage	80.2	72.5	83.1	52.0°	49.6	54.0
Country bean	78.0	58.4	92.2*	52.6°	53.2	52.0

a: When data was available for both rounds or both control groups, t-tests were performed comparing the rounds (denoted by °**)** as well as comparing the treatment and control groups within the rounds (denoted by *). ° and * denote significance at the 5% significance level.

4.3.4 Pests and Pest Management

For pest severity estimates farmers were asked to quantify the severity of a problem they perceived from each pest they have identified impacting their vegetables. Pest severity ranges in value from 1 to 4 with a value of 1 representing a less severe pest problem and a value of 4 representing a very severe pest problem. In round one, 95.7% of households had pest problems affecting their vegetables with an average severity of 2.3 for all pest problems (see Table 4.8). On average, a household had a mean pest severity of 3.0 when growing country bean, 2.6 when growing bitter gourd, 2.3 when growing eggplant, 2.2 when growing cabbage, 2.0 when growing tomatoes, and 2.0 when growing cucumbers.

In round two, 99.4% of households had pest problems affecting production of at least one of the six vegetables with an average pest severity of 2.1 for all vegetables (see Table 4.8). On average a household had a mean pest severity of 2.4 when growing country bean, 2.2 when growing cabbage, 2.1 when growing cucumbers, 2.1 when growing bitter gourd, 2.1 when growing eggplant, and 2.0 when growing tomatoes.

Comparing the two rounds, households in the second round experienced significantly more pest problems for tomatoes, eggplant, cucumbers, and bitter gourd, but with a significantly lower average pest severity (see Table 4.8). Bitter gourd, country bean, and eggplant all significantly decreased in the average severity of pest problems between rounds.

Table 4.8 Pest problems in the last 12 months [a]

	Round 1			Round 2		
	Full Group	Control	Treatment	Full Group	Control	Treatment
Sample Size	838	417	420	784	390	394
% With Pest Problem For Farmers Growing						
Any of the six vegetables	95.7	95.6	95.7	99.4°	99.4	99.4
Tomato	94.5	93.4	95.5	99.1°	99.1	99.0
Eggplant	96.6	97.1	95.9	99.5°	99.0	100.0
Cucumber	85.3	85.7	85.0	99.1°	98.2	100.0
Bitter gourd	95.5	95.6	95.5	99.1°	99.0	99.1
Cabbage	93.9	100.0	91.7	93.5	95.8	91.7
Country bean	100.0	100.0	100.0	100.0	100.0	100.0
Mean Severity of Pest Problem (1-4) For Farmers Growing[b]						
Any of the six vegetables	2.3 ± 0.9	2.3 ± 0.9	2.3 ± 0.9	2.1 ± 0.7°	2.1 ± 0.7	2.1 ± 0.7
Tomato	2.0 ± 0.9	2.0 ± 0.9	2.0 ± 0.9	2.0 ± 0.6	2.0 ± 0.6	2.0 ± 0.6
Eggplant	2.3 ± 0.9	2.3 ± 0.9	2.3 ± 0.8	2.1 ± 0.7°	2.1 ± 0.7	2.0 ± 0.6
Cucumber	2.0 ± 0.8	2.0 ± 0.9	2.0 ± 0.6	2.1 ± 0.7	2.1 ± 0.7	2.2 ± 0.8
Bitter gourd	2.6 ± 1.0	2.9 ± 1.0	2.4 ± 0.9*	2.1 ± 0.7°	2.2 ± 0.7	2.0 ± 0.8
Cabbage	2.2 ± 1.2	2.0 ± 1.0	2.3 ± 1.2	2.2 ± 0.9	2.2 ± 0.9	2.3 ± 0.9
Country bean	3.0 ± 1.0	2.8 ± 1.1	3.2 ± 0.9	2.4 ± 0.8°	2.4 ± 0.8	2.3 ± 0.8

a: When data was available for both rounds or both control groups, t-tests were performed comparing the rounds (denoted by °**)** as well as comparing the treatment and control groups within the rounds (denoted by *). ° and * denote significance at the 5% significance level.

b: Mean ± standard deviation

In round one, 86.6% of households used pesticides, applying pesticides 29.3 times, using 3.8 different pesticides, at an average cost of 5,825.0 taka, and requiring a total of 5.6 person days (see Table 4.9).[11] In round two, 97.2% of households used pesticides, applying pesticides 24.0 times, using 4.8 different pesticides, at an average cost of 5974.1 taka and 4.1 person days.

There is a significant increase in the percentage of households using pesticides between rounds. However, there is a significant decrease in the number of times pesticides were applied in round two compared to round one with significantly lower pesticide application rates for the treatment groups in both rounds. For the variety of pesticides used, there is a significant increase between rounds in addition to a significantly difference in the variety of pesticides used between the treatment and control groups in round one. Additionally, the number of person days spent applying pesticides decreases significantly between rounds with the second round also displaying significant less person days spent applying pesticides for treatment group compared to the control group.

[11] A person day is the amount of work one person can complete during one workday.

Table 4.9 Pesticide use in the past 12 months [a]

	Round 1			Round 2		
	Full Group	Control	Treatment	Full Group	Control	Treatment
Sample Size	838	417	420	784	390	394
% Using Pesticides	86.6	88.9	84.3*	97.2°	97.7	96.7
# of Pesticide Applications[b]	29.3 ± 36.5	33.3 ± 39.1	25.4 ± 33.3*	24.0 ± 28.5°	27.1 ± 31.5	21.0 ± 24.9*
# of Different Pesticides Used [b]	3.7 ± 2.3	3.9 ± 2.2	3.6 ± 2.3*	4.8 ± 2.8°	4.9 ± 2.8	4.8 ± 2.7
Mean Pesticide Costs (taka) [b]	5,810.6 ± 15,124.8	5,512.3 ± 8,548.0	6,105.2 ± 19,568.5	5,974.1 ± 8,278.0	6,611.1 ± 9,268.5	5,309.9 ± 7,053.2*
Mean Person Days Applying Pesticides[b]	5.6 ± 12.5	5.4 ± 8.6	5.9 ± 15.4	4.1 ± 7.6°	4.8 ± 9.6	3.4 ± 4.6*

a: When data was available for both rounds or both control groups, t-tests were performed comparing the rounds (denoted by °**)** as well as comparing the treatment and control groups within the rounds (denoted by *). ° and * denote significance at the 5% significance level.

b: Mean ± standard deviation

In round one, 32.1% of households used at least one IPM practice in response to pest problems (see Table 4.10). A few of the more commonly used IPM technologies in round one were handpicking, with an adoption rate of 16.5%, pheromone traps, with an adoption rate of 8.9%, and soil amendments, with an adoption rate of 7.2%. In round two, 29.7% of households used at least one IPM practice in response to pest problems. The most commonly used IPM technologies in round two were pheromone traps with an adoption rate of 21.6% and handpicking with an adoption rate of 10.1%.

Comparing the two rounds, there was a significant decrease in the use of IPM practices from 32.1% of the sample in round one to 29.7% of the sample in round two (see Table 4.10). Comparing the individual IPM practices between rounds there was a significant increase in the use of pheromone traps in addition to significant decreases in the use of soil amendments and hand picking. The significant increase in pheromone trap usage can be explained by the IPM field officer's use of them in IPM training. When the field officers conducted IPM training, they often gave out the pheromone bait to be used in the traps, significantly encouraging adoption of the pheromone traps in pest management.

Table 4.10 IPM Adoption by IPM practice (last 12 months) [a]

	Round 1			Round 2		
	Full Group	Control	Treatment	Full Group	Control	Treatment
Sample Size	838	417	420	784	390	394
% of households who used:						
Any IPM practice	32.1	34.5	29.8	29.7	29.2	30.2
Pheromone traps	8.9	9.4	8.6	21.6°	19.5°	23.6°
Yellow sticky traps	0.2	0.2	0.2	0.8	0.8	0.8
Tricho compost or Tricho lechate	0.1	0.0	0.2	0.3	0.0	0.5
Soil amendments	7.2	9.4	5.0*	0.6°	1.0°	0.3°
Grafting	0.0	0.0	0.0	0.1	0.0	0.3
Improved/resistant varieties	0.8	0.5	1.2	0.3	0.3	0.3
Biological controls (parasitoids & ladybird beetles)	0.1	0.0	0.2	0.2	0.0	0.3
Hand picking	16.5	18.7	14.3	10.1°	11.3°	8.9
Soapy water	0.8	0.2	1.4	0.4	0.8	0.0°

a: When data was available for both rounds or both control groups, t-tests were performed comparing the rounds (denoted by °**)** as well as comparing the treatment and control groups within the rounds (denoted by *). ° and * denote significance at the 5% significance level.

4.3.5 Adoption Rates

IPM adoption in this study is when a household uses at least one of the IPM practices recommended by the IPM IL for a vegetable. In round one, 32.2% of households used at least one IPM practice (see Table 4.11). In Barisal 37.0% of households used IPM approaches, with 41.4% adopting in the treatment group and 32.7% adopting in the control group. In Jessore 30.8% of households used IPM approaches, with 30.7% adopting in the treatment group and 30.8% adopting in the control group. In Jhalakati 34.6% of households used IPM approaches, with 36.9% adopting in the treatment group and 32.4% adopting in the control group. Finally, in Magura 26.3% of households used IPM approaches, with 29.5% adopting in the treatment group and 23.1% adopting in the control group.

In the second round 33.8% of households used IPM practices (see Table 4.11). In Barisal 40.3% of households used IPM approaches, with 46.0% adopting in the treatment group and 34.8% adopting in the control group. In Jessore 34.3% of households had adopted IPM approaches, with 23.4% adopting in the treatment group and 48.0% adopting in the control group. In Jhalakati 21.7% of households had adopted IPM approaches, with 36.6% adopting in the treatment group and 41.4% adopting in the control group. Finally, in Magura 66 households had adopted IPM approaches, with 36 adopting in the treatment group and 30 adopting in the control group.

Comparing the two rounds there were no significant changes in the number of IPM adopters. Adoption rates in Barisal and Jessore remained relatively constant between rounds with a significant decrease in adoption rates between rounds in Jhalakati and a significant increase in adoption rates between rounds in Magura. Comparing the treatment and control groups, Jessore in round two was the only district with a significant difference between the two groups.

