Two Essays on Evaluation Challenges in Integrated Pest Management: An Evaluation Design for the Onion ipmPIPE and Identifying Women's Crops and Agricultural Technologies

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ABSTRACT

The two papers in this thesis are aimed at solving problems in Integrated Pest Management project, practice, and program evaluations. In the first paper, an evaluation design is constructed for the Onion ipmPIPE website, an onion pest information website. The Bayesian decision theoretic approach may not accurately model onion growers' pest management decisions throughout the season. Randomization of the treatment is possible, but an incomplete grower list proved to be a problem. The analysis shows that an instrumental variables approach may be the most appropriate method for estimating the impact of the Onion ipmPIPE website because its data needs are solved by using USDA-NASS surveying services. In the second paper, the challenge is to develop a practical method to measure benefits accruing to women from agricultural research using secondary data. Donors, governments and others are interested in determining how benefits from agricultural research accrue to women. We develop a three-step framework to identify women's crops and technologies. In step one, total potential benefits from research are estimated; step two allocates those benefits between men and women; step three, incorporates technology-specific parameters to refine the estimates of potential benefits. We apply this framework to Honduras and find that steps one and two provide the most information on the magnitude and distribution of benefits, but that refinements in step three can affect rankings of research program impacts on women.

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Chapter 1: Introduction

Integrated Pest Management (IPM) is a set of pest management practices designed to reduce pest problems in agriculture while minimizing effects on the environment. These practices have become more common over time because a growing body of research has demonstrated the harmful impacts of pesticides and because growing pesticide use has increased pest resistance to pesticides (Mullen, Alston, Sumner, Kreith, & Kuminoff, 2005). IPM practices are designed to minimize pesticide use, which reduces human health problems, keeps harmful chemicals from reaching the environment, and lowers pesticide expenditures for growers (Resosudarmo, 2008).

Social benefits accrue when farmers, gardeners, and others utilize IPM techniques by becoming more economically efficient at both the societal and individual levels. Societal benefits arise from the environmental benefits of using IPM tactics as well as from improved productivity. Individual benefits are realized through lower production costs, yield increases, or both. This increased efficiency may be passed through the market to consumers, increasing total economic surplus in the market.

Projects to develop and disseminate IPM practices or programs are being implemented throughout the United States and around the world. In order to learn whether these projects are beneficial or not, evaluations of IPM projects, practices, or programs must be performed. The two papers in this thesis are aimed at solving problems in IPM evaluations. The first paper, *An Evaluation Design for the Onion ipmPIPE*, develops an evaluation design to estimate the impact of the Onion ipmPIPE website. The second paper, *Identifying Women's Crops and Agricultural Technologies*, develops a framework to identify women's crops and technologies, including IPM technologies, and applies this framework to Honduras.

Although both papers are set in different evaluation environments, one theme is present in both – determining how best to evaluate an intervention in or shock to an agricultural system. There are many ways to evaluate an intervention or shock, but there are constraints inherent in the evaluation problem that restricts which methods or techniques are appropriate. Methodological, statistical, logistical, ethical, political, material, and resource constraints restrict the list of potential evaluation techniques. Some techniques are inappropriate because they do not model the situation accurately, while others are too data intensive or present ethical dilemmas. Selecting or developing an appropriate method is crucial in accurately estimating the effect of an intervention or shock.

In Chapter 2, the evaluation design problem for the Onion ipmPIPE is discussed in *An Evaluation Design for the Onion ipmPIPE*. First, an introduction to the Onion ipmPIPE project, onion pests, and pest information are given, followed by a literature review on methods and techniques available to measure the value of information and an impact. The literature review is followed by a conceptual framework of how pest information affects growers' profits, revenues, and other outcomes. Next, each method's applicability to the Onion ipmPIPE evaluation problem is discussed, and experiences from trying to apply each method are discussed. Additionally, the evaluation framework is constructed using the most advantageous method. Lastly, the paper concludes with a discussion of lessons learned and further research required.

In Chapter 3, a framework is developed and applied to Honduras that addresses the challenges of determining what research will benefit women most in *Identifying Women's Crops and Agricultural Technologies*. After a brief introduction, literature on the benefits of agricultural research, how to measure those benefits, and how to disaggregate them is reviewed. Then, a conceptual framework for identifying crops and agricultural technologies beneficial to a population is developed. Next, the specific challenges in applying this framework to women are discussed. The framework is then applied to identify women's crops and technologies in Honduras. Results are presented, and the paper ends with a discussion of conclusions drawn from the application and opportunities for future research.

Chapter 4 provides a brief summary and conclusions from each paper. Conclusions about the impact of constraints in an evaluation environment are discussed, followed by a discussion of future research needed in this area.

Chapter 2: An Evaluation Design for the Onion ipmPIPE Website

2.1. Abstract

The Onion Integrated Pest Management Pest Information Platform for Extension and Education (Onion ipmPIPE)[1] project provides onion pest information to onion growers and other interested parties via a website. Many methods are available to value information or, in general, an intervention, but, like all evaluation environments, certain constraints restrict the methods that may be used. The Bayesian decision theoretic approach may not accurately model onion growers' pest management decisions throughout the season. Randomization is possible, but an incomplete grower list proved to be a problem. An analysis shows that an instrumental variables approach is the most appropriate method for estimating the impact of the Onion ipmPIPE website because its high data needs can be solved by using USDA-NASS surveying services.

2.2. Introduction

Integrated Pest Management (IPM) is a set of pest management practices designed to reduce pest problems while minimizing effects on the environment. These practices have become more common over time because a growing body of research has demonstrated the harmful impacts of pesticides and because growing pesticide use has increased pest resistance to pesticides (Mullen et al., 2005). IPM practices are designed to minimize pesticide use, which reduces human health problems, keeps harmful chemicals from reaching the environment, and lowers pesticide expenditures for growers (Resosudarmo, 2008).

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[1] See the Onion ipmPIPE website for more information at www.onion.ipmpipe.org.

Social benefits accrue when farmers, gardeners, and others utilize IPM techniques by becoming more economically efficient at both the societal and individual levels. Societal benefits arise from the environmental benefits of using IPM tactics as well as from improved productivity. Individual benefits are realized through lower production costs, yield increases, or both. This increased efficiency may be passed through the market to consumers, increasing total economic surplus in the market.

One IPM project is the multi-state[2] Onion ipmPIPE (Onion integrated pest management Pest Information Platform for Extension and Education). Onions have many pests in the United States, and the importance of particular pests often varies by location due to climate, pest geographical distribution, and weather conditions and by individual growers due to farming practices among other factors. Some pests, however, are important across all regions.

2.2.1. Onion pests

Onion thrips and onion maggots are insect pests that are prevalent throughout all onion growing regions of the United States. Onion maggots (Diptera: Anthomyiidae) are a serious onion pest, particularly in the northern United States (Finch & Eckenrode, 1985). Not by coincidence, onion maggots thrive in cool, moist weather conditions ("Crop Profile for Onions in New York," 1999). Onion maggot larvae feed on the underground parts of the onion plant (Whitfield, Carruthers, Lampert, & Haynes, 1985). During the seedling stage, onion maggots are the most damaging (Whitfield et al., 1985). In severe cases, onion maggots can cause up to 90% yield losses in untreated onion fields ("Crop Profile for Onions in New York," 1999).

Onion thrips (*Thrips tabaci*) is a pest that can cause serious problems by itself and through the disease it carries, Iris Yellow Spot Virus. Thrips directly cause damage when they feed on onion leaves, leaving brown blotches on the leaves; this damages the onion bulb (McKenzie, Cartwright,

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[2] States involved are NY, MI, CO, UT, NM, ID, & WA.

Miller, & Edelson, 1993; Fournier, Boivin, & Stewart, 1995). It is important to control thrips during onion bulbing because this is when they have the greatest impact on bulb size, yield, and quality (Edelson, Cartwright, & Royer, 1989). Thrips should not only be controlled for their direct impacts, but because they carry Iris Yellow Spot Virus (IYSV). IYSV appears as straw colored patches or lesions on the onion leaves (Gent et al., 2006). After a recent outbreak of IYSV in Colorado where crop losses were estimated to be approximately 5 to 10%, Gent et al. (2006) found that similar crop losses could lead to losses of $60 to $90 million across the Western part of the United States.

Purple blotch (*Alternaria porri)*, like IYSV, affects the onion's leaves; however, purple blotch is caused by a fungus. It may spread and affect the onion bulb by causing the bulb to decay during harvest and post-harvest ("Crop Profile for Onions in California," 1999). This disease may cause up to 40% yield losses in severe cases ("Crop Profile for Onions in New York," 1999). Another fungal disease, downy mildew, is also a foliar disease. Downy mildew (*Peronospora destructor)* causes, "… elongated pale to light tan lesions on older leaves as well as some totally collapsed leaves ... [D]ark, sooty to purple-gray fungal growth also was observed on affected leaves" (Langston & Sumner, 2000, p. 489). It is estimated that yield losses from downy mildew could be as high as 50% ("Crop Profile for Onions in New York," 1999).

Botrytis foliar disease (*Botrytis squamosa*), often called "blast", is another fungus that infects onions ("Crop Profile for Onions in New York," 1999). The symptoms of this fungus are the appearance of spots on the onion leaves and, "… a progressive die-back from the leaf tips…" (Shoemaker & Lorbeer, 1977, p. 1267). Yield losses of 7-30% can occur (Carisse, Tremblay, McDonald, Brodeur, & McRoberts, 2011). Unfortunately, the same genus of fungus that causes botrytis foliar disease also causes a destructive storage rot. Botrytis neck rot (*Botrytis allii*) initially infects onions in the field, or the plant is already infected when it is a seed. It causes the onion to rot and is usually evident shortly after the onion has been stored. Historically, storage losses from Botrytis neck rot have been as high as 50% (Maude & Presly, 1977).

2.2.2. Onion ipmPIPE website

Currently, information to help growers diagnose onion insects and diseases, predict their spread, and determine their economic impact is either non-existent or in dispersed locations. The Onion ipmPIPE facilitates the transfer of onion IPM information; current pest locations and severity, their possible spread, and upcoming areas of concern for onion farmers; real-time onion price information; and weather information. This information will be collectively called onion information or onion production information.

Some of the information provided on the Onion ipmPIPE website is available elsewhere, and some of it is available only on the Onion ipmPIPE. The value of the website is from its unique content and interpretation of data, and from the aggregation of information available elsewhere. The Onion ipmPIPE impacts farmers' decisions, creating two long-term outcomes: environmental improvement and improved economic efficiency. The total economic benefits from the Onion ipmPIPE website then are derived from an increase in profits, yields, other farm level outcomes of interest, and total surplus in the onion market and from environmental benefits that result from IPM information influencing growers' decisions.

Those that support the IPM projects, such as the United States Department of Agriculture (USDA), IPM managers, and individual IPM practitioners; onion growers; and future website owners want to know the value of the information created by the Onion ipmPIPE. The USDA is interested in the evaluation because it is funding the Onion ipmPIPE project, and the USDA will make future funding decisions regarding similar projects. IPM managers and practitioners who do not grow onions are interested because if the Onion ipmPIPE is valuable, creating a similar website for their own crops could be valuable. Onion growers are especially interested because valuable information is something they want; it increases their profits. However, onion growers will ignore useless information, and they will not use the Onion ipmPIPE website if the information is not valuable. Future website owners are interested in the value of the website because the value of the website will help determine if they should continue to run the website, and if so, how much they might be able to charge for access to the website.

This study aims to determine the best method to evaluate the economic outcomes from the Onion ipmPIPE project. To evaluate the Onion ipmPIPE, we must determine the value of the website. To do that, we must value what the Onion ipmPIPE website produces – information. The value of information is an extension of the theory of uncertainty (Hirshleifer, 1973). Information changes an individual's beliefs that given states of nature will occur (Eisgruber, 1978). These belief changes may alter actions taken by the individual, or it may reinforce their prior beliefs. The value of this information is the increased economic efficiency of that individual which is represented by higher expected utility, profits, or other outcomes/payoffs of interest (Eisgruber, 1978). When this increased economic efficiency is aggregated at the market level, the whole market is more efficient.

2.2.3. Pest information

How does pest information affect outcomes or payoffs of interest? To start, a framework describing how pests affect outcomes of interest must be developed. In general, farmers' profits and crop production are impacted by exogenous factors that are not known with certainty. Pest presence, pest severity, and other pest factors (wind, temperature, rainfall, etc.) are some variables affecting the pests' negative impacts on production and profits. The uncertainty in these factors impacts yields, pesticide use, revenues, costs, and profits. Information can reduce the uncertainty and improve each of these outcomes.

To see how pest information can improve profits, we must first look at how profits are affected by pests. Farmer profits can be divided into profits from production in the state of nature where no pests are present and profit losses from the presence of pests. Profit losses from pests can be separated into two sources: the number of pests and the per pest damage coefficient. The per pest damage coefficient represents the yield reduction from a single pest unit. This coefficient is multiplied by the number of pests to yield the total damage from all pests. However, pesticides can be used to reduce the number of pests present. The proportion of pests killed by pesticides is represented by a kill function.[3] The number of pests, the damage coefficient, and the kill function are multiplied to estimate the total pest yield losses and then multiplied again by the output price to obtain the profit losses.

The number of pests, damage coefficient, and kill function (collectively pest parameters) are not known with certainty because they are all affected by exogenous pest factors which are not known with certainty. However, the farmer can obtain information which can better refine her/his beliefs about what the pest parameters are or will be. A better idea about the values these pest parameters may take on, may increase farmer yields and profits by making better pesticide use decisions. The information's value can then be estimated by taking the difference between the profit, yield, pesticide use, or other outcome of interest when information is used and the same outcome of interest when information is not used. This pest information model is discussed in detail in the Conceptual Framework section.

2.2.4. Valuing information

The Bayesian Decision Theory approach is the method consistent with the theory of information, which measures the expected value of information. The most critical step in valuing information using this method is typically measuring the changes in beliefs due to new information.

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[3] Pesticide resistance is not modeled in this paper because it is beyond the scope of this research. This topic is discussed more in the Conceptual Framework section.

However, onion pests, onion production, and onion production information are such that growers' beliefs are constantly changing throughout the growing season. Measuring every change in beliefs throughout the season is prohibitively expensive, so a different approach must be taken to measure the value of the Onion ipmPIPE information.

Fundamentally, the information presented on the Onion ipmPIPE website is an exogenous shock or treatment experienced by some onion growers which changes their behavior. By considering information as a shock, we can perform an impact evaluation of the Onion ipmPIPE website and its information to determine its value.

The most critical component of an impact evaluation is the successful identification of the counterfactual. The counterfactual is the outcome had the participant not been exposed to the shock. The difference between the outcome with the shock and the outcome without the shock is the true impact of the shock. This isolates the impact's effect from all other outside forces that influence the outcome. Many methods are available to estimate this impact by looking at various counterfactuals despite never observing the counterfactual in reality.

The most important step then in valuing information provided on the Onion ipmPIPE is isolating the Onion ipmPIPE information's effects from other sources of change in the measured outcome. Two broad methods discussed in the impact evaluation literature can be used to estimate the value of information: randomization and non-randomized econometric methods.

Randomization eliminates selection bias created by not observing the counterfactual. However, care must be taken to ensure that this actually occurs. Furthermore, ethical, political, and logistical constraints may completely keep researchers from implementing a randomized experiment design. For the Onion ipmPIPE, political and logistical constraints did just that. Non-randomized econometric methods could be implemented to also eliminate the selection bias created by the counterfactual problem. Instrumental variable and the Heckman two-step procedures are the two non-randomized econometric methods that best fit the needs of evaluating the Onion ipmPIPE. These methods introduce exogenous variability via an instrument rather than through randomization.