Table 4.11 IPM Adoption (by district) [a]

	Round 1			Round 2		
	Full Group	Control	Treatment	Full Group	Control	Treatment
Sample size	838	413	420	784	394	390
Adoption rate (%)						
All four districts	32.2	34.6	29.8	33.8	32.4	35.3
Barisal	37.0	41.4	32.7	40.3	46.0	34.8
Jessore	30.8	30.7	30.8	34.3	23.4	48.0*
Jhalakati	34.6	36.9	32.4	21.7°	24.7	18.6
Magura	26.3	29.5	23.1	39.1°	36.6	41.4

a: When data was available for both rounds or both control groups, t-tests were performed comparing the rounds (denoted by °**)** as well as comparing the treatment and control groups within the rounds (denoted by *). ° and * denote significance at the 5% significance level.

In round one with all IPM practices included, 32.2% of all households used IPM practices with 34.6% of households in the control group and 29.8% of households in the treatment group (see Table 4.12). Of the households growing tomatoes, 11.4% of households adopted at least one IPM practice, with 13.2% of households adopting in the control group and 9.7% of households adopting in the treatment group. Of the households growing eggplant, 40.7% of households used at least one IPM practice, with 40.7% of households adopting in the control group and 40.8% of households adopting in the treatment group. Of the households growing cucumbers, 5.9% of households adopted at least one IPM practice, with 7.1% of households adopting in the control group and 5.0% of households adopting in the treatment group. Of the households growing bitter gourd, 31.6% of households adopted at least one IPM practice, with 37.8% of households adopting in the control group and 28.4% of households adopting in the treatment group. Of the households growing cabbage, 6.1% of households adopted at least one IPM practice, with no households adopting in the control group and 8.3% of households adopting in the treatment group. Finally, 73.7% of the households growing country beans had adopted at least one IPM practice, with 68.8% of households adopting in the control group and 77.3% of households adopting in the treatment group.

In round two, 33.8% of all households used at least one IPM practice with 32.4% of households adopting in the control group and 35.3% of households adopting in the treatment group (see Table 4.12). Of the households growing tomatoes, 19.0% of households adopted at least one IPM practice, with 20.2% of households adopting in the control group and 17.7% of households adopting in the treatment group. Of the households growing eggplant, 37.3% of households adopted at least one IPM practice, with 35.9% of households adopting in the control group and 38.9% of households adopting in the treatment group. Of the households growing cucumbers, 18.0% of households adopted at least one IPM practice, with 23.2% of households adopting in the control group and 13.1% of households adopting in the treatment group. Of the households growing bitter gourd, 33.7% of households adopted at least one IPM practice, with 29.3% of households adopting in the control group and 37.5% of households adopting in the treatment group. Of the households growing cabbage, 6.5% of households adopted at least one

IPM practice, with 4.2% of households adopting in the control group and 8.3% of households adopting in the treatment group. Finally, 13.9% of the households growing country beans had adopted some sort of IPM technology, with 19.0% of households adopting in the control group and 8.0% of households adopting in the treatment group.

Comparing the two rounds, there is a slight, but insignificant increase in the rate of IPM adoption for all vegetables from round one to round two with significant increases in IPM adoption for tomatoes, no significant changes for eggplant, cucumber, bitter gourd, or cabbage, and a significant decrease in IPM adoption for country bean.

Table 4.12 IPM Adoption (by vegetable) [a]

	Round 1			Round 2		
	Full group	Control	Treatment	Full group	Control	Treatment
Sample size	838	413	420	784	394	390
% Adopting IPM Practices by Vegetable:						
Any of the six vegetables	32.2	34.6	29.8	33.8	32.4	35.3
Tomato	11.4	13.2	9.7	19.0°	20.2	17.7
Eggplant	40.7	40.7	40.8	37.3	35.9	38.9
Cucumber	5.9	7.1	5.0	18.0	23.2	13.1
Bitter gourd	31.6	37.8	28.4	33.7	29.3	37.5
Cabbage	6.1	0.0	8.3	6.5	4.2	8.3
Country bean	73.7	68.8	77.3	13.9°	19.0	8.0

a: When data was available for both rounds or both control groups, t-tests were performed comparing the rounds (denoted by °**)** as well as comparing the treatment and control groups within the rounds (denoted by *). ° and * denote significance at the 5% significance level.

Examining changes in IPM adoption between rounds for all vegetables, IPM adoption in round two decreased by 4.2 percentage points, but the percentages of households adopting two, three, or even four IPM practices for their vegetables increased by 4.2, 1.2, and 0.4 percentage points respectively (see Table 4.13). Comparing the two rounds, more households adopted IPM pest management practices for tomato, cucumber, bitter gourd, and cabbage in round two while less households used IPM practices for eggplant and country bean. The decrease in households adopting one IPM practice and the increase in adopters of multiple IPM practices suggest that previous IPM adopters are beginning to adopt IPM pest management practices for more vegetables and to address more pest problems.

Table 4.13 Intensity of IPM Adoption (by vegetable)[a]

	# of practices recommended	Round 1					Round 2				
# of IPM practices adopted:		0	1	2	3	4[a]	0	1	2	3	4[a]
% of farmers adopting (X # of IPM practices):											
IPM practices for all vegetables	21	68.0	29.2	2.6	0.1	0.0	72.2	19.3	6.8	1.3	0.4
Tomato	3	96.5	3.5	0.0	0.0	-	95.1	4.8	0.1	0.0	-
Eggplant	4	80.1	17.8	2.0	0.1	0.0	83.2	14.4	2.4	0.0	0.0
Cucumber	4	99.8	0.2	0.0	0.0	0.0	97.5	2.5	0.0	0.0	0.0
Bitter gourd	4	95.0	4.9	0.1	0.0	0.0	91.5	8.2	0.2	0.0	0.0
Cabbage	3	99.8	0.2	0.0	0.0	-	99.2	0.8	0.0	0.0	-
Country bean	3	96.7	3.1	0.2	0.0	-	98.2	1.6	0.2	0.0	

a: T-tests comparing both rounds found no significant difference between rounds (at the 5% significance level). T-tests comparing the treatment and control groups within each round found no significant differences between the groups (at the 5% significance level).
b: Tomato, cabbage, and country bean only have three recommended IPM practices.

4.3.6 IPM Training

In round one, 24.3% of all households received IPM training with 26.9% of households in the control group and 24.8% of households in the treatment group. Of those households trained in IPM, training was received 1.3 times and the household knew 4.2 farmers who had adopted IPM pest management practices (see Table 4.14).

In round two, 39.9% of all households had received IPM training with 38.7% of households in the control group and 41.1% of households in the treatment group. Of those households trained in IPM, training was received 3.1 times and the household knew 17.7 farmers who had adopted IPM pest management practices (see Table 4.14).

Comparing the two rounds, the percentage of households trained in IPM increased significantly between rounds in all districts except Jhalakati, though the control group in round two had been trained significantly more times than the treatment group.

Assuming an RCT is properly designed and implemented, the treatment and control groups should be approximately equal in the baseline survey and the RCT should control for selection bias and spillover effects. Referring to Tables 4.11 & 4.12, there are no significant differences in IPM use in the first round. There are, however, significant differences in the IPM training rate for Magura and the number of times IPM training was received in both Jessore and Magura (see Table 4.14). In the second round, if the RCT was properly designed and implemented the treatment group is expected to increase more than the control group. Reexamining Tables 4.11 & 4.12, IPM use for both the treatment and control groups remained statistically similar with the exception of Jessore's treatment group. Examining IPM training, the IPM training rates remained statistically similar for the treatment and control groups in round two, however, the control group was trained in IPM practices significantly more times than the treatment group. Since the control group received IPM training more times than the treatment group, there is a possibility that some spillover occurred between the treatment and control groups. To investigate potential spillover, the sources of IPM training will also need to be evaluated in case there were other sources of IPM training than the subproject (see Table 4.15).

Table 4.14 IPM Training Received [ab]

	Round 1			Round 2		
	Full Group	Control	Treatment	Full Group	Control	Treatment
Sample size	838	417	420	784	390	394
% Trained in IPM						
All four districts	24.3	26.9	21.7	39.9°	38.7	41.1
Barisal	20.8	20.2	21.4	32.7°	33.0	32.3
Jessore	33.8	32.7	34.9	48.8°	41.2	56.3*
Jhalakati	21.6	26.2	17.1	29.2	24.4	34.1
Magura	21.0	28.6	13.3*	47.3°	54.5	40.4*
Sample size: households trained in IPM	203	112	91	313	151	162
Number of times trained in IPM (if training was received)						
All four districts	1.3 ± 2.0	1.3 ± 2.1	1.4 ± 1.9	3.1 ± 2.8°	3.5 ± 3.4	2.7 ± 2.0*
Barisal	1.2 ± 1.6	1.0 ± 1.5	1.4 ± 1.7	1.8 ± 1.4°	1.8 ± 1.4	1.8 ± 1.4
Jessore	1.3 ± 1.9	0.9 ± 1.1	1.8 ± 2.4*	3.1 ± 2.1°	3.2 ± 2.1	3.0 ± 2.0
Jhalakati	1.6 ± 1.8	1.8 ± 2.1	1.2 ± 1.0	3.8 ± 4.6°	4.9 ± 6.4	3.1 ± 2.6
Magura	1.4 ± 2.6	1.9 ± 3.2	0.7 ± 1.2*	3.5 ± 2.6°	4.1 ± 2.9	2.7 ± 1.8*
Number of IPM adopters known	4.2 ± 10.0	4.3 ± 9.9	4.1 ± 10.1	17.7 ± 23.4°	16.5 ± 23.3	19.0 ± 23.6

a: When data was available for both rounds or both control groups, t-tests were performed comparing the rounds (denoted by °) as well as comparing the treatment and control groups within the rounds (denoted by *). ° and * denote significance at the 5% significance level.
b: Mean ± standard deviation

The primary partner for the IPM vegetable technology transfer subproject was BARI. Of all the farmers who received IPM training in round one, 57.6% were trained by the Department of Agricultural Extension (DAE), 46.2% were trained by an IPM club, 9.7% were trained by BARI, 5.1% were trained by a non-governmental organization (NGO), and 11.7% were trained by other training sources (see Table 4.15). Of the IPM training sources, only BARI had a significant difference between the treatment and control groups at the full group level in round one, stemming primarily from Barisal. In Barisal, there was a significant difference between treatment groups with BARI performed IPM training rates of 45% and 0% in the control and treatment groups respectively. The significant difference between the treatment groups for BARI IPM training received suggests the RCT sample may not be balanced between the treatment and control groups and the counterfactual is biased.

Of those farmers trained in IPM in round two, 74.1% were trained by the DAE, 21.7% were trained by BARI, 33.6% were trained by an IPM club, 29.1% were trained by an NGO, and 0.6% were trained by other sources (see Table 4.15). In round two, the only significant difference between the treatment and control groups was for households receiving IPM training by an NGO.

Comparing the two rounds, IPM training received by the DAE, BARI, and NGOs increased significantly between rounds with significant decreases in training for all districts except Barisal (see Table 4.15). In both Barisal and Jessore districts, which received IPM training in the first year of the subproject's rollout, there were no significant differences between the IPM training rates for the treatment and control groups. While BARI is the primary partner for the IPM IL in Bangladesh, another possibility is that households thought the IPM field officers conducting training were associated with a local IPM club or an NGO. Examining those three training sources, the only significant difference in training rates between the treatment and control groups is where NGOs were the training source. For the households trained in IPM by an NGO, the treatment group had a significantly higher rate of training than the control group stemming primarily from a significant difference in Magura where the subproject's rollout has not yet begun IPM training. While the IPM training source data does not explain why the control group received training significantly more times than the treatment group (see Table 4.15), it does show that BARI and the other training sources a household could associate with BARI performed training equally between the treatment and control groups between survey rounds.

Table 4.15 Source of IPM Training [a]

	Round 1			Round 2		
	F	C	T	F	C	T
Sample size (received IPM training)	203	112	91	313	151	162
% trained by BARI						
All four districts	9.7	14.8	3.4*	21.7°	21.2	22.2
Barisal	22.0	45.0	0.0*	26.6	25.0	28.1
Jessore	7.1	8.8	5.6	23.0°	23.8	22.4
Jhalakati	7.0	7.7	5.9	0.0°	0.0	0.0
Magura	4.8	7.1	0.0	28.9°	25.5	33.3
% trained by DAE						
All four districts	57.6	60.6	53.9	74.1°	74.8	73.5
Barisal	57.1	50.0	63.6	67.2	84.4	50.0*
Jessore	51.4	64.7	38.9*	66.0	54.8	74.1*
Jhalakati	77.3	85.2	64.7	90.4	81.8	96.7
Magura	47.6	39.3	64.3	78.4°	81.8	73.8
% trained by IPM Club						
All four districts	46.2	41.3	52.3	33.6°	35.1	32.1
Barisal	48.8	45.0	52.4	1.6°	3.1	0.0
Jessore	54.3	41.2	66.7*	52.0	52.4	51.7
Jhalakati	20.9	15.4	29.4	7.7	9.1	6.7
Magura	55.8	62.1	42.9	49.5	50.9	47.6
% trained by NGO						
All four districts	5.1	3.7	6.8	35.8°	29.1	42.0*
Barisal	7.3	5.0	9.5	20.3	12.5	28.1
Jessore	8.6	5.9	11.1	51.0°	45.2	55.1
Jhalakati	0.0	0.0	0.0	7.7	9.1	6.7
Magura	2.4	3.6	0.0	45.4°	34.6	59.5*
% trained by Other						
All four districts	11.7	12.0	11.4	0.6°	0.7	0.6
Barisal	12.2	10.0	14.3	3.1	3.1	3.1
Jessore	17.1	14.7	19.4	0.0°	0.0	0.0
Jhalakati	0.0	0.0	0.0	0.0	0.0	0.0
Magura	14.3	21.4	0.0	0.0°	0.0	0.0

a: When data was available for both rounds or both control groups, t-tests were performed comparing the rounds (denoted by °**)** as well as comparing the treatment and control groups within the rounds (denoted by *). ° and * denote significance at the 5% significance level.

4.3.7 Yields, Costs, and Pesticide Applications

In round one, on average, a household had a total yield of 104.4 kg per decimal for all vegetables (see Table 4.16). On average, a household had a yield of 89.2 kg per decimal for tomatoes with yields of 93.7 kg per decimal in the control group and 85.0 kg per decimal in the treatment group. A household growing eggplant had a yield of 106.0 kg per decimal with 101.1 kg per decimal in the control group and 113.1 kg per decimal in the treatment group. A household growing cucumbers had a yield of 51.7 kg per decimal with 32.5 kg per decimal in the control group and 65.1 kg per decimal in the treatment group. A household growing bitter gourd had a yield rate of 79.9 kg per decimal with rates of 57.6 kg per decimal in the control group and 91.1 kg per decimal in the treatment group. A household growing cabbage had a yield rate of 154.1 kg per decimal with rates of 119.2 kg per decimal in the control group and 167.2 kg per decimal in the treatment group. Finally, a household growing country bean had a yield rate of 118.9 kg per decimal with rates of 118.8 kg per decimal in the control group and 119.0 kg per decimal in the treatment group.

In round two, on average, a household had a total yield of 191.4 kg per decimal for all vegetables (see Table 4.16). On average, a household had a yield of 137.6 kg per decimal for tomatoes with yields of 172.9 kg per decimal in the control group and 100.3 kg per decimal in the treatment group (see Table 4.16). A household growing eggplant had a yield rate of 184.2 kg per decimal with rates of 205.1 kg per decimal in the control group and 160.9 kg per decimal in the treatment group. A household growing cucumbers had a yield rate of 104.5 kg per decimal with rates of 107.2 kg per decimal in the control group and 101.9 kg per decimal in the treatment group. A household growing bitter gourd had a yield rate of 122.2 kg per decimal with rates of 99.1 kg per decimal in the control group and 142.6 kg per decimal in the treatment group. A household growing cabbage had a yield rate of 154.7 kg per decimal with rates of 102.8 kg per decimal in the control group and 193.4 kg per decimal in the treatment group. Finally, a household growing country bean had a yield rate of 100.9 kg per decimal with rates of 128.2 kg per decimal in the control group and 69.6 kg per decimal in the treatment group.

Comparing the two rounds, the average yield for all vegetables increased significantly in the second round. For the individual vegetables, the average yields per decimal for tomatoes, eggplant, and bitter gourd are significantly higher in round two. One possible explanation for the increase in yields is a decrease in pest problems and severity. All three of those vegetables had significant increases in the number of households with pest problems and both eggplant and bitter gourd had significant decreases in the average severity of those pest problems in round two (see Table 4.8). A second possible explanation for the increase in yields is adoption of IPM practices. However, of the three vegetables with significant yield increases, only tomatoes had a significant increase in the use of IPM practices between rounds.

Table 4.16 Vegetable Yields per decimal (kilograms) [ab]

	Round 1			Round 2		
	Full Group	Control	Treatment	Full Group	Control	Treatment
Sample size	838	417	420	784	390	394
All six vegetables	104.4 137.5	99.5 128.2	109.3 146.2	191.4 313.8°	205.7 297.0	177.1 329.4
Tomato	89.2 ± 113.9	93.7 139.8	85.0 84.3	137.6 204.7°	172.9 231.0	100.3 165.6*
Eggplant	106.0 125.1	101.1 122.9	113.1 128.1	184.2 227.8°	205.1 275.4	160.9 156.5
Cucumber	51.7 60.0	32.5 27.5	65.1 72.6	104.5 158.7	107.2 137.6	101.9 177.2
Bitter gourd	79.9 161.5	57.6 60.0	91.1 193.0	122.2 213.4°	99.1 96.9	142.6 277.8
Cabbage	154.1 151.7	119.2 61.4	167.2 173.4	154.7 230.1	102.8 101.0	193.4 286.3*
Country Bean	118.9 108.4	118.8 133.5	119.0 89.2	100.9 192.7	128.2 236.6	69.6 120.2

a: When data was available for both rounds or both control groups, t-tests were performed comparing the rounds (denoted by °) as well as comparing the treatment and control groups within the rounds (denoted by *). ° and * denote significance at the 5% significance level.

b: Mean ± standard deviation

Table 4.17 Pest Management Costs per decimal (taka) [ab]

	Round 1			Round 2		
	Full Group	Control	Treatment	Full Group	Control	Treatment
Sample size	838	417	420	784	390	394
All six vegetables	523.7 ± 1016.8	531.7 ± 1088.8	515.7 ± 941.3	439.8 ± 1363.1	429.0 ± 698.3	451.1 ± 1818.9

a: When data was available for both rounds or both control groups, t-tests were performed comparing the rounds (denoted by °) as well as comparing the treatment and control groups within the rounds (denoted by *). ° and * denote significance at the 5% significance level.

b: Mean ± standard deviation

To capture pest management costs, households were asked for the cost of pesticides and of the costs of different IPM approaches used across all of the vegetables. In round one, on average, a household had a pest management cost of 523.7 taka per decimal for all vegetables, 531.7 taka per decimal in the control group, and 515.7 taka per decimal in the treatment group (see Table 4.17). In round two, on average, a household had pest management costs of 439.8 taka per decimal for all vegetables combined in the full group, 429.0 taka per decimal in the control group, and 451.1 taka per decimal in the treatment group. Comparing the two rounds there are no significant differences in pest management costs between the two rounds. There are also no significant differences in pest management costs between the control and treatment groups.

In round one, on average, a household had a pesticide application rate of 1.1 applications per decimal for tomato with rates of 1.4 applications per decimal in the control group and 0.9 applications per decimal in the treatment group (see Table 4.18). A household growing eggplant had a pesticide application rate of 2.3 applications per decimal with rates of 2.1 applications per decimal in the control group and 2.7 applications per decimal in the treatment group. A household growing cucumbers had a pesticide application rate of 1.1 applications per decimal with rates of 1.4 applications per decimal in the control group and 0.9 applications per decimal in the treatment group. A household growing bitter gourd had a pesticide application rate of 1.0 applications per decimal with rates of 0.8 applications per decimal in the control group and 1.1 applications per decimal in the treatment group. A household growing cabbage had a pesticide application rate of 0.5 applications per decimal with rates of 0.8 applications per decimal in the control group and 0.3 applications per decimal in the treatment group. Finally, a household growing country bean had a pesticide application rate of 3.5 applications per decimal with rates of 1.5 applications per decimal in the control group and 5.0 applications per decimal in the treatment group.

In round two, on average, a household had a pesticide application rate of 0.6 applications per decimal for tomatoes with rates of 0.8 applications per decimal in the control group and 0.5 applications per decimal in the treatment group (see Table 4.18). A household growing eggplant had a pesticide application rate of 1.6 applications per decimal with rates of 1.8 applications per decimal in the control group and 1.5 applications per decimal in the treatment group. A household growing cucumbers had a pesticide application rate of 0.8 applications per decimal with rates of 0.8 applications per decimal in the control group and 0.7 applications per decimal in the treatment group. A household growing bitter gourd had a pesticide application rate of 1.0 applications per decimal with rates of 1.0 applications per decimal in the control group and 0.9 applications per decimal in the treatment group. A household growing cabbage had a pesticide application rate of 0.5 applications per decimal with rates of 0.6 applications per decimal in the control group and 0.4 applications per decimal in the treatment group. Finally, a household growing country beans had a pesticide application rate of 1.0 applications per decimal with rates of 1.0 applications per decimal in the control group and 0.9 applications per decimal in the treatment group.