Each method or technique has attributes (some advantageous, others disadvantageous) that are subject to constraints. Methodological constraints are those that restrict what situations or scenarios the method or technique can be applied to. Statistical constraints revolve around the assumptions made about data for a method or technique to be valid. These two constraints are the most often discussed constraints, challenges, or assumptions. Other constraints, however, may be more important. Logistical constraints (those concerning the execution of the method, such as ability to randomly assign treatment), ethical constraints (Is the method ethical?), political constraints (those relating to challenges of working with multiple stakeholders, such as project participants or project funders) are all constraints that can completely eliminate methods from being used. Several methods' attributes will be discussed, and how these attributes relate to the constraints brought forth by the Onion ipmPIPE evaluation will be discussed in detail in later sections.

2.2.5. Outline

The following section reviews literature about information, how it has been valued, and impact evaluation methods that can be used to value it. The next section develops the conceptual framework used to show how using better pest information can affect outcomes of interest. The fourth section discusses the advantages and disadvantages of each of the methods discussed in the literature review and lessons learned from trying to apply each method to the Onion ipmPIPE evaluation. This section also determines the most advantageous method to use in evaluating the Onion ipmPIPE website. Finally, the paper concludes by discussing how to move forward in evaluating the Onion ipmPIPE.

2.3. Literature Review

Information is processed raw data (Just, Wolf, Wu, & Zilberman, 2002). Raw data are rarely used by the decision maker (Eisgruber, 1978). Data are transformed into information so that the decision maker can apply the information to the problem at hand (Eisgruber, 1978; Just et al., 2002). Analyses and/or interpretations of the data need to be done so that the data can be changed into information (Eisgruber, 1978; Just et al., 2002). Although this definition and its implications are good to keep in mind, not many economic conclusions can be drawn from it. We must find a more theoretical definition of information.

To move towards a theoretical definition, we start with information's origin. Information comes from the theory of uncertainty (Hirshleifer, 1973). Uncertainty is the set of beliefs a decision maker has about the occurrence of future events or states of nature (Hirshleifer, 1973). There are two fundamental types of uncertainty in economics: market uncertainty and technological uncertainty. Market uncertainty is when the decision maker is only uncertain about the, "… supply and demand offers of others" (Hirshleifer, 1973, p. 33). The decision maker is fully certain about his/her own resources and production possibilities. Technological uncertainty is the flip side of market uncertainty. Under technological uncertainty, the decision maker is only unsure about, "… their [own] resource endowments and/or productive opportunities" (Hirshleifer, 1973, p. 33). The decision maker is sure of the structure of the market and the economic actions of others (Hirshleifer, 1973).

Information affects the decision maker's uncertainty; the decision maker's beliefs about the future are changed by obtaining information (Hirshleifer, 1973). By altering these beliefs, information makes decision makers more economically efficient, and this increased economic efficiency means that the information has value (Norton & Schuh, 1980).

2.3.1. What is the value of information?

The value of information is the difference in the expected value of the outcome of interest with information and its expected value without information (Marschak & Miyasawa, 1968). Information's value is affected by many of its own characteristics. One characteristic is the content of the information. Content is what the information is informing you of (Hirshleifer, 1973). This affects the type of uncertainty that is changing and who uses the information. These both affect its value.

A second attribute of information that affects its value is its quality. The more accurate (better) the information is, the more valuable it is (Hirshleifer, 1973). A third element of information that affects its value is its applicability. Information that is general is of little use to each decision maker, but many decision makers can use it. On the other hand, information that is particular to a specific decision is very valuable to a decision maker, but it is only valuable to that decision maker (Hirshleifer, 1973).

The fourth characteristic of information that affects its value is the information's spread. Hirshleifer (1971) found that information that is known only to one person (private information) provides no social value, and only redistributes wealth through profits of selling the information and speculation on what the information will do to the markets. However, if this information becomes public, then there is social value of the information through the reorganization of resources in the economy (Hirshleifer, 1971).

The value of information is also impacted by the decision maker's attributes. Lindner (1987) summarized several studies that analyzed the impact of certain decision maker characteristics on the value of information. He cites three studies focusing on a decision maker's risk aversion. One study found the value of information to be non-decreasing, one decreasing, and one indeterminate with respect to the decision maker's degree of risk aversion. On the decision maker's wealth, he cites two studies that have found as wealth increases, the value of information increases. And with respect to the decision maker's prior risk level, he found two studies which concluded that the value of information is increasing and two studies stating that the value of information is non-decreasing (Lindner, 1987).

2.3.2. Why is information difficult to value?

Information's value is difficult to determine for three general reasons. One is that information is not concrete. Often, there is no market price; it is not a physical good; and, its impacts are often unobservable (Eisgruber, 1978). These issues relate to the fact that information is a public good. Consequently, information can be used by one person without precluding someone else's use at the same time, and merely because someone uses the information does not mean that there is less information available for everyone else to use (Roberts, Schimmelpfennig, Livingston, & Ashley, 2009).

The second reason the value of a particular information set, system or source is hard to determine is because information's effects are difficult to isolate. This causality problem stems from a decision maker having multiple information sources available. Allocating the benefits from information being used between several sources is impossible to do with complete accuracy. Moreover, how the information is used and the degree to which the information was used to make the decision makes measurement difficult (Norton & Alwang, 1997).

The third difficulty in measuring the value of information is the fundamental counterfactual problem in social sciences. In general, to measure the true impact of a shock, researchers need the value of the outcome of interest with the shock and the value of the outcome of interest if the shock had not occurred for the same observation. Similarly, to measure the value of information, the economist needs the value of the outcome of interest with information and the value of the outcome of interest if the decision maker did not have the information. However, this is impossible to observe in reality because "what ifs" are merely hypothetical (Just et al., 2002).

2.3.3. What is the link between information, technology, and extension?

The theory of the value of information looks similar to the theory and methods used to estimate the impact or value of a new technology or extension service because information, extension, and technology affect the underlying parameters in a decision process and magnitudes of production variables. When choosing to adopt a technology or extension service, the producer determines its value by looking at the difference between expected values of outcomes of interest with the technology or extension service and without it, given different ideas he/she has about future conditions. Similarly, when a producer is choosing to use or subscribe to an information set, he/she determines its value by analyzing the difference between the expected value of outcomes of interest with and without the information set, given the different states of nature he/she expects will occur (Marschak & Miyasawa, 1968).

In essence, information, technology, and extension are exogenous shocks changing people's behavior and affecting their economic outcomes. A shock from the introduction of a new agricultural technology or extension service is measured by an impact evaluation. By viewing information as a shock, like technology and extension, we can perform an impact evaluation to determine the value of the information by measuring the change in actual outcomes realized by those impacted by the information.

The crucial step of performing an impact evaluation is identifying the correct counterfactual. The counterfactual is the outcome had the participant not been exposed to the shock. The research manager compares the outcome of interest in the participating group after the shock to its counterfactual to determine the program's impact. Having a miss-specified counterfactual can result in incorrect magnitudes of impact (Khandker, Koolwal, & Samad, 2010).

Unfortunately, the counterfactual for a given individual is never measured in reality (Khandker et al., 2010). It is a purely theoretical "what if". Impact evaluation methods attempt to circumvent this problem through a number of techniques, such as, difference in difference, instrumental variable estimation, or randomized experiment. All of these methods attempt to eliminate the selection bias which results from not observing the true counterfactual.[4] Because information is a shock, then these methods to place a value on a shock are also applicable to value information.

2.3.4. Methods for valuing information

The literature on the value of information can be broken into four main approaches: net social benefit, Bayesian decision theory (BDT), randomization/experimental, and non-randomized econometric. The last two have a link to impact evaluation literature, and will be discussed briefly from the perspective of the value of information literature and then extensively from the impact evaluation literature.

2.3.4.a. Net social benefit. One of the easiest methods to conceptualize is the net social benefit approach. One of the first studies utilizing this approach was Hayami and Peterson (1972). They described the basic framework for the net social benefit approach and applied it to USDA production forecasts for crops and livestock (Hayami & Peterson, 1972).

Hayami and Peterson stated that statistical error in production forecasts cause errors in market forecasts by producers. This error leads to disequilibrium in the market and social losses. These social losses can be measured as losses in economic surplus. If the statistical error decreases, then the market moves closer to equilibrium, decreasing social losses. This reduction in statistical error is the same as having better information in the market. The value of the better information then is the difference between the social losses with information and the social losses without information. In their case study, they found that the information was highly valuable under many different assumptions about the structure of the market (Hayami & Peterson, 1972).

[4] Selection bias will be discussed further in the randomization section of the Literature Review.

Freebairn (1976) used this method to analyze the value of better price outlook information and its distributional effects. Freebairn (1976) used a model similar to the Hayami and Peterson (1972) model, but went further by disaggregating the market impacts to producers and consumers. Interestingly, he found that for a given time period producers or consumers may lose from better information because it redistributes surplus from one group to the other. However, over multiple periods, better information will benefit both groups (Freebairn, 1976). This finding was consistent with the finding of Hirshleiffer (1971) that information has redistributive effects. In Freebairn's application to major Australian commodities, the value of information was large for both producers and consumers (Freebairn, 1976).

Bradford and Kelejian (1977) critiqued and extended the model of Hayami and Peterson. First, Bradford and Kelejian questioned how information is integrated into the market: who uses it, how do they use it, and the implications of not using it perfectly. A second question they asked was about the connection between sampling and measurement error and forecast error. Their thought was that perfectly collected data may still have error from uncertainty inherent in predictions (Bradford & Kelejian, 1977).

Bradford and Kelejian answered these questions by providing more structure to Hayami and Peterson's framework. To do this they explicitly stated the economic agents, how the agents generate their forecasts, and equilibrium conditions needed for Hayami and Peterson's model to function. They also developed welfare impacts on market actors (Bradford & Kelejian, 1977).

Perhaps the most important finding from this study is the link of the net social benefit approach to the Bayesian decision theory approach. To estimate benefits, Bradford and Kelejian analyzed three cases of how the information was used. One of these ways was through Bayesian decision theory. They showed that the BDT approach used at an individual level could be aggregated to obtain surplus measures at the market level (Bradford & Kelejian, 1977).

2.3.4.b. Bayesian decision theoretic approach. Although the net social benefit approach is easy to conceptualize, the first approach used in agricultural economics to measure the value of information was the Bayesian decision theory or decision theoretic (BDT) approach. This approach is firmly rooted in the economic theory of the value of information. Shimmelpfennig and Norton (2003) provided a good overview of the process of valuing information via the BDT approach. This overview is used as a guide for the following example of the BDT approach, which is needed to discuss the BDT approach literature further.

Consider a decision where a grower can take *k* actions with the y^{th} action represented by a_y; there are *n* possible states of nature, where the i^{th} state of nature is represented by S_i; and, the prior probability or the prior belief that state i will occur is $P(S_i) = \pi_i$. Therefore, there are $n*k$ payoffs where the payoff from the y^{th} action when the i^{th} state of nature occurs is x_{iy}. Then, the expected value of the y^{th} action is

$$E(a_y) = \sum_{i=1}^{n} \pi_i x_{iy}$$

The optimal action without information is the one that maximizes the expected payoff.

$$E(a_y^*) = Max_{a_y} E(a_y) = Max\left(\sum_{i=1}^{n} \pi_i x_{iy}\right)$$

Information is then introduced through a number of *m* messages, where the j^{th} message is Z_j. These messages have likelihoods of presenting themselves given each state of nature, $P(Z_j|S_i)$. Each message has an unconditional probability of being introduced, $P(Z_j)$. By using Bayes formula we can obtain the posterior probabilities, $P(S_i|Z_j)=\pi_{ij}$, as follows

$$P(S_i|Z_j) = \pi_{ij} = \frac{P(S_i)P(Z_j|S_i)}{P(Z_j)}$$

The new expected value of the optimal action y given information message j is now

$$E\left(a_y^{j\prime}|Z_j\right) = \sum_{i=1}^{n} \pi_{ij} x_{iy}$$

The expected value of all optimal actions y, represented by the "optimal action set", A_y, given the new information set Z is

$$E\left(A_y|Z\right) = \sum_{j=1}^{m} P\left(Z_j\right) E\left(a_y^{j'}|Z_j\right) = \sum_{j=1}^{m} P\left(Z_j\right) \sum_{i=1}^{n} \pi_{ij} x_{iy^{j\prime}}$$

The value of information is the difference between the expected value of all optimal actions y given the new information and the expected value of the optimal action given no information. That is,

$$Value\ of\ Information = E\left(A_y|Z\right) - E\left(a_y^*\right)$$

Marshak and Miyasawa (1968) provided a prominent, proof-based theoretical exposition of the BDT approach to valuing information systems. Their analysis provided many theorems and laid-out the fundamental underpinnings of the BDT approach. Interestingly, Marshak and Miyasawa used the term information systems because they make use of messages, which convey information. They said that the information system is the set of messages that the decision maker is receiving. Often in the literature, this collection of messages is referred to as information instead of an information system (Marshak & Miyasawa, 1968).

Marshak and Miyasawa (1968) stated that the value of information ultimately rests on the payoff function and the relationship between events and messages. Note that in the example above, x is referred to as payoffs. This payoff can also be utility, profit, or another outcome of interest. Moreover, a function can link the payoffs, x, to some other outcome depending on the action and state that occurs. This payoff function often links a monetary outcome, such as profits, to utility. This payoff function is often where risk aversion is integrated into the analysis. The relationship between events and messages are seen by the conditional and joint probabilities of events and messages.

An early application of BDT by Nelson and Winter (1964) valued a weather forecasting system compared to using climatological data for open truck bed transport in the Los Angeles area. In the problem, if it rained, much of what was being transported in the truck bed would be lost. However, if the truck owner thought it might rain, then he/she could cover the truck bed (Nelson & Winter, 1964).

The truck owner could cover the bed or not cover the bed, either good or bad weather could occur, and similarly good or bad weather forecasts were the only messages that could be received. By looking at past data and forecasts, marginal forecast (message) probabilities and conditional probability of events occurring given the forecast were calculated. They found that the forecasts were in fact valuable. However, one drawback of this study was that the assumptions made are not rigorously tested to ensure they are correct. For example, the payoff function was assumed to be linear, but it was not tested to see if this was correct (Nelson & Winter, 1964).

Another weather related study by Bacquet, Halter, and Conklin (1976) valued frost forecasts to orchard growers. Frost could damage crops during crucial growing times, but measures could be taken to mitigate or eliminate the damage. Unlike the study by Nelson and Winter (1964), it varied assumptions about the payoff function, informational quality, and the prior beliefs. Bacquet et al. (1976) found that under these assumptions, the value of the frost forecasts was positive for orchard growers. Furthermore, by varying the payoff function they were able to provide an estimate of how much more valuable information was to risk averse farmers v. risk-neutral farmers (Bacquet et al., 1976).

One shortcoming of this research (and another of Nelson and Winter's) study is that it does not take into account market effects. Namely, they do not consider any price changes that occur if a significant portion of the decision makers use the information. This will have an impact on the consequences which will impact the ultimate outcome of interest. One study that does take this into account is Norton and Schuh (1980).

Norton and Schuh calculated the value of price outlook information for Minnesota soybean farmers. In this study, they allowed for changes in the market structure by assuming that information users were a significant part of soybean producers. Under this assumption, the supply curve would shift making the initial value of information from aggregating benefits without changing price incorrect. To account for supply curve shifts, they chose to measure payoffs as economic surplus. This provides another example of linking the net social benefits/economic surplus method and the BDT method. Norton and Schuh found under these conditions that the price outlook information is valuable (Norton & Schuh, 1980).

One of the more recent uses of the BDT method was performed by Roberts, Schimmelpfennig, Livingston, and Ashley (2009) who estimated the value of information for the Soybean ipmPIPE. The information provided by the Soybean ipmPIPE was pest information; the website displayed maps of the location of soybean rust, maps of the potential spread of the disease, region specific reports on the disease and factors affecting it, and other resources that the farmer could browse to make soybean pest management decisions. This study varied the prior probabilities, risk aversion of the farmers, and information quality (Roberts et al., 2009).