Comparing the two rounds, tomatoes, eggplant, and country bean all had significant differences between the two rounds at a 1% significance level with decreases in the average number of pesticide applications per decimal when growing those vegetables. While the average pest severity for tomatoes remained relatively constant between rounds, the decreases in pesticide applications per decimal for both eggplant and country bean can potentially be explained by significant decreases between rounds in the average severity of pest problems for both of those vegetables (see Table 4.8).

Table 4.18 Pesticide Applications per decimal [ab]

	Round 1			Round 2		
	Full group	Control	Treatment	Full group	Control	Treatment
Sample size	838	417	420	784	390	394
All six vegetables	1.8 ± 3.0	1.8 ± 2.3	1.8 ± 3.6	1.2 ± 1.6°	1.3 ± 1.7	1.0 ± 1.5*
Tomatoes	1.1 ± 1.8	1.4 ± 2.3	0.9 ± 1.1*	0.6 ± 0.8°	0.8 ± 0.9	0.5 ± 0.6*
Eggplant	2.3 ± 3.3	2.1 ± 2.4	2.7 ± 4.3	1.6 ± 2.0°	1.8 ± 2.2	1.5 ± 1.8
Cucumbers	1.1 ± 1.5	1.4 ± 1.8	0.9 ± 1.1	0.8 ± 0.9	0.8 ± 0.8	0.7 ± 1.0
Bitter gourd	1.0 ± 1.1	0.8 ± 0.6	1.1 ± 1.3	0.9 ± 1.3	1.0 ± 1.0	0.9 ± 1.5
Cabbage	0.5 ± 0.6	0.8 ± 1.0	0.3 ± 0.3*	0.3 ± 0.6	0.3 ± 0.4	0.4 ± 0.7
Country Bean	3.5 ± 7.4	1.5 ± 1.4	5.0 ± 9.5	1.0 ± 1.6°	1.0 ± 1.5	0.9 ± 1.6

a: When data was available for both rounds or both control groups, t-tests were performed comparing the rounds (denoted by **°)** as well as comparing the treatment and control groups within the rounds (denoted by *). ° and * denote significance at the 5% significance level.
b: Mean ± standard deviation

4.3.7 Agricultural Information Sources

In round one, 79.0% of farmers learned about agricultural information from agricultural officers with 78.6% in the control group and 79.3% in the treatment group (see Table 4.19). 31.7% of farmers learned about agricultural information from field days with 31.5% of the control group and 31.9% of the treatment group. 13.6% of farmers learned about agricultural information from the radio with 13.2% in the control group and 14.1% in the treatment group. 67.9% of farmers learned about agricultural information from the television with 67.8% in the control group and 68.1% in the treatment group. 3.7% of farmers learned about agricultural information from newspapers or leaflets with 3.9% in the control group and 3.6% in the treatment group.

In round two, 90.8% of farmers learned about agricultural information from agricultural officers with 90.8% in the control group and 90.9% in the treatment group (see Table 4.19). 8.4% of farmers learned about agricultural information from farmer field school with 9.0% in the control group and 7.9% in the treatment group. 46.3% of farmers learned about agricultural information from field days with 45.6% in the control group and 47.0% in the treatment group. 16.2% of farmers learned about agricultural information from the radio with 16.2% in the control group and 16.2% in the treatment group. 45.5% of farmers learned about agricultural information from the television with 45.1% in the control group and 45.9% in the treatment group. 24.5% of farmers learned about agricultural information from newspapers or leaflets with 23.6% in the control group and 25.4% in the treatment group. 12.0% of farmers learned about agricultural information from farmers' groups with 13.1% in the control group and 10.9% in the treatment group. 16.3% of farmers learned about agricultural information from IPM clubs with 14.9% in the control group and 17.8% in the treatment group.

Comparing the two rounds, there were significant increases for agricultural officers, field days, and newspapers/leaflets. There was also a significant decrease in the number of farmers learning agricultural information from the television. The significant increases in round two for farmers learning about agricultural information from agricultural officers and field days likely stems from the significant 16.5 percentage point increase between rounds in farmers receiving IPM training from the DAE (see Table 4.15). At 21.7% of farmers trained in IPM, BARI trained the smallest portion of the farmers who received IPM training in round two (see Table 4.19). Comparatively, the DAE provided training to 74.1% of farmers trained in IPM, more than twice the training rate of the other training sources and more than 90% of all farmers surveyed in round two said they learned agricultural information from an agricultural officer (see Tables 4.15 & 4.19). NGOs and IPM Clubs also trained more farmers by round two than BARI, training 35.8% and 33.6%, respectively, of the farmers trained in IPM.

Table 4.19 Agricultural Information Source Characteristics Variables [a]

	Round 1			Round 2		
	F	C	T	F	C	T
Sample size	838	417	420	784	390	394
% of Total Who Learned Agricultural Information in Past 12 months From:						
Agricultural Officer	79.0	78.6	79.3	90.8°	90.8	90.9
Farmer Field School	-	-	-	8.4	9.0	7.9
Field Day	31.7	31.5	31.9	46.3°	45.6	47.0
Radio	13.6	13.2	14.1	16.2	16.2	16.2
Television	67.9	67.8	68.1	45.5°	45.1	45.9
Newspaper/Leaflet	3.7	3.9	3.6	24.5°	23.6	25.4
Farmers' Group	-	-	-	12.0	13.1	10.9
IPM Club	-	-	-	16.3	14.9	17.8

a: When data was available for both rounds or both control groups, t-tests were performed comparing the rounds (denoted by °**)** as well as comparing the treatment and control groups within the rounds (denoted by *). ° and * denote significance at the 5% significance level.

4.4 Conclusion

Evaluating the descriptive statistics, significant initial differences between the treatment and control groups were identified for the HHH gender, the quantity of land farmed with vegetables, vegetables as a percent of total land, the number of pesticide applications, the variety of pesticides used, the number of times trained in IPM, and IPM training received from BARI. No significant differences in IPM use were measured between survey rounds or between the treatment and control groups within each round. By round two of the survey, the control group received IPM training significantly more times than the treatment group suggesting the RCT may be contaminated (see Table 4.14). However, further examination of training rates by district showed the only significant difference in training for the control group took place in Magura, a district that, according to the subproject's rollout, is not expected to have received training by the second round of the survey. In addition to summarizing training by districts, the sources of IPM training were also examined. BARI, the IPM IL's primary partner, the DAE, and IPM clubs showed no significant difference between training given to the treatment and control groups, while NGOs showed a significantly higher rate of training given to the treatment group (see

Table 4.19). Combined with the higher number of times trained in IPM for the control group and the similar levels of IPM use in round two for both the control and treatment groups, the similar levels of IPM training by BARI for both the treatment and control groups, and the amount of training conducted by BARI in comparison to the other IPM training sources suggest the RCT could very likely be contaminated. If the RCT is contaminated, it will no longer be possible to draw strong conclusions from its results and the adoption models, impact models, and economic surplus analysis will be less representative of the subproject's impacts and more indicative of region wide impacts and determinants of IPM adoption.

Chapter Four introduced the data used in this evaluation of the IPM vegetable technology transfer subproject laying out the survey design and data collection as well as descriptive statistics from both of the two rounds of data collected. In Chapter Five the results of the evaluation using the methods laid out in Chapter Three and the data described in Chapter Four will be presented.

5. Results

5.1 Introduction

Chapter Five presents the results for the analysis of the four objectives using the methods outlined in Chapter Three. The first section examines the IPM adoption rates for the vegetables and the determinants affecting those rates. The second section examines the impact of IPM technology adoption on vegetables yields, pest management costs, and pesticide applications. The third section evaluates the economic surplus impacts of the technology and the changes in economic surplus between the two rounds. Finally, the last section examines the effectiveness of the different technology transfer methods used and the cost efficiency of their usage.

5.2 Adoption

Adoption in this study was defined as a household's use of at least one of the recommended IPM practices for vegetables grown. Overall, adoption of IPM practices remained statistically constant, increasing by only 1.6 percentage points from 32.2% to 33.8% between rounds (see Tables 4.11 & 4.12).

5.2.1 Traditional Probit Model

To identify the determinants of IPM adoption, two approaches were laid out in Chapter Three: the traditional probit model and the ordered probit model. The traditional probit model used a binary variable representing adoption of any IPM practices. To help control for the other IPM training sources, a binary variable representing receiving IPM training from BARI was added to the model and interacted with the treatment variable. For all vegetables combined, there were 666 observations while eggplant had observations (see Table 5.1). There were no significant determinants of adoption for all vegetables combined, eggplant, or cucumber. For the tomato, cucumber, bitter gourd, cabbage, and country bean, there were not enough observations to perform a panel data regression in STATA to analyze determinants of adoption.

Table 5.1 Random Effects Probit Regression – Panel Data[a]

	All Vegetables	Eggplant
Number of Observations:	666	360
Treatment[b]	0.031 (2.016)	0.1012245
Trained by BARI[b]	0.323 (20.886)	0.2685991
Jessore District[b]	-0.465 (-30.11)	-0.302775
Jhalakati District[b]	-0.533 (-34.497)	-0.4365112
Magura District[b]	-0.393 (-25.443)	-0.2168942
Vegetable area % of total land operated (by vegetable)	-0.002 (-0.102)	-0.0036823
Household members working (#)	-0.006 (-0.375)	-0.0050329
Average severity all pests (1-4)	-0.032 (-2.072)	-0.0131061
Household members per room (#)	0.193 (12.473)	0.5128226
Farming is Primary Occupation[b]	0.266 (17.214)	0.5141416
HHH Age (years)	-0.008 (-0.516)	-0.0056528
HHH Primary Education[b]	-0.04 (-2.623)	-0.049703
HHH Experience (years)	0.013 (0.873)	0.0169604
Times Trained in IPM (#)	0.044 (2.835)	0.0595376
IPM adopters known (#)	0.01 (0.645)	0.004728
Learns agricultural Information from:		
Social Network[b]	-0.027 (-1.762)	0.1313987
Agricultural Authorities[b]	0.868 (56.205)	0.8948964
Agricultural Training Events[b]	0.375 (24.288)	0.4606474
Media[b]	-0.228 (-14.746)	-0.3891021

a: Values are marginal effect (robust standard error). ***, **, and * denote significance at the 1%, 5%, and 10% significance levels respectively.
b: Binary variable

Since there were not enough observations for most of the vegetables to run a random effects probit regression and none of the vegetables had enough observations to run a regular random effects regression, a pooled probit regression was also used. Even with a pooled probit regression, both cabbage and country bean still did not have enough observations to perform the regressions in STATA (see Table 5.2).

For all vegetables combined, households located in Jessore, Jhalakati, or Magura had significant negative impacts on adoption suggesting Barisal had a significant positive impact on adoption (see Table 5.2). Learning agricultural information from media sources also had a significant negative impact on adoption. The years of agricultural experience of the HHH, the number of IPM adopters known, and learning agricultural information from agricultural training events all have significant positive impacts on the likelihood of IPM adoption. The significant negative effects of being located in any district other than Barisal implies that regional conditions such as climate or IPM training were more conducive to IPM adoption in Barisal than in the other districts. The significant positive effect of the HHH's years of agricultural experience implies that more experienced farmers are more open to adopting IPM practices than less experienced farmers. As expected, the number of IPM adopters known has a positive sign, suggesting that farmers are more likely to adopt IPM practices after they have seen other farmers using them. Learning information from agricultural training events also has a significant positive effect on IPM adoption, suggesting farmers are more likely to adopt IPM practices learned at agricultural training events such as field days, farmer's field schools, and farmer's fairs than from other sources. The significant negative effect from learning agricultural information from media sources such as radio and television suggests that farmers are less likely to adopt IPM practices learned from mass media sources.

For tomato IPM adoption, there were 198 observations with similar results as all vegetables for the following variables: Jessore and the number of IPM adopters a farmer knows (see Table 5.2). There were significant negative impacts on adoption for households located in the Jessore and HHHs with at least a primary level of education. The number of IPM adopters known has a small, but significant positive impact on adoption. The negative sign for having at least a primary education suggests that having a formal education makes farmers less likely to adopt IPM practices for tomatoes.

There were 360 observations for eggplant IPM adoption with similar results as all vegetables for the following variables: Jhalakati, HHH years of experience, learning agricultural information from agricultural training events, and learning agricultural information from media sources (see Table 5.2). There were significant negative impacts for a household located in Jhalakati and learning agricultural information from media. The number of household members per room, the HHH's years of experience, the number of times trained in IPM, and learning agricultural information from agricultural training events all had significant positive impacts on adoption. The number of household members per room has a positive coefficient, suggesting that potentially less wealthy households with smaller houses were more likely to adopt IPM practices than households with more space for each member of the household. Considering that eggplant was one of the vegetables with the most pesticide use, this could be a reflection of less wealthy houses pursuing more affordable, IPM practices for pest management (see Table 4.18). The positive effect of the number of times trained in IPM suggests that greater frequency of training may encourage adoption of eggplant IPM practices.

There were 108 observations for cucumber IPM adoption with similar results as all vegetables for the following variables: Jessore, Jhalakati, Magura, the number of IPM adopters known, learning agricultural information from agricultural training events, and learning agricultural information from the media (see Table 5.2). There were significant negative impacts on IPM adoption for households located in Jessore, Jhalakati, Magura, and learning agricultural information from media sources. Receiving IPM training from BARI, HHH age, achieving at least a primary level of education, the number of IPM adopters known, and learning agricultural information from agricultural training events all had significant positive effects on the probability of IPM adoption. Receiving IPM training from BARI had a significant positive effect on IPM adoption suggesting that BARI trained households are more likely to adopt IPM practices for cucumbers. The positive effect for HHH age suggests older farmers may be more likely to adopt IPM practices for cucumbers. The positive effect of having at least a primary level of education suggests educated farmers are more likely to adopt IPM practices for the cucumber.

There were 203 observations for bitter gourd IPM adoption with similar results as all vegetables for the following variables: Jessore, Jhalakati, Magura, the number of IPM adopters known, learning agricultural information from agricultural training events, and learning agricultural information from media sources (see Table 5.2). There were significant negative impacts on IPM adoption for households located in Jessore, Jhalakati, and Magura, as well as households learning agricultural information from media sources. The number of IPM adopters known and learning agricultural information from agricultural training events both have significant positive impacts on adoption of IPM practices.

Table 5.2 Probit Regression - Pooled Data[a]

	All Vegetables	Tomato	Eggplant	Cucumber	Bitter gourd
	666	205	360	108	203
Treatment[b]	0.012 (0.035)	-0.048 (-0.049)	0.034 (0.048)	-0.056 (-0.069)	0.029 (0.059)
Trained by BARI[b]	0.109 (0.072)	0.073 (0.109)	0.093 (0.092)	0.355 (0.156)**	0.176 (0.121)
Jessore District[b]	-0.146 (-0.056)***	-0.2 (-0.085)**	-0.096 (-0.082)	-0.601 (-0.151)***	-0.272 (-0.082)***
Jhalakati District[b]	-0.167 (-0.051)***	-0.092 (-0.062)	-0.139 (-0.08)*	-0.202 (-0.07)***	-0.422 (-0.083)***
Magura District[b]	-0.123 (-0.054)**	-0.106 (-0.17)	-0.069 (-0.076)	-0.264 (-0.091)***	-0.398 (-0.086)***
Vegetable area % of total land operated (by vegetable)	0 (-0.001)	0 (0.001)	-0.001 (-0.001)	-0.001 (-0.003)	0 (-0.002)
Household members working (#)	-0.002 (-0.019)	-0.012 (-0.031)	-0.002 (-0.026)	-0.032 (-0.03)	-0.028 (-0.03)
Average severity all pests (1-4)	-0.01 (-0.028)	-0.027 (-0.036)	-0.004 (-0.038)	-0.047 (-0.038)	-0.045 (-0.041)
Household members per room (#)	0.061 (0.056)	0.066 (0.098)	0.163 (0.076)**	-0.055 (-0.084)	-0.086 (-0.11)
Farming is Primary Occupation[b]	0.084 (0.099)	Omitted	0.164 (0.126)	Omitted	-0.052 (-0.127)
HHH Age (years)	-0.003 (-0.002)	-0.002 (-0.003)	-0.002 (-0.003)	0.006 (0.003)*	-0.004 (-0.003)
HHH Primary Education[b]	-0.013 (-0.046)	-0.204 (-0.06)***	-0.016 (-0.063)	0.136 (0.082)*	-0.055 (-0.08)
HHH Experience (years)	0.004 (0.002)**	0.004 (0.003)	0.005 (0.003)*	-0.007 (-0.005)	0 (-0.003)
Times Trained in IPM (#)	0.014 (0.008)	-0.006 (-0.009)	0.019 (0.011)*	0 (-0.009)	0.006 (0.009)
IPM adopters known (#)	0.003 (0.001)***	0.009 (0.002)***	0.002 (0.001)	0.006 (0.002)***	0.004 (0.002)***
Learns agricultural Information from:					
Social Network[b]	-0.008 (-0.074)	-0.136 (-0.087)	0.042 (0.137)	0.073 (0.103)	0.093 (0.109)
Agricultural Authorities[b]	0.273 (0.171)	Omitted	0.285 (0.173)*	Omitted	Omitted
Agricultural Training Events[b]	0.118 (0.039)***	0.009 (0.054)	0.147 (0.05)***	0.147 (0.083)*	0.13 (0.067)**
Media[b]	-0.072 (-0.037)*	0.036 (0.045)	-0.124 (-0.053)**	-0.173 (-0.065)***	-0.122 (-0.063)*

a: Values are marginal effect (robust standard error). ***, **, and * denote significance at the 1%, 5%, and 10% significance levels respectively
b: Binary variable

5.1.2 Ordered Probit Model

The second approach used to identify the determinants of IPM adoption is the ordered probit regression. Only the regression for all vegetables combined successfully ran with 666 observations, but it had no significant determinants (see Table 5.3). Tomato, eggplant, cucumber, bitter gourd, cabbage, and country bean all needed more observations to properly perform the ordered probit regression.

Table 5.3 Random Effects Ordered Probit Model – Panel Data[a]

	All Vegetables
Number of Observations:	666
Treatment[b]	0.012 (0.739)
Trained by BARI[b]	0.113 (5.702)
Jessore District[b]	-0.151 (6.27)
Jhalakati District[b]	-0.173 (7.184)
Magura District[b]	-0.128 (5.298)
Vegetable area % of Total Land (by vegetable)	-0.001 (0.021)
Household members working (#)	-0.002 (0.079)
Pest Severity (1-4)	-0.01 (0.432)
Household members per room (#)	0.063 (2.598)
Farming is Primary Occupation[b]	0.086 (3.585)
HHH Age (years)	-0.003 (0.107)
HHH Primary Education[b]	-0.013 (0.547)
HHH Experience (years)	0.004 (0.182)
Times Trained in IPM (#)	0.014 (0.59)
IPM adopters known (#)	0.003 (0.134)
Learns agricultural Information from:	
Social Network[b]	-0.009 (0.372)
Agricultural Authorities[b]	0.282 (11.705)
Agricultural Training Events[b]	0.122 (5.058)
Media[b]	-0.074 (3.071)

a: Values are marginal effects at outcome=1 (standard error). ***, **, and * denote significance at the 1%, 5%, and 10% significance levels respectively
b: Binary variable

Since there were not enough observations for most of the vegetables to run a random effects ordered probit regression, a pooled ordered probit regression was also used (see Tables 5.3 & 5.4). Even with a pooled ordered probit regression, cabbage still did not have enough observations to perform the regressions in STATA (see Table 5.4).

Evaluated at one IPM practice for all vegetables combined, households located in the districts of Jessore and Jhalakati, HHH age, and learning agricultural information from media sources all had significant positive effects on the probability of adopting one IPM practice (see Table 5.4). Receiving IPM training from BARI, the number of IPM adopters known, and learning agricultural information from agricultural training events all have negative effects on the probability of adopting one IPM practice. When evaluated at two IPM practices for all vegetables combined, there are significant negative effects on the probability of adopting two IPM practices for households located in Jessore, Jhalakati, and Magura, as well as households learning agricultural information from media sources. HHH years of agricultural experience, the number of IPM adopters known, and learning agricultural information from agricultural training events all had positive effects on the probability of a household adopting two IPM practices.

Comparing the significant determinants of IPM adoption at the two different outcomes, all of the determinants are the opposite sign in outcome two, suggesting that households located in Barisal, with more years of experience, more IPM adopters known, and learning agricultural information from agricultural training events were significantly more likely to adopt multiple IPM practices. At the same time, the negative effect at outcome two for learning agricultural information from media sources suggests that while farmers may be more likely to adopt a single IPM practice when learning agricultural information from those sources, they are less likely to adopt multiple IPM practices.