One interesting aspect of this study was that Roberts et al. (2009) divided the nation's soybean producers into regions. As a result, they were able to refine the decision parameters, such as payoffs and prior probabilities, by region rather than a national aggregate. This meant that the value of information could be disaggregated into regions, and it provided a more realistic value of information (Roberts et al., 2009). This study is also important because the information it valued was very similar to that on the Onion ipmPIPE. However, this method will not be used for reasons to be discussed more fully in the Methods Analysis section.

2.3.4.c. Randomization/experiments. The value of information can also be estimated using experimental methods. In general, researchers use these techniques, especially randomization, to mitigate statistical problems and make as few structural assumptions as possible. In this way, economic theory can be directly tested in a controlled setting satisfying the *ceteris paribus* so often cited in economics (Ehmke & Shogren, 2010).

In the value of information literature, experimental techniques have been used to directly estimate the value of information from experiment participants. Marette, Roosen, and Blanchemanche performed an experiment to value nutritional information on omega-3 and mercury content in fish (2008). Swallow and Mazzotta estimated the value of additional experiment station research to the public via contingent valuation methods (2004). These experimental studies were experimental in that they directly ask participants about the value of something. However, we are interested in experimental studies that randomize treatments across a population of interest.

Randomization eliminates the bias caused by the counterfactual problem. As discussed earlier, this is caused by the fact that only one outcome per individual is ever observed in the human sciences; impact evaluators only observe the treated outcome given the individual is treated and the outcome of an untreated (control) individual given he or she was in the untreated (control) group (Khandker et al., 2010). The difference between these two values is not the same as the difference between the outcome of an individual with treatment and the outcome of the same individual untreated given they are in the treatment group because the impact may affect each individual differently. The difference is called the selection bias (Duflo, Glennerster, & Kremer, 2008).

The chapter by Duflo et al. (2008) has been used as the outline for the following illustration of the counterfactual problem and randomization's effects. Let y_i^j be the j^{th} outcome, y, for individual i. Let j=T if treated (experiences the shock), C if untreated or in the control (does not experience the shock). Also, let E[.] be the expected value operator as before. For example, $E[y_i^T|T]$ reads as the expected value of individual i's treated outcome given individual i is in the treatment group.

For the population of interest, we observe either $E[y_i^T|T]$ or $E\left[y_i^C|C\right]$. That is we observe either the mean treatment outcome given individual i is in the treatment group or the mean control outcome given individual i is in the control group. What we want to observe is $E[y_i^T|T]$ and $E\left[y_i^C|T\right]$, the average treatment outcome of individual i and the average control outcome of individual i. This difference is often called the average treatment effect on the treated, $TOT = E[y_i^T|T] - E\left[y_i^C|T\right]$.

If we only look at the observable difference, $D = E[y_i^T|T] - E\left[y_i^C|C\right]$, which is what we actually observe, there is a bias $B = E\left[y_i^C|T\right] - E\left[y_i^C|C\right]$ that is added to the average treatment effect on the treated, or $D = TOT + B$.[5] In words, the average difference observed between the treatment and control groups is equivalent to the average treatment effect on the treated and a bias.

B is the selection bias discussed earlier. Selection bias occurs when the agents impacted by the shock are systematically different than those that did not experience the shock. Selection bias affects the estimated impact of a shock when taking the observable difference, if (i) the systematic differences affect the outcome of interest, and (ii) they are not taken into account when estimating the impact. The goal of the impact evaluator is to use an evaluation method that eliminates the selection bias, B.

[5] In regression form, $y_i = \alpha + \beta T + \varepsilon_i$, where T is a dummy variable that is 1 if individual i receives the treatment and 0 otherwise. If β is estimated via ordinary least squares, then $\beta_{OLS} = E[y_i^T|T] - E[y_i^C|C]$. So, $\beta_{OLS} = D$.

A theoretically sound way to eliminate the bias and to measure the real impact of the treatment is by randomizing who experiences the treatment and who does not experience the treatment. This bias disappears because when treatment is randomized, $E\left[y_i^C|T\right] = E\left[y_i^C|C\right]$; and the observed difference, D, equals the average treatment effect on the treated.[6]

Enforcement; spillovers; the effects of the treatment; resource, political, and ethical constraints; and the level of randomization must be considered when integrating randomization into impact evaluations.

Enforcement or compliance refers to making sure individuals who are assigned to the treatment group truly get treated, and those assigned to the control group truly **do not** receive the treatment (Barrett & Carter, 2010). Spillovers are benefits that accrue to the control group from the treatment group being treated even though the control group has not received the treatment (Miguel & Kremer, 2004). If non-compliance and/or spillovers exist and are unaccounted for, then impact estimates will be biased (Duflo et al., 2008). It is important to have an idea of the outcomes of interest affected by the treatment and how they will be affected (collectively referred to as the nature of the treatment) so that enforcement problems and spillovers can be predicted, ex-ante.

Resource, political, and ethical constraints must be considered before randomization is implemented. Resource constraints, such as time, monetary, and computational constraints, must be taken into account because this will affect the size of the randomization, the level of randomization, and the randomization design used. Sometimes, randomization is difficult to implement because it is ethically unsound. Randomization inherently restricts some individuals from receiving the treatment (Barrett & Carter, 2010). However, when resource constraints preclude the research manager from offering the treatment to all those who want it, randomization may actually be the most ethical way

[6] A sampling bias may exist because the sample difference may not exactly equal the true population difference, but this bias decreases as sample size increases (Ravallion, 2001).

to provide the treatment. Related to ethical constraints are political constraints. Often treatments or programs not executed by one group, but are often implemented with multiple partners. Many times, those implementing the project will not want to restrict people from receiving the project. Also, those being randomized may resist because they may not receive the benefits from the treatment if they are placed in the control group (Duflo et al., 2008).

The above constraints, enforcement issues, spillovers, and the nature of the treatment all affect the level of randomization. The level of randomization refers to the observational unit at which randomization occurs. The size of the groups across which randomization occurs are important because the larger the size of each group, the larger the necessary overall sample; a larger sample increases costs. The level of randomization also determines the level at which the treatment effects can be measured (Duflo et al., 2008).

Considering the above factors, randomization can be implemented using one of four designs: full randomization, randomized phase-in, within group randomization, and randomized encouragement. In the classic randomized experiment; one group is assigned the treatment and another is assigned the control (Duflo et al., 2008). Glewwe, Kremer, Moulin, and Zitzewitz (2004) applied this method in a pilot study analyzing the impacts of flip chart use in schools. The authors partnered with a Dutch non-governmental organization to pilot test the effectiveness of providing flip charts to schools. Schools (not students) were randomly assigned to receive the charts or not. Enforcement and spillovers at this level of randomization is minimal. The study determines that flip charts did not provide a significant improvement to children's education because test scores did not improve (Glewwe et al., 2004). Interestingly, these estimates are drastically lower compared to retrospective estimates of flip chart impact, which found that flip charts can increase test scores by 20% of a standard deviation (Glewwe et al., 2004). By comparing results from different methods, this article has shown how important implementing the proper method is to performing a good impact evaluation.

The flip chart pilot study represents a somewhat ideal situation to implement randomization: fully randomized, backing of the partner organization, and little concern for spillovers and non-compliance. Unfortunately, most randomized studies do not fall within these ideal conditions. One method taking advantage of randomization, while working within constraints is the randomized phase-in design. The randomized phase-in design is a design where a treatment is implemented across groups randomly over a period of time. The entire population of interest will eventually have access to the treatment or receive the treatment, but the timing of treatment received by each population sub-group is randomly assigned (Duflo et al., 2008).

One of the most widely known randomized programs is the Progresa cash transfer program in Mexico. Progresa was randomly phased-in over three years from 1998-2000 and paid poor mothers who had children attending school. Schultz (2004) estimated its impacts on children's school attendance, and found that Progresa increased school attendance by 0.66 years onto an average of 6.80 years. Another seminal randomization study analyzed the impact of a randomly phased-in program to eliminate intestinal worms from Kenyan children (Miguel & Kremer, 2004). Randomized phase-in was the chosen design because of financial and administrative constraints. Two important things to note here are the level of randomization and spillovers. Medical literature indicated that untreated people living around those who had received the treatment would experience some indirect benefits from the de-worming treatment. If treatment were applied on an individual basis, these spillovers would cause a bias in impact estimates, understating benefits from de-worming. Therefore, randomization was made at the school level to minimize spillovers from treatment (Miguel & Kremer, 2004).

Unfortunately, these two randomized phase-in studies do not provide an agricultural context. However, they do illustrate how this method can be implemented in "less than ideal" randomization conditions. The within-group randomization design is another "less than ideal" randomization method when the population is divided into sub-groups and within each group the treatment is assigned randomly (Duflo et al., 2008). Sacerdote's (2001) analysis of peer effects on educational performance was a classic example of within-group randomization. Dartmouth University randomly assigned freshman roommates conditional on their answers to five questions about lifestyle and study habits. Each possible combination of the answers to the five questions constituted a group. Sacerdote (2001) found that roommates affected grade point average (GPA) and fraternity/sorority decisions, while dorm mates only affected fraternity/sorority decisions. Randomization within each group allowed Sacerdote (2001) to analyze the effects of a student's roommates and dorm mates on GPA and other outcomes of interest without any confounding factors (such as self-selection into a peer group or a person's background) complicating the results.

The fourth way randomization can be incorporated into an impact evaluation is through an encouragement design. In an encouragement design, "... researchers randomly assign subjects an encouragement to receive the treatment" (Duflo et al., 2008, p. 3917). "Since the invitation [or encouragement] was randomly assigned, it provides a natural instrumental variable with which to evaluate the impact of the treatment" (Duflo et al., 2008, p. 3918). The instrumental variables approach is also considered a non-randomized econometric approach that can utilize instruments other than those assigned randomly. Therefore, discussion of the instrumental variable analysis will take place in the non-randomized econometric section of this Literature Review.

Ashraf, Gine, and Karlan (2009) studied the impacts of a project (DrumNet) in Kenya designed to increase the production of horticultural crops by smallholder farmers. Randomly selected farmers in the selected region were offered services provided by DrumNet, but only some of these selected farmers chose to use the services. In this study, the services offer can be thought of as the encouragement. By using IV techniques, Ashraf et al. (2009) found that DrumNet services did not increase income for the full sample. However, for those that started to grow horticultural crops as a result of using the services, incomes increased by 32% (Ashraf et al., 2009). This study is of particular interest because it estimated the value of crop production and marketing services, a shock similar to the introduction of information.

2.3.4.d. Non-randomized econometric approaches. Aside from randomization and experimental methods, many non-randomized econometric techniques can be used to eliminate selection bias in evaluating the impacts of a shock. Two of these are of interest: instrumental variables and the Heckman two-step procedure. The instrumental variables (IV) approach is a method that uses an instrument or instruments to be a surrogate(s) for randomization to eliminate the selection bias, B; the instrument creates exogenous variability. The Heckman two-step procedure is a specific IV approach used when outcomes of interest are not observed for those that did not receive the treatment.

Wooldridge (2009) and Greene (2008) have been used as a guide for the following exposition on the two stage least squares IV estimation and the Heckman two-step methods. Consider the following model:

$$y_i = \boldsymbol{x_i'\beta} + \delta T_i + \varepsilon_i$$

where y_i is the outcome for individual i, $\boldsymbol{x_i'}$ is a vector of regressors upon which the outcome depends, $\boldsymbol{\beta}$ is the vector of coefficients of $\boldsymbol{x_i'}$, T_i is a dummy variable that is 1 if individual i receives the treatment and 0 otherwise, δ is the effect of receiving treatment, and ε_i is the error term.

Now, assume that treatment is not randomly assigned; individuals self-select into the treatment group. Selection into the treatment group can be modeled like a latent variable as follows:

$$T_i^* = \boldsymbol{w_i'\gamma} + u_i$$

$$T_i = 1 \; if \; T_i^* > 0, and \; 0 \; otherwise$$

where $\boldsymbol{w_i'}$ are the regressors in the impact equation above, $\boldsymbol{x_i'}$, an instrument, z_i, and u_i is the error term. This treatment dummy variable can then be treated as an endogenous variable in the above impact equation. This means that IV can be used.

In the first stage, estimate T_i^* via a linear probability model. At first glance, a logit or probit model seems the most appropriate estimation method because T_i is a binary variable. However, if these are used, the estimates of impact in the second stage are inconsistent unless the functional form is correct. The estimate of impact in the second stage is consistent using a linear probability model even if the relationship is non-linear (Angrist 2001).

To complete the first stage, generate a predicted value, π_i, for each observation where π_i is the probability estimate from the linear probability model estimation of T_i^*. Here, the predicted probability estimate from the linear probability model is the instrument. This first stage is often conceptualized as "purging" the treatment variable's link with the error term in the impact equation (Wooldridge, 2008).

In the second stage, compute the ordinary least squares estimate of the impact equation above with the exception that π_i replaces T_i. This is represented in the following equation.

$$y_i = \boldsymbol{x_i'\beta} + \theta\pi_i + v_i$$

The coefficient, θ, on π_i identifies the local average treatment effect of receiving treatment, T_i, if the instrument, z_i, is binary. The local average treatment effect measures the impact of the treatment on those induced to receive the treatment through a change in the value of the instrument (Cameron & Trivedi, 2005).

Now, the same setup is used to show how the Heckman two-step procedure is used:

$$y_i = \boldsymbol{x_i'\beta} + \delta T_i + \varepsilon_i$$

where y_i is the outcome of individual i, $\boldsymbol{x_i'}$ is a vector of regressors uncorrelated with the error term, $\boldsymbol{\beta}$ is the vector of coefficients of $\boldsymbol{x_i'}$, T_i is a dummy variable for treatment or no treatment, δ is the effect of receiving treatment, and ε_i is the error term. Assume again that individuals self-select into the treatment group, meaning that T_i is correlated with the error term. This model requires additional information, though, for the structure of T_i:

$$T_i^* = \boldsymbol{w_i'\gamma} + u_i$$

$$T_i = 1 \; if \; T_i^* > 0, and \; 0 \; otherwise$$

$$Prob(T_i = 1|\boldsymbol{w_i}) = \boldsymbol{\Phi}(\boldsymbol{w_i'\gamma})$$

$$Prob(T_i = 0|\boldsymbol{w_i}) = 1 - \boldsymbol{\Phi}(\boldsymbol{w_i'\gamma})$$

where $\boldsymbol{w_i'}$ now includes both the regressors, $\boldsymbol{x_i'}$, and additional regressors. Furthermore, assume that both ε_i and u_i are jointly normally distributed. The inclusion of $\boldsymbol{x_i'}$ in $\boldsymbol{w_i'}$ in addition to the joint normality assumption of the error terms allows us to use this Heckman two-step estimation procedure. The treatment effect on the treated is

$$E[y_i|T_i = 1, \boldsymbol{x_i w_i}] = \boldsymbol{x_i'\beta} + \; \delta + \beta_\lambda \lambda(-\boldsymbol{w_i'\gamma})$$

where $\lambda(-\boldsymbol{w_i'\gamma}) = \boldsymbol{\varphi}(\boldsymbol{w_i'\gamma}) / \boldsymbol{\Phi}(\boldsymbol{w_i'\gamma})$ is the inverse mills ratio, $\varphi(\cdot)$ is the normal pdf, $\boldsymbol{\Phi}(\cdot)$ is the normal cdf, and β_λ is the coefficient for the inverse mills ratio.

The first step in the Heckman two-step procedure is to estimate the selection equation above via the probit method and compute the inverse mills ratios for each observation from the probit. The second step is to estimate $\boldsymbol{\beta}$ and β_λ by a least squares regression on $\boldsymbol{x}$ and $\lambda(-\boldsymbol{w_i'\gamma})$ using data from observations where $T_i = 1$.

The IV approach and its derivatives are exceedingly popular.[7] One of the most oft-cited IV article is a study by Angrist (1990). Angrist used a data set from the Social Security administration and used the random assignment of being drafted to serve during the Vietnam War as an instrument for estimating the impact of military service on lifetime earnings. He found that some veterans were earning as much as 15% less than non-veterans into the early 1980s (Angrist, 1990). Unfortunately, this data set was not available at an individual level but at an aggregate level by veteran status, race, and birth year. Also, this study did not analyze the impact of a technology.

A more recent article used the IV approach to estimate the value of extension in Ethiopia (Dercon, Gilligan, Hoddinott, & Woldehanna, 2009). By using time-variant household variables as instruments and taking into account time-invariant household variables, they were able to estimate the impact of extension and rural roads on poverty and consumption. Dercon et al. (2009) found that extension reduces poverty by 9.8 percentage points and increases consumption growth by 7.1%. This study is of particular interest because extension provides information, just like the Onion ipmPIPE website.

ReJesus, Palis, Lapitan, Chi, and Hossain (2009) estimated the impact of farmer field schools (FFS) and the "No Early Spray" campaign (NES) to reduce pesticide use using a Heckman two-step procedure to account for self-selection. Farmers chose to attend FFS and chose to use information gathered from FFS and NES; they are not randomly treated with using information. Rejesus et al. (2009) found that FFS significantly reduced the amount of pesticide used, but had no significant effect on the number of applications. NES had no impact on the amount of pesticides applied and the number of applications. This study is interesting for two reasons. One reason is that it, like Dercon et al. (2009), estimated the value of an extension service. The second reason is that the

[7] Look at any economics journal over the past six months and there is bound to be at least one article in each journal that makes use of this approach.

technologies and techniques propagated by the FFS and NES were IPM technologies and techniques, which are the methods propagated by the Onion ipmPIPE.

Finally, an article by Livingston (2010) used a Heckman two-step model to estimate the impacts of the Soybean ipmPIPE on fungicide management decisions. Livingston (2010) analyzed the determinants of beliefs that a grower would experience an economically damaging soybean rust (fungus new to the United States) outbreak, the determinants of fungicide use, the determinants of the Soybean ipmPIPE website visitation, and the impact of the Soybean ipmPIPE on fungicide management changes. He found that website use depended on operator education, farm sales, farm debt-to-asset ratio, and the beliefs the grower had about the likelihood of experiencing a rust outbreak. Age and spouse's primary occupation were found to be insignificant. He then found that fungicide use depends on age, farm sales, whether the grower had federal crop insurance or not, the location of the field, and if the county the grower was in experienced a soybean rust outbreak.

Livingston (2010) also found that use of the Soybean ipmPIPE changed growers' fungicide management decision. To do this, Soybean ipmPIPE website use was estimated with a probit model. He then incorporated a correlation coefficient into another probit model to estimate whether farmers altered their management of fungicide use based on website use and prior infection beliefs (Livingston, 2010). The Livingston (2010) study is important to this Onion ipmPIPE study because it estimated the impact of the Soybean ipmPIPE using a Heckman two-step procedure, which provides a framework to estimate the value of the Onion ipmPIPE website by using similar variables in either non-randomized econometric approach discussed in detail.

2.4. Conceptual Framework

To estimate the value of pest information, a framework must first be developed that shows how pests and the uncertainty surrounding them impact a farmer's objective function. Feder's (1979) pest management model is used as a guide. However, uncertainty is made explicit by introducing "exogenous factors," and assuming that profit is the farmer's objective function, instead of farmer utility.[8] We begin with a very general profit function, and then add more assumptions about functional form to make the framework more tractable.

$$\pi = \pi(q_A, x, i; p, o, c_x, c_i)$$

where

$\pi = \pi(q_A, x, i; p, o, c_x, c_i)$ is the profit function of a given onion grower.

A is the technology used (pest application method, varieties chosen, irrigation method, etc.).

q_A is the quantity produced under technology A. $q_A \geq 0$

x is level of pesticide. $x \geq 0$

i is a vector of all other inputs. $i \geq 0$

p is the output price. $p > 0$

o are exogenous factors affecting production and pest management (e.g. current and future wind speed, current and future rainfall, current and future daily high temperatures, current and future pest pressure, and nearby pest populations).

c_x is a vector of prices for pest management inputs. $c_x > 0$

c_i is a vector of prices for all other inputs. $c_i > 0$

Like a typical profit function, this shows that profit depends on the quantity produced, the price received for the product, the inputs used, and the prices of those inputs. Profit also explicitly depends on other exogenous factors affecting production and pest management, the effects of which will be discussed later. Output price, input prices, and other exogenous factors are assumed to be given. The technology used, quantity produced and input levels are chosen.

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[8] Or, profit is a linear approximation for a farmer's utility function.

This profit function can be separated into revenue and costs.

$$\pi = f_A(x, i; o)p - c(x, i; c_x, c_i) = Revenue - Costs$$

where

$f_A(x, i; o)$ is the production function using technology A given o.

$c(x, i; c_x, c_i)$ is the total costs of production.

To gain more insight, additional assumptions are made. The first is a functional form assumption; assume that costs are linear and there are no fixed costs in production. Second, it is assumed that the production function can be broken down into (i) a production function with no pests and (ii) a pest damage function. This pest damage function estimates the losses in production from pests being present dependent on the level of pesticide use, x, and exogenous factors, o. The overall production function, $f_A(x, i; o)$, is the difference between the production function in the state with no pests and the pest damage function.

$$f_A(x, i; o) = g_A(i; o) - h_A(x; o)$$

where

$g_A(i; o)$ is the production function using technology A in the state with no pests given o.

$h_A(x; o)$ is the pest damage function under technology A given o.

By incorporating $g_A(i; o)$ and $h_A(x; o)$ into the profit function, the profit without pests and profit losses from pest presence can be isolated. The profit with no pests present is equal to the output produced without pests using other inputs given exogenous factors, $g_A(i; o)$, multiplied by the output price, p, minus the cost of using other inputs, c_i. The profit losses when pests are present is the output price, p, multiplied by the damage function, $h_A(x; o)$, plus the costs of using pesticides, c_x.

$$\pi = (pg_A(i;o) - c_i i) - ph_A(x;o) - c_x x = \pi_{No\ pests}(i;p,o) - \lambda_{pests}(x;p,o)$$

where

$\pi_{No\ pests}(i;p,o)$ is the profit with no pests

$\lambda_{pests}(x;p,o)$ are the profit losses when pests are present

The pest damage function can be broken into three parts: the pest damage coefficient, the kill function, and the number of pests. The pest damage coefficient is the damage (in output/pest) destroyed by the pest. The kill function measures the proportion of pests killed by pesticides. The kill function is a number between zero (no pests killed) and one (all pests killed), and it depends on the level of pesticides being used and exogenous factors. However, as constructed here, this kill function does not consider pest resistance. Pest resistance would decrease the magnitude of the kill function over time, and this would necessitate a multi-period model. A multi-period model could be used, as advocated by Quiggin and Chambers (2006), instead of a stochastic model like the one used here, but this is beyond the scope of this paper. By using this pest damage function, we get the following:

$$\pi = (pg_A(i;o) - c_i i) - p(\delta_A(o)N_A(o)[1 - k_A(x;o)]) - c_x x$$

where

$\delta_A(o)$ is the pest damage coefficient under technology A given o. $\delta_A(o) > 0$

$N_A(o)$ is the number of pests present under technology A given o. $N_A(o) \geq 0$

$k_A(x;o)$ is the "kill function"; the fraction of pests eliminated using pest management measures x under technology A given o. Note that $0 \leq k_A(x;o) \leq 1$ for all $x \geq 0$.

Now that the farmer's profit function has been fully disaggregated, parameters of the function that are known with certainty and those that are *not* known with certainty can be identified. Parameters p, c_i, and c_x are known with certainty which implies that the farmer has market certainty.

However, exogenous factors, o, and all parameters that depend on it are not known with certainty. This means that $g_A(i;o)$, $\delta_A(o)$, $N_A(o)$, and $k_A(x;o)$ are not known with certainty. From Hirschleifer (1973), the farmer experiences technological uncertainty. Because of the uncertainty in the exogenous factors and the parameters depending on it, the grower must solve the maximization problem in expectation:

$$\max_{i,x} E\{(pg_A(i;o) - c_i i) - p(\delta_A(o)N_A(o)[1 - k_A(x;o)]) - c_x x\}$$

where

$\max_{i,x} E\{\cdot\}$ means maximizing the expected value of $\cdot$

Because o affects g_A, k_A, N_A, and δ_A, decisions about the levels of i and x are affected by o. Growers obtain information about the exogenous factors, o, so that they can increase expected profits through their choices of i and x. Having a better estimate of o increases their expected profit.

The first order condition in solving the maximization problem with respect to x is

$$\frac{\partial E(\pi)}{\partial x} = p\delta_A(o)N_A(o)\frac{\partial k}{\partial x} - c_x = 0$$

This condition shows that the marginal benefit of implementing pest management practices is equal to the (marginal) cost of the pesticide. To check for a maximum, the second derivative is

$$\frac{\partial^2 E(\pi)}{\partial x^2} = p\delta_A(o)N_A(o)\frac{\partial^2 k}{\partial x^2} < 0$$

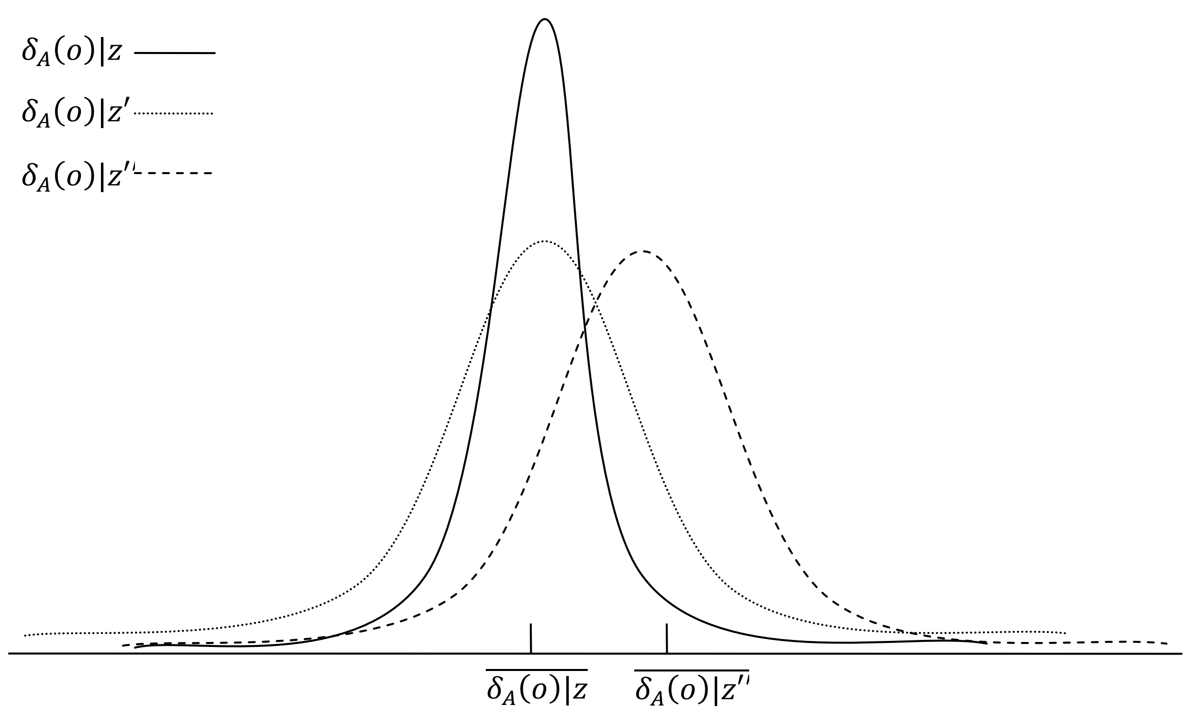
This condition is true if $\frac{\partial^2 k}{\partial x^2} < 0$ because p, $\delta_A(o)$, and $N_A(o)$ are assumed to be nonnegative. Intuitively, this would mean that the effectiveness of pesticides decreases as more and more pesticide is applied. This is very plausible and follows from typical assumptions that there are decreasing marginal returns to inputs.

Maximizing expected profits with respect to i follows from typical profit maximization.

2.4.1. Effect of exogenous factors, o, and information

Because exogenous factors, o, are uncertain, values that $g_A(i;o)$, $\delta_A(o)$, $N_A(o)$, and $k_A(x;o)$ take on can be represented by distributions dependent on o. For a given o, there is a value of each $g_A(i;o)$, $\delta_A(o)$, $N_A(o)$, and $k_A(x;o)$. $g_A(i;o)$ and $k_A(x;o)$ are special cases; to obtain their values for a given o, the values of i and x where expected profits are maximized with that given o must be incorporated. Ex ante, uncertainty about o can impact $g_A(i;o)$, $\delta_A(o)$, $N_A(o)$, and $k_A(x;o)$ in three ways. It can either change the mean value of each, it can alter the distribution of each, or it can do both. For a concrete example, we analyze the damage coefficient, $\delta_A(o)$:

Figure 2-1. Effect of Information on a Parameter Known without Certainty



z can be thought of in two ways. It is the information received about the unknown variables in o, or it can represent the level of uncertainty a grower has about unknown variables in o. The original distribution, $\delta_A(o)|z$, is represented by the solid black line. The dotted line distribution, $\delta_A(o)|z'$, represents a different z changing only the distribution, but preserving the mean. Both

$\delta_A(o)|z$ and $\delta_A(o)|z'$ represent a situation of imperfect information. Intuitively, the latter could represent a grower with the same information, but he/she has lower confidence in it. The dashed line distribution, $\delta_A(o)|z''$, represents a different z or new information changing the mean. This distribution is another representation of imperfect information. If the grower believes the true mean is $\overline{\delta_A(o)|z''}$, but in fact it is $\overline{\delta_A(o)|z}$, this can be thought of misinformation. In this case, the grower would over-apply pesticides because the believed marginal benefit would be higher than the real marginal benefit from application. If the grower had perfect information about o, then the distribution would be a vertical line on $\delta_A(o^*)$, where o^* is the true value of o. This case is not shown.

In the case where the grower is risk neutral, only expected value matters. When the grower is risk averse, then the change of distribution without a change in mean becomes important. This is because the variation in the damage creates disutility. Because profit is assumed to be a linear approximation for utility, it is assumed that the grower is risk neutral.

2.4.2. Value of information

Until this point, expected outcomes have been analyzed, not actual (realized, real) outcomes. New, better information will improve *expected* outcomes, but not necessarily *realized* outcomes. But, as discussed before, the actual value of the information is more important than the expected value of information.

Actual outcomes are more relevant and interesting than expected outcomes because growers will only use the Onion ipmPIPE website if they receive real or actual benefits. These real impacts affect the future use of the website; if growers do not experience any benefits from using the website in the first year or two, they will not continue to use it. These real benefits are the differences between realized outcomes when growers use information from the Onion ipmPIPE and realized outcomes *if* growers had not used the information. This difference is the counterfactual problem that can be solved using one of the methods discussed in the literature review.

For an individual, the realized value of information can be represented in the following equation:

$$Value\ of\ Information_i = y_i|z - y_i|nz$$

where

$y_i|z$ is an outcome of interest given information was used

$y_i|nz$ is an outcome of interest given information was not used

An aggregated value of information can be estimated by summing the value of information across farmers in the population. The average value of information could be estimated by dividing the aggregate value by the number of farmers in the population. This calculation assumes that using information, which on average should improve some outcomes of interest, has no market effects; prices remain constant. However, market effects can be considered by using a surplus framework. The effect of new, beneficial information would shift out the supply curve similar to a new technology.[9]

The actual outcomes of interest using this framework and given the way that onion pests affect onions are actual profits, π, yields, $f_A(x, i; o)$, revenue, $f_A(x, i; o)p$, pesticide use, x, pesticide costs, $c_x x$, pest populations, $N_A(o)$, and pest damage, $\delta_A(o)$. Collectively profits, yields, revenue, pesticide use, pesticide costs, pest populations, and pest damage will be referred to as outcomes of interest.