Table 5.4 Ordered Probit Model – Pooled Data[a]

	All Vegetables (at outcome 1)	All Vegetables (at outcome 2)	Tomato (at outcome 1)	Eggplant (at outcome 1)	Cucumber (at outcome 1)	Bitter gourd (at outcome 1)	Country Bean (at outcome 1)
Number of Observations:	666	666	213	360	113	205	106
Treatment [b]	-0.012 (0.035)	0.012 (0.035)	0.047 (0.047)	-0.034 (0.048)	0.053 (0.066)	-0.029 (0.059)	0.104 (0.056)
Trained by BARI [b]	-0.109 (0.072)***	0.109 (0.072)	-0.07 (0.105)**	-0.093 (0.092)	-0.339 (0.149)**	-0.174 (0.12)	0.161 (0.034)***
Jessore District [b]	0.146 (0.056)***	-0.146 (0.056)***	0.193 (0.082)	0.096 (0.082)*	0.574 (0.146)***	0.269 (0.082)***	0.248 (0.124)**
Jhalakati District [b]	0.167 (0.051)**	-0.167 (0.051)***	0.088 (0.059)	0.139 (0.08)	0.193 (0.067)***	0.418 (0.082)***	0.034 (0.077)
Magura District [b]	0.123 (0.054)	-0.123 (0.054)**	0.102 (0.163)	0.069 (0.076)	0.252 (0.087)***	0.394 (0.086)***	-0.003 (0.097)
Vegetable area % of Total Land (by vegetable)	0 (0.001)	0 (0.001)	0 (0.001)	0.001 (0.001)	0.001 (0.003)	0 (0.002)	0.002 (0.003)
Household members working (#)	0.002 (0.019)	-0.002 (0.019)	0.012 (0.03)	0.002 (0.026)	0.031 (0.029)	0.028 (0.029)	-0.008 (0.041)
Pest Severity (1-4)	0.01 (0.028)	-0.01 (0.028)	0.026 (0.035)	0.004 (0.038)**	0.045 (0.036)	0.045 (0.041)	0.035 (0.036)
Household members per room (#)	-0.061 (0.056)	0.061 (0.056)	-0.063 (0.094)***	-0.163 (0.076)	0.053 (0.08)	0.085 (0.109)	0.035 (0.12)
Farming is Primary Occupation[b]	-0.084 (0.099)	0.084 (0.099)	-0.91 (0.114)	-0.164 (0.126)	-0.841 (0.163)***	0.051 (0.126)	0.28 (0.112)***
HHH Age (years)	0.003 (0.002)**	-0.003 (0.002)	0.002 (0.003)***	0.002 (0.003)	-0.006 (0.003)*	0.004 (0.003)	-0.001 (0.003)
HHH Primary Education[b]	0.013 (0.046)	-0.013 (0.046)	0.196 (0.058)	0.016 (0.063)*	-0.13 (0.079)*	0.055 (0.079)	0.048 (0.089)
HHH Experience (years)	-0.004 (0.002)	0.004 (0.002)**	-0.004 (0.003)	-0.005 (0.003)*	0.007 (0.005)	0 (0.003)	-0.002 (0.003)
Times Trained in IPM (#)	-0.014 (0.008)	0.014 (0.008)	0.006 (0.009)	-0.019 (0.011)	0 (0.008)	-0.005 (0.009)	0.009 (0.009)
IPM adopters known (#)	-0.003 (0.001)***	0.003 (0.001)***	-0.009 (0.002)***	-0.002 (0.001)	-0.006 (0.002)***	-0.004 (0.002)***	-0.002 (0.002)
Learns agricultural Information from:							
Social Network[b]	0.008 (0.074)	-0.008 (0.074)	0.131 (0.084)	-0.042 (0.137)	-0.07 (0.099)	-0.092 (0.108)	-0.016 (0.104)
Agricultural Authorities[b]	-0.273 (0.171)	0.273 (0.171)	Omitted	-0.285 (0.173)*	-0.616 (0.165)***	-1.066 (0.185)***	-0.617 (0.191)***
Agricultural Training Events[b]	-0.118 (0.039)***	0.118 (0.039)***	-0.008 (0.052)	-0.147 (0.05)***	-0.141 (0.08)*	-0.129 (0.066)**	-0.019 (0.083)
Media[b]	0.072 (0.037)*	-0.072 (0.037)*	-0.035 (0.044)	0.124 (0.053)**	0.165 (0.062)***	0.121 (0.063)*	-0.175 (0.069)***

a: Values are marginal effects at outcome=1 (standard error). ***, **, and * denote significance at the 1%, 5%, and 10% significance levels respectively b: Binary variable

5.2 Impact Results

To examine the effect IPM adoption had on vegetable yields, pest management costs, and the number of pesticide applications, a difference-in-difference (DD) model was used. The first section will present the DD results for vegetable yields in kilograms per decimal, the second section will present the DD results for pest management costs per decimal, and the final section will present the DD results for the number of pesticide applications per decimal.

5.2.1 Vegetable Yields

Across all vegetables, adoption of IPM practices had a negative, but non-significant DD impact on vegetable yields (kg sold/decimal). For individual vegetables, adoption of recommended IPM practices had negative DD impacts on both tomato and eggplant yields, but only eggplant's impact was significant (see Table 5.5). Adoption of IPM practices for cucumber, bitter gourd, cabbage, and country bean had positive, but non-significant impacts on vegetable yields. Both tomato and eggplant had significant differences in round two with significantly lower yields in the treatment group than the control group.

Table 5.5 Yield Difference-in-Difference Results (kg sold/decimal)[a]

	Round One			Round Two			DD
Outcome Variable	Control	Treated	Difference	Control	Treated	Difference	Dif. In Dif.
All vegetables yield	223.849	232.603	8.754	366.542	350.185	-16.356	-25.111
Tomato yield	277.333	255.316	-22.017	335.817	279.220	-56.597***	-34.580
Eggplant yield	31.438	50.728	19.290	136.203	105.150	-31.053*	-50.343**
Cucumber yield	30.169	-6.058	-36.227	107.227	103.900	-3.327	32.900
Bitter gourd yield	28.854	49.975	21.122	107.606	132.995	25.389	4.268
Cabbage yield	349.092	346.709	-2.383	322.140	374.665	52.526	54.908
Country bean yield	43.651	1.424	-42.227	88.897	53.713	-35.184	7.043

a: ***, **, and * denote significance at the 1%, 5%, and 10% significance levels respectively

5.2.2 Pest Management Cost Results

For the pest management cost DD results, adoption of IPM practices for any vegetable had a positive, but non-significant impact on the total pest management costs per decimal (taka/decimal) (see Table 5.6). Since farmers were only asked about pest management costs across all vegetables, no analysis was performed for the pest management cost DD impacts of individual vegetables.

Table 5.6 Pest Management Cost Difference-in-Difference Results[a]

	Round One			Round Two			DD
Outcome Variable	Control	Treated	Difference	Control	Treated	Difference	Dif. In Dif.
All pest management costs	670.591	676.845	6.254	555.723	581.016	25.293	19.039

a: ***, **, and * denote significance at the 1%, 5%, and 10% significance levels respectively

5.2.3 Pesticide Applications Results

Across all of the vegetables, adoption of IPM practices had a negative, but non-significant DD impact on the number of pesticide applications (per decimal) (see Table 5.7). Individually, adoption of IPM pest management practices for tomato, eggplant, and cucumber all had positive DD impacts on the number of pesticide applications, but only tomato had a significant result (see Table 5.7). The significant positive DD impact of IPM adoption on tomato pesticide applications per decimal suggests that adoption of IPM practices for tomatoes slightly increases the number of pesticide applications per decimal rather than decreasing the number of pesticide applications per decimal as expected. Adoption of IPM pest management practices for bitter gourd, cabbage, and country bean all had negative impacts on the number of pesticide applications, but only country bean had a significant result. Country bean's negative DD impact suggest that adoption of IPM practices for country beans decreases the number of pesticide applications per decimal of country bean land farmed.

Table 5.7 Number of Pesticide Applications Difference-in-Difference Results[a]

	Round One			Round Two			DD
Outcome Variable	Control	Treated	Difference	Control	Treated	Difference	Dif. In Dif.
All vegetables pesticide applications	1.857	1.970	0.113	1.514	1.394	-0.120	-0.233
Tomato pesticide applications	0.839	0.702	-0.137***	0.887	0.836	-0.051	0.085*
Eggplant pesticide applications	0.871	0.887	0.015	0.929	0.948	0.019	0.003
Cucumber pesticide applications	0.961	0.948	-0.013	0.954	0.957	0.003	0.017
Bitter gourd pesticide applications	1.011	0.980	-0.031	1.053	1.008	-0.046*	-0.014
Cabbage pesticide applications	0.540	0.672	0.133	0.830	0.780	-0.050	-0.182
Country bean pesticide applications	0.258	0.461	0.203**	0.941	0.906	-0.035	-0.238**

a: ***, **, and * denote significance at the 1%, 5%, and 10% significance levels respectively

5.3 Economic Surplus Analysis

An economic surplus analysis approach was used to estimate the economic impacts of the technology transfer. Of the six vegetables in the survey, IPM adoption only had a significant impact on eggplant yields (see Table 5.5). Since IPM adoption only significantly affected eggplant, yield information from survey data and the DD impact information from the yield impact analysis were used to calculate the proportionate change in eggplant yield (kg sold per decimal) from IPM adoption (see Table 5.8). For the other five vegetables, the proportionate change in yields was assumed to be zero. Since IPM adoption had no significant impact on pest management costs, the proportionate cost change was assumed to be zero for all six vegetables (see Table 5.6).

Table 5.8 Proportionate Change in Eggplant Yields (kg)

	Eggplant
DD impact	-50.34
Average Yield[a]	116.10
Proportionate yield change	-0.443

a: Average yield is the average yield from the treatment group in round one.

Once the proportionate change in yield and the proportionate change in pest management costs were known for all vegetables, those values were used to estimate the economic impacts of IPM use. Since only the Jessore and Barisal districts received IPM training from the subproject in the first round of the subproject's rollout, the economic surplus analysis focused on those two districts with all values inflation adjusted to 2013. Over the two rounds of the survey the Jessore and Barisal districts respectively lost $757,529.90 and $78,944.54 in total economic surplus from the use of IPM vegetable practices with a combined decrease in total economic surplus of $836,474.43 (see Table 5.9). Jessore, which accounts for 87.8% of average total production (in metric tons) for the two districts combined (see Table 3.6), accounted for 90.6% of the decrease in total economic surplus while Barisal accounted for the remaining 9.4% of the decrease. As only eggplant had significant change in yields from IPM adoption (see Table 5.5) and there was no significant change in pest management costs from IPM adoption (see Table 5.6), eggplant accounts for the entirety of the $836,474.43 decrease in economic surplus.

While the overall economic surplus for both rounds provides information about how the economy is affected overall by IPM use, it does not give information on how the economic surplus changed between rounds of the survey. Using the changes in IPM use between the two rounds to calculate the change in surplus between rounds rather than the overall IPM use for each round, Jessore's economic surplus increased by $47,890.05 between rounds and Barisal's economic surplus increased by $19,119.43 between rounds (see Table 5.10). Overall, the total surplus increased by $67,009.47 (see Table 5.10). As the only vegetable with a significant change in yields from IPM adoption (see Table 5.5) and with no significant change in pest management costs for any vegetable, eggplant accounted for the entirety of the $67,009.47 increase in economic surplus between rounds.

Table 5.9 Overall Economic Surplus From IPM Use

Net Present Value	All Vegetables	Tomato	Eggplant	Cucumber	Bitter gourd	Cabbage	Country Bean
Jessore	($757,529.90)	$0.00	($757,529.90)	$0.00	$0.00	$0.00	$0.00
Barisal	($78,944.54)	$0.00	($78,944.54)	$0.00	$0.00	$0.00	$0.00
Combined Total	($836,474.43)	$0.00	($836,474.43)	$0.00	$0.00	$0.00	$0.00
% of Total	100%	0%	100%	0%	0%	0%	0%

Table 5.10 Economic Surplus Changes From IPM Use

Net Present Value	All Vegetables	Tomato	Eggplant	Cucumber	Bitter gourd	Cabbage	Country Bean
Jessore	$47,890.05	$0.00	$47,890.05	$0.00	$0.00	$0.00	$0.00
Barisal	$19,119.43	$0.00	$19,119.43	$0.00	$0.00	$0.00	$0.00
Combined Total	$67,009.47	$0.00	$67,009.47	$0.00	$0.00	$0.00	$0.00

Table 5.11 Economic Surplus Changes From BARI Training

Net Present Value	All Vegetables	Tomato	Eggplant	Cucumber	Bitter gourd	Cabbage	Country Bean
Jessore	($378.66)	$0.00	($378.66)	$0.00	$0.00	$0.00	$0.00
Barisal	($28.41)	$0.00	($28.41)	$0.00	$0.00	$0.00	$0.00
Total	($407.07)	$0.00	($407.07)	$0.00	$0.00	$0.00	$0.00

Economic surplus changes can also be evaluated based on changes in IPM use by farmers receiving IPM training from BARI. In round one of the survey, 0.8% of the farmers surveyed had adopted IPM practices and received IPM training from BARI. In round two, 4.6% of farmers had adopted IPM practices and received IPM training from BARI, a 3.8 percentage point increase between rounds. Evaluating the change in economic surplus using those adoption rates, the total surplus decreased by $407.07 between rounds with decreases of $378.66 and $28.41 in Jessore and Barisal, respectively (see Table 5.11).

5.4 Relative Efficiency of Technology Transfer methods

Of the eight public cost information sources surveyed, learning agricultural information from an agricultural officer, newspaper, and farmer's group all had negative impacts on adoption of IPM practices (with soil amendments left out), but only learning agricultural information from a newspaper was significant (see Table 5.12). Farmer's field school, field days, radio, televisions, and IPM clubs all had positive impacts on the use of IPM practices with learning agricultural information from both field days and television having significant positive impacts on IPM use.

Table 5.12 Agricultural Information Source Determinants of IPM Adoption[ab]

	Model	
	Panel Probit model	Pooled Probit model
TV	0.21 (10.495)	0.062 (0.043)
Radio	0.217 (10.864)	0.065 (0.067)
Farmer Field School	0.222 (11.088)	0.066 (0.061)
Seed/Fertilizer/Pesticide Salesmen	0.585 (29.252)	0.174 (0.044)***
Field Day	0.232 (11.601)	0.069 (0.038)*
Farmer's Fair	0.09 (4.487)	0.027 (0.039)
Neighboring Farmer	-0.029 (1.478)	-0.009 (0.064)
Family	-0.242 (12.109)	-0.072 (0.044)
Other Means	0.105 (5.293)	0.031 (0.153)
IPM club	0.324 (16.221)	0.096 (0.05)**
Farmer's Group	-0.274 (13.726)	-0.082 (0.061)
Mobile Phone Providers	-0.559 (27.979)	-0.166 (0.075)**
Newspaper/Leaflet	-0.471 (23.556)	-0.14 (0.064)**
Agricultural Officer	-0.107 (5.374)	-0.032 (0.062)

a: Values are marginal effect (standard error). ***, **, and * denote significance at the 1%, 5%, and 10% significance levels respectively

b: See Apendix B for covariate results

Comparing the significant agricultural information source variables to the percentage of the surveyed population who learned agricultural information from a source in the previous 12 months, field days and television are used as an agricultural information source by 46.3% and 45.5% of the population respectively with newspapers used as an agricultural information source by 24.5% of the population (see Table 4.19). Field days and television are the second and third most relied upon sources of agricultural information after agricultural officers which 90.8% of the surveyed population received agricultural information from in the previous 12 months.

Of all sources of agricultural information in the survey, IPM clubs had the highest likelihood of a household adopting IPM practices for the six vegetables in round two with a 46.55% adoption rate (see Table 5.13). Overall, the information sources with the highest percentage of surveyed farmers adopting were agricultural officers, neighboring farmers, and salesmen with respective IPM use rates of 27.20%, 27.08%, and 25.54% of all farmers surveyed.

For the agricultural information sources with a cost to the public, in round two IPM clubs had an adoption rate of 46.55%, field days had a 40.72% adoption rate, television had a 34.70% adoption rate, farmer's field schools had a 35.94% adoption rate, agricultural officers has a 34.08% adoption rate, radio had a 32.04% adoption rate, farmer's groups had a 28.92% adoption rate, and newspapers/leaflets had a 25.63% adoption rate.

To calculate the cost per farmer adopting, the percentage of farmers using IPM for each agricultural information source was first divided out of 100% to find the number of farmers needing to receive IPM training before one farmer will adopt IPM practices. The number of farmers needed for one IPM adoption was then multiplied by the cost per farmer trained to get the cost per farmer adopting IPM practices (see Tables 3.8 and 5.14).

Of all the public agricultural information sources, television and radio had the lowest cost per farmer adopting IPM practices at $0.09 per farmer (see Table 5.14). Newspapers/leaflets had a cost of $0.51 per farmer adopting IPM practices, IPM clubs had a cost of $0.58 per farmer adopting IPM practices, field days had a cost of $0.66 per farmer adopting IPM practices, farmer's groups had a cost of $0.93 per farmer adopting IPM practices, agricultural officers had a cost of $3.96 per farmer adopting IPM practices, and farmer's field school had a cost of $20.49 per farmer adopting IPM practices. The mass media information sources were the most efficient of those surveyed with radio, television, and newspapers/leaflets all coming in at the lowest cost per adoption. IPM clubs, field days, and farmer's groups all cost less than $1.00 per farmer adopting IPM practices. Farmer's field schools were by far the least efficient of the transfer methods with a cost of $20.49 per farmer. While that is higher than the other information sources, the vegetable technology transfer subproject did not utilize farmer's field schools to train farmers in IPM practices for the vegetables in this study. Since the subproject did not utilize that transfer method, it is likely that farmer's learning agricultural information from farmer's field schools were primarily learning IPM information for other crops not included in this study.

Table 5.13 IPM Adoption Rates by Agricultural Information Source

	Round One			Round Two		
Agricultural Information Source	# Farmers Using	% Using IPM	% of Total Using IPM	# Farmers Using	% Using IPM	% of Total Using IPM
IPM Club	N/A	N/A	N/A	54	46.55	3.21
Field Day	265	45.28	14.32	334	40.72	17.37
Farmer's Fair	309	42.39	15.63	333	38.74	16.48
Seed/Fertilizer/ Pesticide Salesmen	N/A	N/A	N/A	518	38.61	25.54
Farmer’s Field School	N/A	N/A	N/A	64	35.94	2.94
Television	564	32.98	22.20	317	34.70	14.05
Neighboring Farmers	800	32.00	30.55	611	34.70	27.08
Agricultural Officer	659	33.69	26.49	625	34.08	27.20
Family	N/A	N/A	N/A	506	33.60	21.71
Radio	114	26.32	3.58	103	32.04	4.21
Mobile Phone Provider	15	6.67	0.12	138	29.71	5.24
Farmer's Group	N/A	N/A	N/A	83	28.92	3.07
Newspaper/Leaflet	31	32.26	1.19	160	25.63	5.24

Table 5.14 Cost per Farmer Adopting IPM Practices

Agricultural Information Source	Likelihood of IPM Use	Farmers trained per 1 adoption	Cost ($USD) per 1 farmer trained	Cost ($USD) per 1 farmer adopting
Television	34.70%	2.88	$0.03	$0.09
Radio	32.04%	3.12	$0.03	$0.09
Newspaper/Leaflet	25.63%	3.90	$0.13	$0.51
IPM Club	46.55%	2.15	$0.27	$0.58
Field Day	40.72%	2.46	$0.27	$0.66
Farmer's Group	28.92%	3.46	$0.27	$0.93
Agricultural Officer	34.08%	2.93	$1.35	$3.96
Farmer's Field School	40.72%	2.46	$8.33	$20.49

6. Conclusion

First, the motivation behind this study, its objectives, and initial hypotheses were set out. Then background information on the IPM IL, Bangladesh, the IPM IL vegetable technology transfer subproject, the vegetables, vegetable pests, and IPM practices was presented. Next, the methods used in this study were laid out, including: the design of the RCT, traditional and ordered probit adoption models, difference-in-difference models for measuring impacts on vegetable yields, pest management costs, and pesticide use, economic surplus analysis, measuring the effectiveness of different transfer methods. After that, the sampling approach, survey design, and the data used were described, noting potential issues from training and the RCT. Finally, the methods and the data were used to evaluate the impacts of the technology transfer.

The first objective was to measure the IPM technology adoption rates and the determinants affecting those rates. IPM use measured as part of the first two rounds of the survey shows overall IPM adoption rates of 32.2% in round one and 33.8% in round two (see Table 4.11). For the individual vegetables, IPM use increased significantly for tomatoes and decreased significantly for country bean with a significant decrease in the use of handpicking negatively affecting country bean IPM adoption (see Tables 4.10 & 4.12). In Chapter Five pooled probit and ordered probit regression models were used to identify the determinants of IPM adoption. Significant positive determinants of adoption included living in Barisal district, having more years of agricultural experience, the number of IPM adopters known, and learning agricultural information from agricultural training events (see Tables 5.2 & 5.4). Significant negative determinants of adoption included living in any district other than Barisal and learning agricultural information from media sources (see Tables 5.2 & 5.4). Three hypotheses were tested as part of the first objective:

H1a: Learning agricultural information from field days will not increase the likelihood of adopting IPM technologies.