2.4.3. Choice of technology

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[9] See Alston, Norton, & Pardey (1995) for a detailed description of how to apply economic surplus to estimate the benefits from research.

The choice of technology, A, is important because it affects all of the parameters in our framework. The choice of technology also critically depends on the expected value of exogenous factors, o. In Livingston (2010), the type of irrigation used (type of technology) significantly impacted whether a farmer visited the Soybean ipmPIPE website. The choice of technology is made at the beginning of the season and so cannot be changed if new information about o comes about. Therefore, forecasting before the season and general information about climate and pests can greatly affect the outcomes of interest and, in turn, the value of information.

2.5. Methods Analysis

In this section, advantages and disadvantages of the Bayesian Decision Theoretic (BDT) approach, randomization, and non-randomized econometric methods are examined.[10] Furthermore, the possible and attempted applications of each method to the evaluation of the Onion ipmPIPE website are discussed.

2.5.1. Bayesian decision theoretic approach

One of the benefits of using the BDT approach is that it has relatively low data needs. Only three pieces of data are needed to complete an analysis of the value of information using the BDT approach: the expected outcomes of interest for each action-state pairing, prior probabilities, and joint probabilities. Outcomes of interest are typically elicited from the economic agents who may use the information, and joint probabilities are obtained from observing the actual states of nature occurring.

Obtaining prior probabilities are much more difficult (Eisgruber, 1978). One way to obtain the probabilities is to use historical data. This method was used by Nelson and Winter (1964) and

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[10] The net social benefit approach will not be discussed in detail because it does not apply to the information provided on the Onion ipmPIPE website during its first year, and it can be incorporated into the BDT approach.

Norton and Schuh (1980). However, when that is impossible, such as in valuing research, probabilities must be obtained directly from the economic agents, like in Shimmelpfennig and Norton (2003).

Another benefit of the BDT approach is that it is a structural model; it has a direct link with theory. Bayesian decision theory describes exactly how economic agents incorporate information into their decision making. However, this is also a drawback; economic agents may incorporate information in a completely different way. This assumption about how information is used is the reason for low data needs as well. The BDT method will not provide a correct estimate of the value of information if the decision maker does not integrate information via Bayes' theorem. Another disadvantage is that the BDT method does not specify how information becomes available (Roe & Antonovitz, 1985).

2.5.1.a. Onion ipmPIPE applicability. The BDT approach is not the most appropriate method for valuing the information on the Onion ipmPIPE website because the BDT model only looks at a single decision, but onion farmers make pest decisions continuously throughout the growing season. This means that the farmers' prior probabilities would need to be known each time (or at least for several of the times) they made a pest management decision without the Onion ipmPIPE information as well as their confidence level in the information provided by the Onion ipmPIPE. Aggregating these decisions into one aggregate decision would be too rough and destroy the link the BDT approach has with theory.

2.5.2. Randomization approach

Randomization has many positive aspects. First, as discussed in the literature review, randomization provides the strongest results compared to other evaluation methods. This is because it eliminates the selection bias inherent in measuring the impact of a shock with minimal assumptions (Duflo et al., 2008). Also, it does not make assumptions about how information is integrated into decision making, a major criticism of the BDT approach. Additionally, the required data is fairly low. In theory, only the average outcomes of interest are needed for the treated and control groups. Moreover, results are relatively easy to obtain because randomization eliminates the need to perform complicated statistical analyses.[11] Finally, using a randomization approach would be consistent with the conceptual framework discussed earlier.

Spillovers and enforcement problems discussed in the literature review are problems that may arise in any randomization study; these can be mitigated or eliminated through proper planning and implementation. Ethical, political, and resource constraints, however, cannot be eliminated as easily. Often, these determine the method used or even eliminate randomization as a potential method. Although the data and analysis requirements are low, the planning requirements are high. Before any treatment can be given, the randomization procedure must be thoroughly planned and correct. If the randomization is at the wrong level or does not account for spillovers or potential enforcement problems, then the randomization is unhelpful and only restricts people from receiving a potentially helpful treatment. Another negative is that randomization estimates only the improvement in outcomes and does not describe *how* information improved outcomes of interest.

In addition to these general advantages and disadvantages, each randomization method has its own advantages, disadvantages, and best uses. Full randomization is often best to implement when not all those interested in the receiving the treatment can get it because of logistical or resource constraints. In this case, full randomization is often referred to as oversubscription (Duflo et al., 2008). The drawbacks of this approach are the same as any randomization problem (ethical constraints, possible spillovers, etc.)

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[11] This is not true for all randomization techniques, but in theory, the difference between the outcomes of interest of those treated and those untreated is the treatment effect on the treated.

Randomized phase-in is popular because programs are often initiated in steps, for example one area at a time. Randomly determining what areas or groups receive the treatment can be an ethically sound way that will also yield more accurate estimates of a treatment or programs impacts. Non-compliance, too rapid phase-in, and difficulty in measuring long-run impacts are different areas of concern in this method. Non-compliance issues in a randomized phase-in design often arise when people are treated before they are supposed to be treated. To counter this, an intention to treat analysis can be used. The speed of the phase-in is important because if it is too rapid, then impacts cannot be detected. Finally, this method makes it difficult to estimate long-run impacts because eventually all individuals will receive the treatment (Duflo et al., 2008).

Within-group randomization is often used when the treatment is desired to be spread more evenly across a population than with the oversubscription or randomized phase-in design. However, this method is prone to enforcement and spillover problems because individuals receiving the treatment are close (geographically, socially, etc.) to those in the control group.

Lastly, the encouragement design is best to use when randomly assigning the actual treatment is impossible. This design automatically results in non-compliance because not all those receiving the encouragement will be treated and some of those not receiving the encouragement will be treated.

2.5.2.a. Onion ipmPIPE applicability. The unique aspect of using randomization to value information from the Onion ipmPIPE website is that the treatment is ***using*** or at least ***viewing*** the information found on the Onion ipmPIPE website. However, at best, only ***access*** to the website is randomized, not ***use*** of the information or website. So, any randomization design used with the Onion ipmPIPE must use the same analysis methods as used by the encouragement design because non-compliance exists. For example, if we fully randomized who had access to the website, we could not just look at the difference between those with access and those without. We would need to use instrumental variables to estimate the value of the information on the website.

In the case of the Onion ipmPIPE project, randomization could have been implemented. Randomizing at the level of the farmer provided the most advantages out of all levels at which to randomize because there would be few spillovers, and enforcement (actually using the information & not sharing it) would be difficult to ensure at any level. Also, the value of information at the individual level, not at the county, state, or other level, is the desired estimate. However, these other levels could be used.

Implementing a randomization design into the Onion ipmPIPE project was attempted, but two constraints kept it from being successfully implemented. Fundamentally, randomization proved impossible because of logistics. Principal among these logistical problems was that there was no comprehensive list of onion growers. Using 2007 United States Agricultural Census data, our list accounted for approximately 19% of the onion growers in the project states and 9% nationwide (United States Department of Agriculture-National Agricultural Statistics Service, 2009). Without a list of growers, we could not randomize treatment or encouragement. Also, restricting access (even with a list) would be difficult from an IT perspective because it requires more IT resources than are currently available. Those with access would need to register or be assigned a username and password so that those without access would not be able to use the website.

Secondly, it was politically infeasible. Although the director understood that randomization provided the strongest results, he did not want to restrict potential users from viewing the website. The director felt that doing so would deter them from using the website in the future. And now that the Onion ipmPIPE website is running, randomization by assigning groups that can and cannot access the website cannot be implemented because some onion farmers may have already viewed the website and use the information, biasing any randomization results.

However, the encouragement approach may still be implemented. This method could be used by sending randomly selected growers email alerts or regular email updates about new information on the Onion ipmPIPE. The instrumental variables approach could be used to estimate the value of the Onion ipmPIPE website with the email as an instrument. Unfortunately, the results would only be relevant for the growers on the incomplete list because the same logistical constraint of not having a representative list is present. Randomization for all onion growers is not possible unless a more comprehensive list of onion growers is obtained.

2.5.3. Non-randomized econometric approaches

A non-randomized econometric approach has the advantage that many, well-developed methods exist to estimate the impact of a shock. In addition to those discussed in the literature review, propensity score matching, difference in difference, and others are available to estimate the impact of a shock. Furthermore, these approaches, including instrumental variables (IV) approach and the Heckman two-step or Heckit procedure, are versatile; they can be modified to meet the challenges of specific evaluation problems and data sets. Non-randomized econometric methods avoid strict assumptions about how information is integrated into decisions (Roe & Antonovitz, 1985). Also, like randomization, non-randomized econometric methods can be used to analyze actual outcomes not expected outcomes, which shows the actual impact, not a theoretical or potential impact.

Unlike randomization, however, non-randomized econometric models rely on statistical assumptions about the data. If these assumptions are incorrect, then the analysis using econometric methods will be biased. This is because the assumptions that assured the elimination of the selection bias do not hold, so the selection bias may still be present. Another drawback is that non-randomized econometric methods tend to have high data requirements. Data on several regressors are needed to control for selection bias in addition to the outcomes of interest.

2.5.3.a Onion ipmPIPE applicability. After randomization became difficult, a set of questions was developed for an online survey to collect data sufficient for econometric analysis. Unfortunately, the first several iterations were lengthy and exceeded the capacity of the software. After shortening the survey, it was still too long for an online survey to provide an adequate response rate, and it would have to be sent to the growers on the inadequate onion grower list discussed above.

The United States Department of Agriculture – National Agricultural Statistics Service (USDA-NASS) state office in Colorado was contacted and their assistance was enlisted to obtain a more complete random sample of growers. They recommended shortening the survey further to reduce costs and raise the response rate. In addition to having a more comprehensive onion grower list, they would be able to access the onion grower lists in other project states. Moreover, they could guarantee a minimum response rate by following up with growers that did not initially respond to the mail survey. They could not share the grower list, but could send out the survey to the growers.

For the Onion ipmPIPE, the non-randomized econometric approach appears to provide the most advantages and be the most logistically feasible because the USDA-NASS can be utilized to obtain the required data and observations from a large random population of onion growers. The IV approach is appropriate if outcomes of interest can be obtained for both website users and non-users. Profits, yields, and pesticide costs are outcomes of interest that could be obtained from those that used the website and those that did not use the website. However, if outcomes of interest cannot be collected for both users and non-users, then the Heckman two-step or Heckit procedure may be the preferred approach. An example of an outcome of interest that could only be gathered from website users would be a binary variable of management change. The binary variable would be one if the grower's management practices changed from obtaining information from the website and 0 if their practices did not change. The next section shows the IV two stage least squares model that can be used to estimate the value of the Onion ipmPIPE.

2.5.3.b. Applying the IV approach. In applying the instrumental variables approach to the Onion ipmPIPE evaluation, y_i is one of the outcomes of interest discussed in the conceptual framework section; $\boldsymbol{x_i}$ are variables upon which the outcome of interest depends; T_i is a binary variable that is 1 if the onion grower used the Onion ipmPIPE website and 0 if the onion grower did not use the website; and, $\boldsymbol{w_i}$ are the variables upon which website use depends. Because of survey length restrictions, pesticide use, pest populations, and pest damage outcomes cannot be determined at the farm level.

The difficulty in applying instrumental variables to the Onion ipmPIPE is in determining elements to include in $\boldsymbol{x_i}$ and $\boldsymbol{w_i}$, factors that affect the outcome and factors that affect website use. Livingston (2010) analyzed the determinants of beliefs that a grower would experience an economically damaging soybean rust (fungus new to the United States) outbreak, the determinants of fungicide use, the determinants of the Soybean ipmPIPE website visitation, and the impact of the Soybean ipmPIPE on fungicide management changes. He found that website use depends on operator education, farm sales, farm debt-to-asset ratio, and the beliefs the grower had about the likelihood of experiencing a rust outbreak. Age and spouse's primary occupation were found to be not significant. He then found that fungicide use depends on age, farm sales, whether the grower had federal crop insurance or not, the location of the field, and if the county the grower was in experienced a soybean rust outbreak. Lastly, he found that use of the Soybean ipmPIPE changed growers' fungicide management decisions (Livingston, 2010).

For the Onion ipmPIPE, similar variables can be tested, but there will be survey limitations. Livingston (2010) was able to add questions to and used data from the USDA ARMS questionnaire, which is sent to thousands of soybean producers. However, the Onion ipmPIPE project does not have this luxury. Onion growers do not have this regular, comprehensive survey, nor are there as many onion growers.

To minimize surveying problems, the USDA-NASS's surveying services will be utilized to send out a survey to their lists of onion growers in each of the seven states involved with the Onion ipmPIPE project. The USDA-NASS survey will have a guaranteed response rate higher than one we could have sent out online because it is mailed with follow-up phone calls instead of being emailed. Second, the USDA-NASS has a comprehensive list of onion growers, which solves the problem of not having a large or random list of onion growers. However, farmers still may not respond, so it is important to keep the survey short.

With respect to the variables that may affect website visitation and outcomes, detailed questions, such as "What is your debt-to-asset ratio?" cannot be asked. But, simple, critical questions about total onion sales, total pesticide costs, and the education level of the grower can be asked in a short questionnaire. The following are suggested equations to use in the two stage least squares IV framework applied to the Onion ipmPIPE.

In the first stage, the website use variable is regressed against the exogenous variables in the impact equation and the instrument, int_i. This is represented in the following equation:

$$t_i = \gamma_0 + int_i\gamma_1 + age_i\gamma_2 + edu_i\gamma_3 + rev_i\gamma_4 + likely_i\gamma_5 + rain_i\gamma_6 + loc_i\gamma_{7-12} + ac_i\gamma_{13} + temp_i\gamma_{14} + pest_i\gamma_{15} + yld_i\gamma_{16} + irr_i\gamma_{17} + var_i\gamma_{18} + cost_i\gamma_{19} + \varepsilon_i$$

where

t_i = 1 if the grower used the website and = 0 if the farmer did not use the website

int_i = internet access variable (1 = highspeed, 0 = otherwise)

age_i = age of the grower

edu_i = number of years of education the grower has gone through

rev_i = onion revenue made by the farmer during the most recent season

$likely_i$ = grower believed that he would have an economically significant pest problem

$rain_i$ = rainfall variable (e.g. average rainfall per day over entire season , total rainfall for particular months, deviations from mean, positive deviations from mean, deviations/average during particular part of season, total amount of rain received over entire season)

loc_i = state located in (6 dummy variables – NY, MI, UT, CO, ID, WA. If all 0, then location is NM)

ac_i = number of acres grown by grower

$temp_i$ = temperature variable (e.g. mean temp per month over entire season, variance, deviations from mean, positive deviations from mean, deviations/mean during particular part of season, grower degree days)

$pest_i$ = pest pressure variable (e.g. pests per plant or field by state, pests per plant or field by section of a state, grower evaluation of pest pressure (i.e. grower ranking of pressure))

yld_i = yield variable (e.g. average yield, most recent yield, usual yield)

irr_i = irrigation dummy (type of irrigation used)

var_i = variety dummy

$cost_i$ = pesticide costs

To complete the first step, the predicted values of the probability estimate from the selection equation above. These predicted values are denoted as θ_i. These are used in the second stage.

Before moving to the second stage, however, the instrument should be discussed. The instrument being used in the selection equation is int_i. Its use implies that access to high-speed internet affects use of the Onion ipmPIPE website, but it is independent of profit. Most likely, more growers with high-speed internet access will use the website more than those without high-speed internet access because it takes less time for them to check the website and because they are perhaps more technologically savvy. However, the high-speed internet access is independent of profits because the type of access available to growers cannot be selected by the grower, but is decided by another entity (government, private company, others).

In the second stage, the outcome of interest is regressed on exogenous regressors and the predicted values, θ_i. This is seen in the impact equation below:

$$\pi_i = \beta_0 + \theta_i\beta_1 + age_i\beta_2 + edu_i\beta_3 + rev_i\beta_4 + likely_i\beta_5 + rain_i\beta_6 + loc_i\beta_{7-12} + ac_i\beta_{13} + temp_i\beta_{14} + pest_i\beta_{15} + yld_i\beta_{16} + irr_i\beta_{17} + var_i\beta_{18} + cost_i\beta_{19} + u_i$$

where

π_i = outcome of interest by grower (profit, yield, revenue, or pesticide costs).

The impact of the website then is the coefficient on the predicted values, β_1. In fact, this represents the local average treatment effect discussed in the literature review because the instrument is a binary variable. Therefore, the interpretation of the value of β_1 is as the impact of the website for those induced to use the website because they have high-speed internet access.

The Livingston equations give some idea about what to add for demographic information (age, education, infestation belief, location). The other variables originate from the conceptual framework and discussion with an onion expert. Revenue, rain, acreage, temperature, pest pressure, yield, and irrigation method either play an important part in pest management or are directly affected by pests.[12]

2.6. Conclusions

Methodological, statistical, logistical, political, resource, and ethical constraints are real and should not to be set aside for cursory discussion or left as a side note. Methodological and statistical constraints are often discussed when an author uses a method, and these constraints and their solutions are subjects of many articles and books in the economics literature. Other constraints, such as data collection issues, political impasses, ethical dilemmas, and project execution problems, are

[12] Using similar variables as those used in Livingston (2010) will also determine if the same variables are as important to basic grain farmers as vegetable farmers.

less often discussed. However, these "other" constraints may often be more restrictive than the methodological or statistical constraints. There are several methods available to measure the value of the Onion ipmPIPE in a situation where these "other" constraints do not exist. However, fewer methods are viable when political and logistical constraints are present, and even these methods must still overcome significant challenges. *All* constraints are important and must be considered when performing an evaluation and determining the most appropriate method to use.

In the case of the Onion ipmPIPE evaluation, several methods could be used and would be methodologically valid. The Bayesian Decision Theoretic is the structural model that could be used, but would not accurately describe the pest decision process faced by onion growers. Therefore, it might inaccurately estimate the value of information provided by the Onion ipmPIPE. This method was not chosen because of methodological constraints. Although, randomizing access to the Onion ipmPIPE website would provide strong estimates of the value of information, it proved politically and logistically infeasible. Non-randomized econometric approaches provide the most methodologically and logistically sound options. In particular, the instrumental variable approach appears to be the most advantageous. This method provides insight into important factors affecting website use, in addition to estimating the website's value because it estimates website use and website impact separately.

However, the selection and impact equations discussed in the previous section are developed ex ante. The variables in these equations may change in performing the evaluation in (2013) and significant variables have yet to be determined. A variable currently in the equation may be insignificant, or another variable not currently in an equation may be important. These issues cannot be worked out prior to having the data. Once the data is obtained, these initial regression equations can be run, and after that other variables may be added or taken out. Also, high-speed internet access is being used as the instrument, but this may not be an appropriate instrument. If it is not, then another instrument must be used. Future research into the appropriateness of high-speed internet access as an instrument should be done.

Obtaining a more comprehensive onion grower list is another avenue of work that should be further explored. The current solution is to avoid it by using the USDA-NASS surveying service to send-out a survey to their list of onion growers. However, researchers cannot directly access their list of growers. If a list of onion growers can be created or found, randomization can be incorporated into the evaluation via an encouragement design to obtain a better instrument for the instrumental variable approach. Furthermore, this would provide an example for researchers on other projects and other crops to follow in trying to evaluate their projects.

Another area for future research is to improve current surveying methods and determine other methods to obtain primary data in the United States. People living in the United States are inundated with junk mail, both electronic and physical, many requesting some sort of feedback. A survey for academic purposes via postage mail may obtain a better response rate than via email, but it is also more expensive. Using either mailing method, the survey may get lumped into this "junk mail" category. Telephone surveys are an alternative to mail surveys but are very costly. Door-to-door surveys across the U.S. are impractical for any single project. Alternatives to these traditional surveying methods should be developed, and techniques to increase the response rate of these traditional methods should be researched more thoroughly.

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Chapter 3: Identifying Women's Crops and Agricultural Technologies

3.1. Abstract

Donors, governments and others are becoming more interested in determining how benefits from agricultural research accrue to women. We develop a three step framework to identify women's crops and technologies. In step one, total potential benefits from research are estimated; step two allocates those benefits between men and women; step three, incorporates technology-specific parameters to refine the estimates of potential benefits. We apply this framework to Honduras and find that steps one and two provide the most information on the magnitude and distribution of benefits, but that refinements in step three can affect rankings of research program impacts on women.

3.2. Introduction

Women disproportionately make up the poor in developing countries, and they make up a large proportion of poor farmers (Doss, 2001). Women produce on their own farms, and assume roles as laborers, processors, transporters, traders and entrepreneurs. They produce food for the family and undertake many household chores. Women, however, are at a disadvantage compared to males. They have fewer assets; higher demands on their time; less secure property rights; and less access to markets, extension, and new technology than men (Quisumbing & Pandolfelli, 2010).

Agricultural research is intended to raise productivity, increase food supply, and improve incomes and food security. Evidence, however, indicates that the flow of benefits to women is low relative to their roles in agriculture (Quisumbing & Pandolfelli, 2010). Donors, governments and others have become increasingly interested in using agricultural research as a vehicle to improve the lives of women and other disadvantaged groups (Byerlee, 2000). The literature shows substantial evidence of development spillovers from improved food production by, and incomes of, women. These include food security, better educational outcomes for children, and others (FAO, 2011). Re-orienting research programs so that more benefits flow to women is becoming increasingly important.[13]

A first step in designing an agricultural research program to benefit women is to identify "women's crops", but the notion of what constitutes a women's crop is vague and fraught with difficulties. For example, one might consider women's crops to be those where women predominate in production (such as home gardens and food crops in Africa). Alternatively, one might focus on crops where women constitute the largest share of laborers, such as protected agriculture in Central America. Another focus might be those crops that constitute the largest share of women's consumption or provide the most nutritional benefits to women and children—high-energy staple crops, for example. Each of these considerations would lead to different research priorities and different information needs to prioritize the research.

This paper provides a framework for identifying women's crops, women's technologies, and how agricultural research can be designed to impact women. We discuss agricultural research and how benefits flow to women and others. We explore and analyze indicators of impact and show how different indicators are appropriate for different program objectives. We apply the framework to data from Honduras, a country where broad-based agricultural growth is needed to reduce rural poverty, particularly among women and children. We find substantial differences in research priorities depending on available data and research manager goals.

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[13] A quick visit to the World Bank, USAID and CGIAR web-sites shows the prominence of development programs focused on women and agricultural research is no exception.

The paper has six sections including this introduction. The following section describes the benefits of agricultural research and how these benefits flow to population sub-groups. The third section develops a conceptual framework for understanding and measuring impacts of agricultural research on population sub-groups, and the fourth section applies it to women. The fifth describes application of the model to Honduras, and the sixth discusses results.

3.3. Benefits and Impacts of Agricultural Research

Agricultural growth is an important means of improving welfare, reducing poverty, and benefitting society. At its core, this growth depends on technical innovation. Research, through technical change, lowers the unit cost of agricultural production, creating direct, indirect, and induced impacts on different population groups (de Janvry & Sadoulet, 2002). Direct impacts accrue to farmers who adopt the technology. These impacts include increased production for home consumption, higher sales, lower production costs, and higher incomes. Indirect effects flow through markets and create impacts through lower sales prices (a negative effect, especially for non-adopting producers), lower prices for consumers, and employment and wage increases. Indirect effects also include backward linkages between agriculture and the rest of the economy; increased input purchases can stimulate output in other sectors. Induced effects are economy-wide and result from overall growth in agricultural productivity.

Because impacts accrue to population sub-groups differently, it is important to determine their size and distribution. Agricultural research managers often have multiple objectives and are forced to trade off efficiency (which research program has the largest aggregate impact?) with equity concerns (how benefits affect population subgroups). If efficiency is the sole objective, the research manager should allocate resources so as to maximize the expected sum of net benefits. While information requirements for such an allocation are not trivial, accommodating multiple objectives complicates things.

Alston, Norton, and Pardey (1995) note that agricultural research is a "blunt instrument" for redistribution and recommend non-efficiency social objectives be attained through alternative policies where possible, while research should be used primarily to maximize efficiency gains. Renkow (2000) supports this notion and suggests agricultural productivity-enhancing investments in marginal areas are more costly than those in more favorable areas, noting that alternative investments such as education and infrastructure may benefit the poor in marginal areas more than research.

Despite these arguments, there is increasing pressure to tailor agricultural research to benefit specific populations (Byerlee, 2000), in part because alternative means for meeting distributional objectives may not be feasible, politically or practically. The question now is not **whether** to target agricultural research to population sub-groups, but rather **how** to target them. To answer this question, we must first determine how and under what conditions research benefits accrue to different groups. The challenge is to disaggregate expected changes in impacts to alternative groups as the agricultural research portfolio changes.

Many authors have examined the distribution of agricultural research benefits ex-post, or after the research occurred. Scobie and Posada (1978) found surprisingly that research benefits from a technology adopted mainly by large farms accrued mostly to the poorest households. The distribution of producer benefits was determined by who adopted the technology, where non-adopting producers lost from sales price declines, but consumers benefited from that decline. Alwang and Siegel (2003) provided a simple, ex-post model to disaggregate effects of agricultural research on farmers. They applied it to maize research in Malawi. However, because that model only takes into account impacts on farmers, it ignores many of the indirect effects of technologies and these effects can be substantial. Like Scobie and Posada (1978), the distribution of benefits depends on rates of adoption.

Moyo, Norton, Alwang, Rhinehart, and Deom (2007) modified the Alwang and Siegel model to predict, ex ante, the impacts of agricultural research on the poor. Their model takes into account direct and indirect effects, and predicts poverty changes based on expected adoption of disease-resistant peanut varieties. Because adoption of the new variety varies by household income, wealth, farm size, etc., the direct effects of technical innovation are unevenly distributed. Again, the key parameter affecting the incidence of the direct effect is the household-specific probability of adoption. The distribution of indirect effects is affected by the share of household expenditures going to peanuts, which also depends on income and wealth. The paper presents a simple method for disaggregating market-level effects among households of different types, but data requirements are substantial—a detailed household survey is needed and proxies predicting expected adoption must be identified.

3.3.1. Agricultural research and women

Women's roles in agriculture are diverse, and agricultural research can impact them in many ways. It is important to disentangle these roles in order to understand how research will affect women. For example if research is targeted toward crops where women predominate in production, the direct impacts might disproportionately flow to them. Such targeting can have the additional effect of empowering women by focusing development resources directly on their needs.[14]

Social, cultural, or economic conditions might prevent women from accruing research benefits even when the research is targeted toward crops they produce. Because they have less access to extension and credit than men and frequently lack secure property rights, adoption of new

[14] For examples of non-agricultural programs targeting women, see Ashraf, Karlan, & Yin (2010), Janssens (2010), and Handa, Peterman, Davis, & Stampini (2010).

technologies by women may lag behind men, even if the research is focused on women's crops (Quisumbing & Pandolfelli, 2010). An example of this effect was found by von Braun, Puetz, and Webb (1989) in an analysis of rice irrigation in the Gambia. The new irrigation project was implemented as a means of increasing "...women's role in crop production" (von Braun et al., 1989, p. 105). However, as rice yields increased and the crop became more profitable, men took over the most productive rice-growing areas and women benefited far less than expected.

Women frequently produce food for home consumption and perform activities outside of the home such as marketing and working as wage laborers (World Bank, 2009). Thus, many indirect benefits of research can flow to them. Indirect effects may be especially beneficial to women because research-driven declines in prices of major food commodities (an indirect effect) increase real income. Where women are responsible for food purchases, this increased real income flows directly to them; a consensus has formed in the development literature that incomes controlled by women are more likely to be spent on food and child-focused expenditures (FAO, 2011). Consumer surplus-related benefits would be especially difficult for men to expropriate.

3.3.2. Measuring research benefits to women

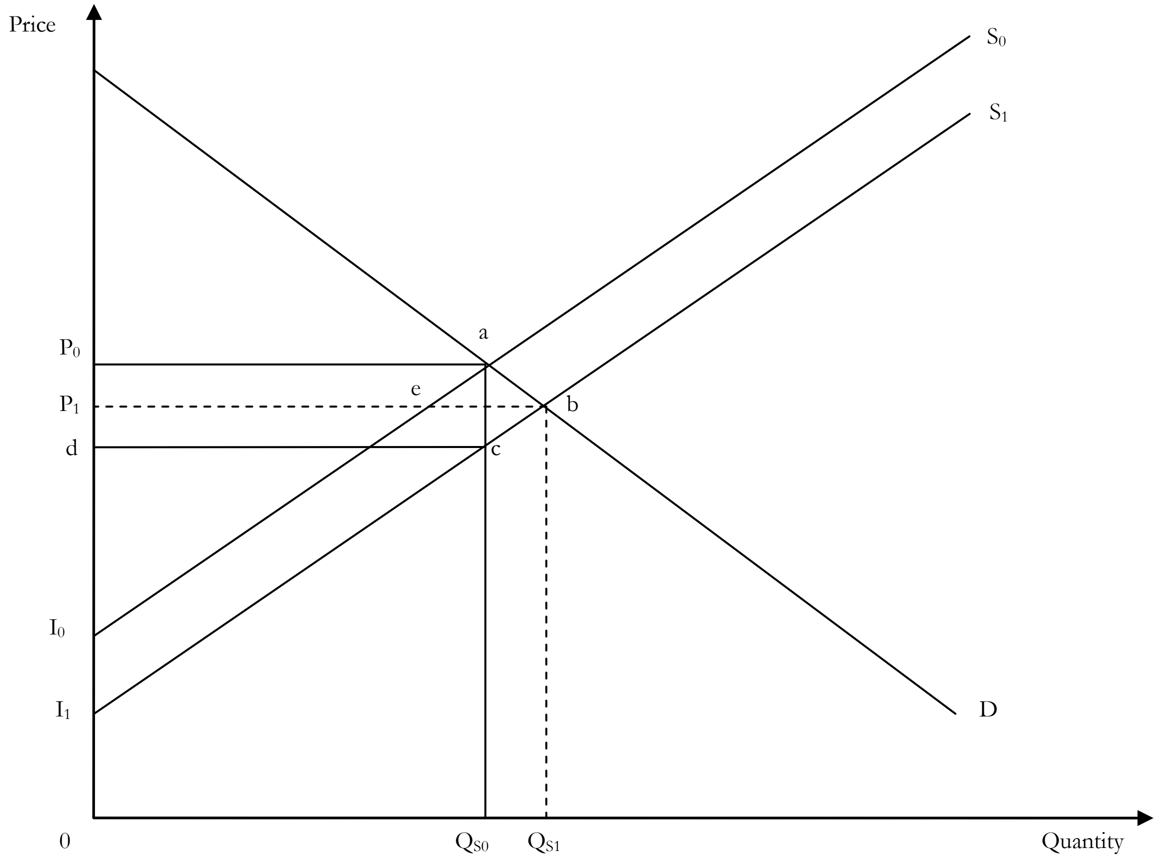
No known studies have analyzed both direct and indirect impacts of agricultural research on women. However, recent studies have begun to investigate some of the parameters affecting the incidence of research benefits to women. Doss and Morris (2001) found that the female-headed households adopted fewer modern maize varieties and chemical fertilizer in Ghana than male-headed households. They also found that less access by women to resources was the cause. Lilja and Sanders (1998) analyzed direct income changes from a generic technological change resulting in more acres of cotton being planted in southern Mali. They found that returns on women's labor were greater on private cotton fields and suggested that increased female access to productive resources will positively impact incomes because these resources would be used on private plots.

The challenge in measuring benefits accruing to women is in determining what to measure and how to measure it. Most agricultural statistics are not associated with a gender, but rather a household or field. Intra-household factors may mask how benefits are distributed to women.