H1b: Learning agricultural information from agricultural officers will not increase the likelihood of adopting IPM technologies.

H1c: Learning agricultural information from the newspaper and other media sources will not increase the likelihood of adopting IPM technologies.

For hypothesis *H1a*, the results from the probit regression performed in Chapter Five found that learning agricultural information from agricultural training events, such as field days, has a significant positive effect on the likelihood of IPM adoption (see Table 5.2). For hypothesis *H1b*, the results from the probit regression found that learning agricultural information from agricultural authorities, such as agricultural officers, has a positive, but non-significant effect on the likelihood of IPM adoption (see Table 5.2). Finally, for hypothesis *H1c*, the results from the probit regression found that learning agricultural information from media sources, such as the newspaper, has a significant negative effect on the likelihood of IPM adoption (see Table 5.2).

The second objective was to measure the impacts of the IPM technology transfer on vegetable yields, pest management costs, and pesticide use. Data for the kilograms sold of each vegetable, total pest management costs, and the number of times pesticides were applied was collected in the survey. Overall, vegetable yields significantly increased between rounds (see Table 4.16), pest management costs remained level (see Table 4.17), and the number of pesticide applications significantly decreased (see Table 4.18). Difference-in-difference models were used to identify the impacts of IPM adoption on vegetable yields, pest management costs, and the number of pesticide applications. For vegetable yields there was an overall negative, but non-significant impact across all vegetables from IPM adoption with a significant decrease in only eggplant yields for IPM users (see Table 5.5). For pest management costs there was a positive, but non-significant increase in pest management costs from IPM adoption (see Table 5.6). For the number of pesticide applications there was a non-significant decrease in the number of pesticide applications for all vegetables from IPM adoption with a significant increase in pesticide applications for tomato IPM users and a significant decrease in pesticide applications for country bean IPM users (see Table 5.7). Three hypotheses were tested as part of the second objective:

H2a: Adoption of IPM practices will not increase vegetable yields.

H2b: Adoption of IPM practices will not increase production costs per hectare.

H2c: Adoption of IPM practices will not decrease pesticide use.

For hypothesis *H2a*, the results of the impact analysis found IPM adoption had a non-significant impact on vegetable yields (see Table 5.5). For hypothesis *H2b*, the results of the impact analysis found IPM adoption had a non-significant impact on total pest management costs (see Table 5.6). For hypothesis *H2c*, the results of the impact analysis found IPM adoption did decrease the number of times farmers applied pesticides, but only for country bean (see Table 5.7).

The third objective was to estimate the total economic impacts of the IPM technology transfer. With no significant changes in pest management costs and as the only vegetable with a significant change in yield, eggplant yield changes were measured using survey data and the results of the impact analyses for eggplant yields (see Table 5.8). The proportionate yield change was then used with IPM use data from the survey to estimate the total economic impacts of IPM adoption using economic surplus analysis. Overall, IPM use has decreased the total economic surplus by an estimated $836,474.43 over the two years of the survey (see Table 5.9).

There was, however, an increase in the total economic surplus of $67,009.47 between the two years from IPM use (see Table 5.10). Estimation of the economic impacts of IPM training performed by BARI, the subproject's primary partner, found that BARI training resulted in a net loss in economic surplus of $407.07 (see Table 5.11). One hypothesis was tested as part of the third objective:

H3: This technology transfer will generate an economic rate of return higher than ten percent.

For hypothesis *H3,* the results of the economic surplus analysis found that IPM training performed by BARI as part of the technology transfer had a negative economic impact on the districts where training was performed, disproving the hypothesis.

The fourth objective was to compare the relative effectiveness of the different technology transfer methods in terms of adoption rates and programmatic transfer costs per farmer. Data on farmers' agricultural information sources and IPM use collected in both rounds of the survey. In round two of the survey, 90.8% of farmers learned agricultural information from agricultural officers, 46.3% learned agricultural information from field days, and 45.5% learned agricultural information from the television (see Table 4.19). A probit regression for IPM adoption found that learning agricultural information from salesmen, field days, and IPM clubs significantly increased the likelihood of IPM adoption and learning agricultural information from mobile phone providers and newspapers significantly decreased the likelihood of IPM adoption (see Table 5.12). Analysis of IPM use by agricultural information source found that IPM clubs had the highest direct rate of IPM use, but one of the lowest overall rates of IPM use. Farmers learning agricultural information from agricultural officers, neighboring farmers, and salesmen had the highest overall IPM use rates at 27.20%, 27.08%, and 25.54%, respectively (see Table

5.13). The overall IPM use rates were then combined with cost data for public cost technology transfer methods to find the estimated cost per farmer adopting IPM practices. Television and radio had the lowest cost per farmer adopting IPM practices at $0.09 per farmer, but newspapers, IPM clubs, field days, and farmer's groups all cost less than $1.00 per farmer adopting (see Table 5.14). One hypothesis was tested as part of the fourth objective:

> *H4a: Field days have a higher cost per farmer adopting the technology than other technology transfer methods.*

For hypothesis *H4a*, the results of cost per IPM adopter analysis found that, while not the lowest cost transfer method, field days only cost $0.66 per farmer adopting IPM practices, less than three other public cost agricultural information sources measured.

There were three main findings from this study: adoption of IPM practices stayed relatively constant across the two rounds of the survey, negative impacts of IPM adoption were found for vegetable yields and pest management costs, and IPM use seems to have a negative economic impact on the regions the subproject has performed IPM training in. However, several indicators in this study suggest the RCT was contaminated, potentially affecting those findings. First, the control group received IPM training and even received significantly more IPM training than the treatment group in the second round of the survey (see Tables 4.14 & 4.15). Second, the primary partner for the subproject, BARI, performed less IPM training than all the other IPM training sources included in the survey (see Table 4.15). Finally, the control and treatment groups were unbalanced in IPM training received from BARI in the first round of the survey, with significantly less IPM training received from BARI in the treatment group (see Table 4.15). As a result of the aforementioned problems affecting the RCT, it is no longer possible to draw strong or confident conclusions from the results comparing the treatment and control groups.

As only Barisal and Jessore were expected to have received IPM training from the subproject by the second round of the survey, it will be important to observe the impacts of the technology transfer on Jhalakati and Magura districts in the third round of the survey and observe the continued impacts on the technology transfer on Jessore and Barisal districts. In particular, the effects of IPM adoption on vegetable yields, pest management costs, and economic impacts need to be further monitored and studied to insure IPM adoption is not negatively impacting those areas. Since the supply chains for many IPM products, including pheromone traps and Tricho compost, are still under development in many parts of Bangladesh it is important to continue monitoring IPM use by practice. Any weaknesses in the supply chain should be recognizable in the third round of the survey and can then be addressed going forward.

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Appendices

Appendix A RCT Village List

		Treatment	Control
District	Upazila	Village	
Jessore	Bagharpara	Budhopur	Allaipur
		Dorajhat	Bolorampur
		Shadipur	Syed Mahmudpur/Dadpur
	Chowgacha	Ber Gobindopur	Isa pur
		Dighori	Muktodaho
		Shahjadpur	Pativila
	Jessore	Kodalia	Bijoy nagar
		Lebutola	Khojarhut
	Jhikorgacha	Lau jani	Lakkhipur
		Nil konthi nagar	Misri deyara
	Moniram pur	Dodaria	Chalkidanga
		Khalia	Horer gati
		Krishnobati	Kandabpur
Barisal	Babuganj	Lakutia	Chondipur
		Pangsha	Khudro kathi
		Rafadia	Lohalia
		Rakudia	Moddho Bokshirchor
		Shingher Kathi	Rajguru
			Rampotri
	Barisal	Batna	Khanpura
		Kakashura	Sharshi
		Ulal Batna	
	Ujirpur	Dottoshar	Baherghat
		Guthia	Bilgabbadi
		Jolla	Dohorpara
		Karfa	Kochua
		Nittonondi	Madra
Magura	Magura	Atharokhada	Boroi
		Durgapur	Chandon protap
		Kanda baskotha	Goyal khali
		Krishnopur	Maloncho
		Nij nanduali	Naran pur
		Shoilodubi	Nischinto pur
			Okkur para
			Pakuria

			Ramchandrapur
			Srikundi
	Shalikha	Choi ghoria	Chandra
		Dewadanga	Deshmukh para
		Horishpur	Rampur
		Kushkhali	
		Pach kaunia	
		Pearpur	
		Shotokhali	
Jhalakathi	Jhalakathi	Balighona	Aksharapara
		Baruhar	Bermohol
		Bau kathi	Char vatara
		Dumuria	Darkhi
		Gabkhan	Deo Kathi
		Hosenpur	Gobindo dhobol
		Protap pur	Noiari
		Purbo Taruli	Poschim Binnapara
		Ramchandrapur	Ramnagar
		Ronomoti	Runshi
		Ruposhia	Shimuleshwar
		Shotodosh kathi	Tarpasha
		Vimruli	Uttor Pipolita

Appendix B Covariates for Agricultural Information Source Determinants[a]

	All Vegetables	
	Panel Probit model	Pooled Probit model
Number of Observations:	666	
Treatment[b]	0.031 (1.549)	0.011 (0.034)
Trained by BARI[b]	0.252 (12.596)	0.082 (0.073)
Jessore District[b]	-0.198 (9.908)	-0.059 (0.057)
Jhalakati District[b]	-0.615 (30.763)	-0.183 (0.052)***
Magura District[b]	-0.035 (1.766)	-0.01 (0.058)
Vegetable area % of Total Land (by vegetable)	-0.002 (0.09)	-0.001 (0.001)
Household members working (#)	0.015 (0.75)	0.004 (0.017)
Pest Severity (1-4)	-0.123 (6.164)	-0.037 (0.029)
Household members per room (#)	0.209 (10.465)	0.062 (0.056)
Farming is Primary Occupation[b]	0.234 (11.708)	0.07 (0.095)
HHH Age (years)	-0.008 (0.413)	-0.002 (0.002)
HHH Primary Education[b]	0.008 (0.42)	0.002 (0.046)
HHH Experience (years)	0.016 (0.801)	0.005 (0.002)**
Times Trained in IPM (#)	0.045 (2.233)	0.013 (0.008)*
IPM adopters known (#)	0.011 (0.566)	0.003 (0.001)***

a: Values are marginal effect (robust standard error). ***, **, and * denote significance at the 1%, 5%, and 10% significance levels respectively.
b: Binary variable