3.4. Conceptual Framework

Our method for disaggregating changes in potential benefits from the introduction of a new technology uses existing and easily obtained data to apportion the shares of benefits accruing to women and men. This 'rough cut' method has several advantages over previous ex-ante methods by capturing indirect effects ignored by other studies like equilibrium changes in price and quantity (Alwang & Siegel, 2003). For those wishing to use this method to guide policy decisions, it enjoys the added benefits of being easily adaptable to a number of policy objectives beyond gender targeting and of being widely accessible due to its relative technical simplicity and flexibility. We present the overall framework and then discuss its application to women.

Figure 3-1. Adoption of a New Agricultural Technology: Economic Surplus Approach



When a new agricultural technology is introduced and adopted, effects are felt at the household and market levels. In general, as a new technology is adopted, unit costs of production fall and direct effects are realized.[15] As market supply shifts outward, indirect and induced effects occur. The direct and indirect effects are best reflected in a partial-equilibrium economic model. In Figure 3-1, technology adoption leads to a lower unit cost of production and a right-ward shift in the market supply curve (from S_0 to S_1). As the supply shifts outward, equilibrium quantity increases and equilibrium price decreases.[16] The total change in economic surplus is I_0abI_1. The gross change in

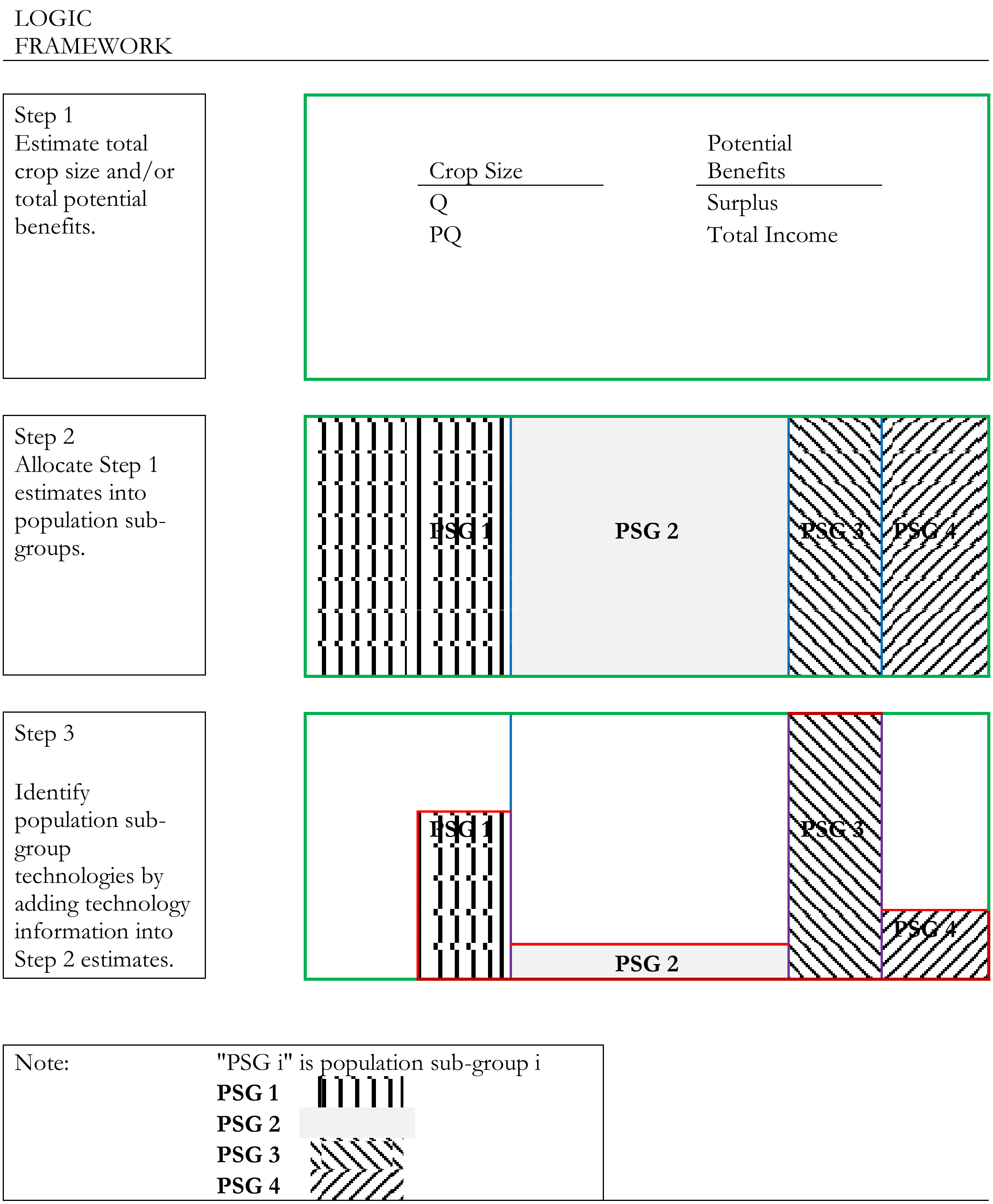
[15] The proportional reduction in unit cost of production is known in the literature as the "k-shift".
[16] Assuming demand is less than perfectly elastic. A perfectly elastic demand is consistent with a small, open economy – quantities produced do not affect equilibrium prices.

consumer surplus is the area P_0abP_1. The net producer surplus change is the area $P_1bI_1 - P_0aI_0$. When there is a parallel supply shift, this difference is equal to the area P_1bcd (Alston et al., 1995). The trick is apportioning these surplus changes to specific population sub-groups.

A surplus-based approach has the advantage of representing direct and indirect effects in a theoretically consistent manner. It shows the importance of the "size" of the crop and the technology. Furthermore, its straightforward, relatively simple calculations make it a useful method for prioritizing agricultural research in developing countries.

Determining the research mix that will benefit a given population sub-group most is done in three broad steps. First, identify the "size" of each crop and magnitude of potential benefits from research applied to that crop. In the surplus approach these are the initial PQ and total surplus, respectively, found in Figure 3-1. Second, determine how these potential benefits are distributed among the population sub-groups. Third, identify potential impacts of new technologies on each crop and each population sub-group, which involves determining the size of the shift in Figure 3-1. At the end of each step, the crops and crop-technology pairings with the largest impacts on women are deemed "women's crops" or "women's technologies." Steps one & two are repeated for *each crop* of interest, and step three is repeated for each crop *and technology* of interest. Figure 3-2 illustrates these steps for a given crop and technology in a logic framework.

Figure 3-2. Identifying Population Sub-group Crops and Technologies Logic Framework



In step one, the overall importance of each crop is estimated. The size of the crop can be determined in a number of ways: number of people growing it, quantity sold, quantity consumed, value of consumption, total earnings by laborers, total economic surplus associated with it, or another relevant measure. These indicators provide a rough idea of potential benefits from introducing a new technology. In Figure 3-2, the large box next to step one represents a crop's size or potential benefits from research devoted to it. In equation form, step one estimates the following for each crop,

$$Crop\ j's\ Size = Q_j$$

Or

$$Potential\ Benefits\ from\ crop\ j = PB_j$$

where Q_j is a measure of the size of the crop.

In the second step, we allocate these potential benefits and the size of the crop to population sub-groups. The challenge is two-fold. First, most agricultural statistics are collected at the household level, but often population sub-groups are represented at the intra-household level. This means that intra-household distributions of benefits are important, but often unknown. Therefore, assumptions must be made about how benefits are distributed within households. The second challenge is in deciding the appropriate population sub-group-specific indicator. Prior information about the area and population sub-group provides an idea of the best indicators to use and possible intra-household distributions. We later illustrate how these challenges apply to women. The initial box, in Figure 3-2, is now divided into four smaller boxes representing the allocation of the initial overall benefit and crop size to four population sub-groups. To give concreteness to this logic framework, these four population sub-groups can be thought of as households divided into income quartiles.

In equation form, step two estimates the following for each crop,

$$Population\ sub-group\ i's\ (PSG\ i's)\ share\ of\ crop\ j's\ size = s^i Q_j$$

Or

$$Potential\ Benefits\ from\ crop\ j\ accruing\ to\ PSG\ i = s^i * PB_j$$

where s^i is a measure of the share of benefits accruing to or crop size contributed by population sub-group i. This measure introduces differences between population sub-groups. Step 1 assumes that everyone shares equally in the benefits, but in step 2 we examine this assumption. A population sub-group's share establishes how much of the benefits flow to that sub-group. Certain shares are important because they can be readily obtained from secondary data, such as the share of female-headed households consuming a crop & the share of women in households producing a crop. The choice of share is important, and it will be discussed later in its application to women.

The third step refines our concept of potential benefits by incorporating information about specific technologies under research or that could be researched. These benefits are best understood in an economic surplus analysis framework. To better organize this step we break it into two mini-steps. The first, step 3a, is accomplished by incorporating specific technology characteristics, ignoring differences between them by population sub-groups. Technology characteristics include the costs of research, probability of success, yield changes, input cost changes, and adoption rate. These parameters affect the size of the supply shift in Figure 3-1.

In equation form, step 3a estimates the following for each crop,

$$Potential\ Benefits\ from\ crop\ j\ accruing\ to\ PSG\ i\ from\ introducing\ technology\ r = s^i * PB_j^r$$

The second mini-step, step 3b, incorporates differences in technology characteristics for the same crop by population sub-group. Some technology characteristics differ by population sub-group, affecting the distribution of benefits. A good means of incorporating population sub-group-specific information is through the adoption rate. Costs of research and probability of success are unrelated to population sub-group, and yield and input cost changes often do not differ by population sub-group. The adoption rate is most likely to vary, and we need information on differences in likely adoption by population sub-group.

In step 3b, we estimate for each crop and technology,

$$Potential\ Benefits\ from\ crop\ j\ accruing\ to\ PSG\ i\ from\ introducing\ technology\ r = s^{ir} * PB_j^r$$

In Figure 3-2, introducing technology and population sub-group characteristics alters the distribution and size of potential benefits. In the example, benefits to population sub-groups 1, 2, and 4 decrease compared to their step two estimates. Benefits accruing to population sub-group 3, however, are unaffected by technological and population sub-group refinements. The most dramatic decline in estimated benefits affects population sub-group 2. Continuing the quartile example, the decrease in benefits received by quartile 2 could be the result of a large contribution to overall production of the commodity (large size in step 2), but a very low rate of adoption of the technology for the population sub-group (a smaller share in step 3). In the surplus example, technology-specific parameters and population sub-group-specific adoption will impact both the size of the surplus change and the accrual of surplus changes to population sub-groups.

The chokepoints to measurement in step three are in introducing adoption rates for population sub-groups.[17] These are difficult to obtain because they are affected by different levels of credit access, input ownership, budget control, and other factors. However, adoption rates specific

[17] The size of the k-shift will be affected by total adoption.

to population sub-groups are important because adoption affects the size of the change in producer surplus, which is then accrued by population sub-groups. To introduce these adoption rates, primary data must be collected, estimates from other studies can be transferred to the current crop, or they can be estimated from adoption signals using secondary data. For example Moyo, et al. estimate household-specific adoption rates of hybrid maize and use the estimated adoption propensities to reflect the propensity to adopt the improved peanut variety.

3.5. Applying the Framework to Women

The framework can be applied either ex-ante, to set priorities with respect to agricultural research, or ex-post, to examine impacts of past agricultural research on women. Our application will be ex-ante and requires us to estimate or predict key parameters.

In applying the conceptual framework to women, it is important to note the relative impact of the three steps on identifying "women's crops & technologies." We believe that steps one, two, and 3a are more important than step 3b. From step one, we obtain estimates of overall crop size and potential benefits; these are the biggest determinants of a crop's importance. In steps 2 and 3a, these potential benefits are allocated to population sub-groups and made more realistic with better information about technology options, respectively. Step 3b is a refinement that helps better measure benefits women receive, and if significant barriers to adoption are present, these need to be understood.

The discussion of women's role in agriculture suggests several plausible indicators of the degree to which any crop can be considered a "women's crop". These indicators involve both the choice of Q or PB and s^i. The suitability of these alternative indicators depends on policy goals. For example, if policy makers are interested in focusing on women's empowerment, they may maximize the expected direct effect on women and target crops that women are known to produce or focus on technologies that women are most likely to adopt. Alternatively, if policy makers are interested in increasing incomes accruing to women, they should focus on women's shares of the three effects and the overall size of the effects. For reasons noted above, consumer surplus-related gains to women have benefits in addition to their pure transfer effects; policy makers may choose to place more weight on these gains.

In general, policy goals will point to analyzing one or more of the three effects (direct, indirect, and induced) discussed earlier. Table 1 organizes indicators of crop size and potential benefits into the three effects, in addition to the three steps.

Table 3-1. Alternative Indicators of Crop Size and Potential Benefits by Effect and Step

Effects	**Step 1**	**Step 2**
Direct	*Number (#) of growers	Number of female growers
	*Acres (ac)	$\frac{\#\, fem\ growers}{\#\, growers} * ac$
	*Tons produced (q prod)	$\frac{\#\, FHH}{\#\, hhs} * ac$
	*Tons sold (q sold)	$\sum_{i=1}^{n} \left(\frac{\#\, wom\ in\ hh\ i}{\#\, peo\ in\ hh\ i} * ac\ in\ hh\ i \right)$
	*Sales value (v sold)	$\frac{\#\, fem\ growers}{\#\, growers} * I_0 adI_1$
	PS (from surplus analysis)	$\frac{Tons\ sold\ by\ FHH}{Tons\ sold\ by\ hhs} * I_0 adI_1$
	I_0adI_1 (from surplus analysis)	$\frac{\sum(\#\, wom\ in\ hh\ i * ac\ in\ hh\ i)}{\sum(\#\, peo\ in\ hh\ i * ac\ in\ hh\ i)} * I_0 adI_1$
Indirect	*Number of households consuming	$\frac{\#\, fem\ consumers}{\#\, consumers} * val\ con$
	*Number of people (peo) working	$\frac{\#\, FHH\ consuming}{\#\, hhs\ consuming} * val\ con$
	*Quantity consumed (q con)	$\sum_{i=1}^{n} \left(\frac{\#\, fem\ in\ hh\ i}{\#\, peo\ in\ hh\ i} * val\ con\ by\ hh\ i \right)$
	*Value of consumption (v con)	$\frac{\#\, fem\ consumers}{\#\, consumers} * \Delta CS$
	*Hours Worked (h)	$\frac{q\ con\ by\ FHH}{q\ con\ by\ hhs} * \Delta CS$
	*Labor Income (LI) & ΔLI	$\sum_{i=1}^{n} \left(\frac{\#\, fem\ in\ hh\ i * q\ con\ in\ hh\ i}{\#\, peo\ in\ hh\ i * q\ con\ in\ hhi} \right) * \Delta CS$
	CS & ΔCS (from surplus analysis)	
Direct & Indirect	Total Income (TI) & ΔTI	$\frac{\#\, fem\ consumers}{\#\, consumers} * \Delta CS + \frac{\#\, fem\ growers}{\#\, growers} * \Delta PS$
	TS & ΔTS (from surplus analysis)	$\frac{\sum(\#\, wom\ in\ hh * ac\ in\ hh)}{\sum(\#\, peo\ in\ hh * ac\ in\ hh)} * \Delta PS$
	ΔPS (from surplus analysis)	
Direct, Indirect, & Induced	Use a Social Accounting Matrix (SAM) or Computable General Equilibrium (CGE)	

Table 3-1. Continued

Effects	Step 3a	Step 3b
Direct	$\frac{\# \, fem \, growers}{\# \, growers} * I_0 adI_1{}'$	$\frac{\# \, adptg \, female \, growers}{\# \, adptg \, growers} * I_0 adI_1{}'$
	$\frac{\# \, FHH}{\# \, hhs} * I_0 adI_1{}'$	$\frac{\# \, adptg \, FHH}{\# \, adptg \, hhs} * I_0 adI_1{}'$
	$\frac{\sum(\# \, wom \, in \, adptg \, hh)}{\sum(\# \, peo \, in \, adptg \, hh)} * I_0 adI_1{}'$	$\frac{\sum(\# \, adptg \, women \, in \, hh * ac \, in \, hh)}{\sum(\# \, adptg \, people \, in \, hh * ac \, in \, hh)} * I_0 adI_1{}'$
	$\frac{\sum(\# \, wom \, in \, adptg \, hh * ac \, in \, adptg \, hh)}{\sum(\# \, peo \, in \, adptg \, hh * ac \, in \, adptg \, hh)} * I_0 adI_1{}'$	
Indirect	$\frac{\# \, female \, consumers}{\# \, consumers} * \Delta CS'$	
	$\frac{q \, con \, by \, FHH}{q \, con \, by \, hhs} * \Delta CS'$	
	$\sum_{i=1}^{n} \left(\frac{\# \, fem \, in \, hh \, i * q \, con \, in \, hh \, i}{\# \, peo \, in \, hh \, i * q \, con \, in \, hhi} \right) * \Delta CS'$	
Direct & Indirect	$\frac{\# \, fem \, consumers}{\# \, consumers} * \Delta CS' + \frac{\# \, fem \, growers}{\# \, growers} * \Delta PS'$	$\frac{\# \, fem \, consumers}{\# \, consumers} * \Delta CS' + \Delta PS''$
	$\frac{\sum(\# \, wom \, in \, hh * ac \, in \, adptghh)}{\sum(\# \, peo \, in \, hh * ac \, in \, adptg \, hh)} * \Delta PS'$	$\Delta PS''$
Direct, Indirect, & Induced	Use a Social Accounting Matrix (SAM) or Computable General Equilibrium (CGE)	

Notes:
1. FHH is an abbreviation for Female-Headed Households
2. hhs is an abbreviation for households
3. PS, CS, and TS refer to Producer, Consumer, and Total Surplus respectively.
4. The "Δ" symbol is read as "change in".
5. "adptg" reads adopting
6. An asterisk in step one denotes that the indicator is a crop size indicator.
7. One apostrophe after a potential benefits indictor means that crop specific technology parameters were used. Two apostrophes after a potential benefits indicator means that gendered adoption has been integrated.
8. In steps one and two changes in surplus are from the introduction of a technology that is constant across all crops. This means that we assume a technology can be produced for each crop with identical proportional yield changes, input cost changes, probabilities of success, costs of research, and adoption rates & profiles the same for all crops.

3.5.1. Table 3-1

Table 3-1 provides some indicators of crop size and benefits from a technology. The rows of Table 1 are the effects or combination of effects discussed earlier, while the columns are the steps discussed earlier. Crop size indicators are denoted with an asterisk.

To use Table 3-1, the research manager must first set a goal. This goal is usually influenced by stakeholder needs, including those of the donor and the research organization. This decision will tell the research manager which effects to analyze and measure, and which indicators to use. For example, direct effects are most important for a policy maker with a goal of empowering women. Both direct and indirect effects are most important for a goal of transferring income to women, and the distribution of the effects between consumer and producer surplus might affect a woman's ability to retain control of the income. Consumer surplus accruing to women, for example, would be difficult for men to expropriate. Second, the research manager must decide whether to measure the impact on females, women, or female-headed households. This decision will rely on program objectives and available data; data by household head are readily available and few data sets contain information on intra-household distributions. This decision will determine what share to use in steps 2 and 3. Third, the manager must determine constraints related to the study of identifying women's crops. This decision is impacted by data availability and resource constraints such as time limits, skills, staffing availability and or monetary limitations. After these decisions have been made, the research manager chooses an indicator in the appropriate row and column and performs the calculations.

3.5.1.a. Information input. When identifying women's crops, there is a tradeoff between readily available and ideal data. Different indicators imply different data needs. As one moves across and through the steps in Table 3-1, the indicators become more accurate estimates of the true impact, but data and computational requirements increase. As one moves down the table, the indicators become more difficult to measure, as indirect and induced effects are harder to measure than direct effects.

3.5.1.b. Intra-household distributional assumptions. Use of the framework to identify impacts of agricultural research on women requires several assumptions as it is extremely difficult to look inside households. When the i index in equations for step 2 and 3 refers to household groups such as producers, poor families, or female-headed households, household data are sufficient (e.g. Moyo et al., 2007). When impacts on women are considered, care is needed in the analysis because it is difficult to predict intra-household effects and how technology adoption can change them.

One assumption is that of intra-household equity. If benefits accrue to household members identically, a survey of adopting and non-adopting households can be used to determine adoption rates, and demographic information can be used to apportion benefits to men and women. For example, the direct-effect income gain could be apportioned among men and women according to the percentage of men and women in adopting households; this gain is the third direct effect indicator under step 3a.

In an interesting article, Carr (2008) pits “theory” versus “practicality.” Using an example from Ghana, he shows that categorizing crop production into static male and female categories (practicality) will misidentify women’s crops. But, if the intra-household relationships between men, women, and the crops they produce are taken into account (theory), utilizing a more dynamic approach, women’s crops will be properly identified. Carr says that taking a “mainstream” or “practical” approach to gender analysis (like the one taken in this article) is inadequate; one must look inside the household to properly identify women’s crops.

However, this dichotomy of practical versus theoretical is too simple. Those using the practical approach are trying to implement the theoretical approach on a large scale with available data; they are not mutually opposed. Detailed data describing intra-household relationships would be ideal and should be used, but often they are unavailable, especially not at the national level. Therefore, instead of abandoning the pursuit of identifying women's crops and technologies because of a lack of ideal data, a next best alternative is to make assumptions about intra-household benefit distribution. Research managers must make assumptions about intra-household distributions (among other things) subject to the constraints they have. Alternative assumptions to intra-household equity can be used, but would require different calculations with additional complexity.

3.5.1.c. Estimating economic surplus. In steps one and two, for purposes of illustration, the proportional unit-cost decrease (the k-shift) will be assumed to be constant across all crops. This assumption means that a technology can be produced for each crop with identical proportional yield changes, input cost changes, probabilities of success, costs of research, and adoption rates & profiles. The only parameters that vary between steps one and two are the crop's size (initial price and quantity), market characteristics (elasticities of supply and demand), and women's shares.

When crops and technologies are introduced in steps 3a and 3b, the assumptions change. In step 3a specific technology characteristics are introduced into the surplus calculations. Three broad steps are required in an economic surplus analysis. The first is to determine the k-shift associated with the crop-specific technology. Second, adoption rates must be estimated; these rates depend on household/farm characteristics and technology attributes. The k-shift, combined with the adoption rate, determines the total rightward supply shift. Third, this information is combined with data and assumptions about the market, such as elasticities, quantity, price, size, and openness (Alston et al., 1995).

One way to predict the k-shift is to interview scientists and extension specialists (this is the most common practice; see Alston et al. (1995)). Adoption rates are frequently estimated in an ex-ante framework by interviewing extension agents or other knowledgeable sources; gender-specific adoption rates are more difficult to estimate. Three alternative estimates of adoption rates can be used, each of which can be found in Table 3-1: (i) proportion of females in adopting households, (ii) adoption rate of female-headed households, and (iii) adoption rate of females managing each crop. Adoption rate (i) is used in the third indicator in Table 3-1, step 3a. Adoption rate (ii) and (iii) are used in the second and first indicators in step 3b, respectively. Adoption rates (i) and (ii) require farm-household data on household headship and composition combined with crop production and signals of probability of technology uptake. The adoption rate (iii) requires data on control of crops or specific fields, which are difficult to come by and are usually only found in project-level data sets.[18] Demand elasticities may be found in many ways including borrowing from other studies, observing market characteristics, and estimating them directly (see Alston et al. (1995) for more details). By calculating these new surplus measures with specific technology parameters and crop-specific elasticities, the distribution of benefits accruing to women may change from step 2 to step 3a.

3.5.1.d. Non-surplus effects. To predict changes in labor demand, information on labor use by crop before and after adoption is needed. One possibility is to use experimental data on labor use (these data are needed to compute the k-shift) and assume that changes in labor use accrue proportionally to each gender according to the gender-specific share of labor used in the production of each crop. Detailed employment data or labor use by gender and crop are needed to implement such a procedure, and such data are rarely available from typical household surveys.

Changes in input demands will have a "ripple effect" into input markets with potential spillovers to the rest of the economy. To measure the potential benefits, the use of a Computable General Equilibrium model or a SAM is suggested. The information and computational

[18] See Moyo et al. (2007) for a propensity transfer index to estimate adoption by household that can be adjusted for gender of household head or for gender of individuals if data allows.

requirements for this level of analysis are high. If potential benefits are estimated using a CGE or SAM, shares (s^i) are still needed to apportion them.

3.6. Honduras Application

The method developed in this paper is applied to Honduras. One goal of this application is to determine how well the indicators provide information about gendered impacts of alternative research portfolios. Another objective is to highlight strengths and limitations of typically available data sets for purposes of measuring technology impacts. Based on these strengths and limitations, we make recommendations relative to data needs.

Honduras is among the poorest countries in the western hemisphere with a per capita GDP of $4,200 and 65% of the population under the poverty line in 2010 (CIA, 2011). Of those below the poverty line, 74% live in rural areas, and approximately 70% of the rural population is poor (IFAD, n.d.). Women in rural areas are particularly poor, especially household heads. Female-headed households receive 30% less income than male-headed households in hillside areas (IFAD, n.d.). Many women and particularly poor women in rural Honduras are engaged in agriculture, either as producers or laborers. Agricultural research thus presents a good avenue to help poor women (IFAD, n.d.).

Most agricultural research is conducted by the Honduran Foundation of Agricultural Research (FHIA), and an important goal of FHIA is to produce technologies that are accessible to and benefit poor producers (FHIA, n.d.). FHIA receives funding from the U.S. Agency for International Development (USAID), and research performed in Honduras by the Integrated Pest Management Collaborative Research Support Program (IPM CRSP) is conducted in collaboration with FHIA scientists. Both USAID and IPM CRSP have explicit gender goals, and their projects must consider their effects on women (OIRED, 2010; USAID, 2011). FHIA, as it plans for activities in conjunction with the IPM CRSP, wishes to know how its research portfolio can be altered to have increased impacts on women.

3.6.1. Crops

We present stylized indicator estimations for four crops: maize, onions, tomatoes, and peppers. Maize is one of the most important crops produced and consumed in Honduras. Onions are also important in the diet, but they are not grown or traded extensively. Consequently, the Honduran onion market can be modeled under a closed economy assumption. Peppers are major non-traditional export crops, and the peppers market is open. Somewhere in between onions and peppers are tomatoes. Although tomato is a major part of the Honduran diet, it is less important than the onion and, correspondingly, a considerable amount of tomato production is exported. The tomato market displays both open and closed characteristics depending on the specific tomato variety. FHIA is conducting integrated pest management research on onions, tomatoes and peppers, but not maize.

3.6.2. Technology

Four IPM technologies will be considered in our analysis: solarization, biological controls, cowpea cover/green manure, and backpack sprayer pressure regulating valve. Solarization is a technique in which farmers cover planting beds with black plastic. The sun heats the soil and kills weed seeds among other soil pests. The biological control technology involves introducing other insects, fungi, or other biological agents to prey on pests. These techniques have been developed by FHIA for tomatoes, peppers, and onions. Cowpea acts as a cover crop and green manure to provide a habitat for predatory pests and provide nutrients for the tomato crop. The backpack sprayer pressure valve has been developed for onion growers to more efficiently and evenly spray their fields to control thrips (Sparger et al., 2011). Each of these technologies have different yield and input cost changes, adoption rates, adoption rates, probabilities of success, and annual research costs. These are summarized in Table 3-2.

Table 3-2. Technology Parameters

Tomato Tech	***Yield Δ per Ha (%)***	***Input Cost Δ per Ha (%)***	***Net Yield Δ (%)***	***Prob of Succ (%)***	***Max Adpt Rate (%)***	***Years to Max Adpt***	***Ann Res Cost (USD)***	***Years of Res***
Solarization	2	-6	0.079	100%	67%	3	1,500	4
Bio Control	9	-3	0.118	100%	60%	2	3,000	2
Cowpea	3	-1.6	0.046	100%	20%	3	3,000	5
Pepper Tech	***Yield Δ per Ha (%)***	***Input Cost Δ per Ha (%)***	***Net Yield Δ (%)***	***Prob of Succ (%)***	***Max Adpt Rate (%)***	***Years to Max Adpt***	***Ann Res Cost (USD)***	***Years of Res***
Solarization	9	1	0.081	100%	67%	3	1,500	2
Bio Control	1	-3	0.127	100%	58%	2	3,000	4
Onion Tech	***Yield Δ per Ha (%)***	***Input Cost Δ per Ha (%)***	***Net Yield Δ (%)***	***Prob of Succ (%)***	***Max Adpt Rate (%)***	***Years to Max Adpt***	***Ann Res Cost (USD)***	***Years of Res***
Solarization	3	-6	0.088	100%	67%	3	1,500	4
Bio Control	4	-1.4	0.053	10%	40%	1	500	3
Pressure Valve	3	-6	0.346	100%	50%	3	1,500	4

Source: Sparger et al. (2011)

Notes:

1. Abbreviations
    a. Bio = biological
    b. Δ = change
    c. Ha = hectare
    d. Prob of Succ = probability of success
    e. Max = maximum
    f. Adpt = adoption
    g. Ann = annual
    h. Res = research

3.6.3. Data

Three data sets are used for estimating gendered indicators of impacts of agricultural research shown in Table 3-1. Each can be viewed as representative of data sets that may be available to research managers in many countries.

We first analyze the Honduran Encuesta Nacional de Hogares sobre Condiciones de Vida (ENCOVI). These data are from a nationwide survey of 8,175 households performed in 2004 as part of the MECOVI program sponsored by the World Bank, Inter-American Development Bank, and the United Nations. The ENCOVI includes household demographic, economic, and health data. ENCOVI data are important for estimating indirect effect indicators in Table 3-1 because they include household income, expenditures, and consumption. Labor market participation data were collected at the individual level. Additionally, the ENCOVI contains data on household composition which allows income and expenditures to be separated by gender of the household head and sometimes by the gender of the individual ("ENCOVI", 2007). Because agricultural production data from this survey have not been made available, no direct indicators from Table 3-1 can be obtained from the Honduran ENCOVI. To compensate for this shortcoming, we employ a second data set.

The Honduran Encuesta de Hogares de Propósitos Múltiples (EPHPM) comes from a survey of 21,630 households performed by the Honduran government and contains information similar to that of the ENCOVI. The EPHPM is more recent (2007 data are used) and contains agricultural data. The agricultural data include quantity produced, prices received, and value of a given crop in all forms (e.g. storage, own use, etc.). Because the EPHPM also has household composition data, agricultural data can be broken down by household and gender. These are useful in measuring direct effect indicators found in Table 1 through step 2. However, indirect indicators, such as shares of consumer surplus accruing to population sub-groups, cannot be estimated with the EPHPM alone because it lacks consumption data ("EPHPM", 2008).

Unsurprisingly, the EPHPM data set still lacks the agricultural detail needed to estimate a gendered adoption rate which is a critical factor affecting the gendered impact of a technology. Any indicators generated will be approximate because we lack information on adoption; we can only estimate step 2 indicators. For example, instead of estimating the number of adopting female-headed households growing a certain crop, a step 3b indicator, only the number of female-headed households growing the crop can be estimated, a step 2 estimate.

The third data set comes from research on rural development and sustainable agriculture in the Trifinio region of Honduras, Guatemala, and El Salvador. The survey obtained information on demographics, household composition, consumption, income, farming, credit use, and others from 493 households. The data contain a small number of observations and only surveys a particular region, but has in-depth information on each respondent. This data set represents what a research manager may have from a baseline survey for a typical development project (SET Trifinio, 2007).

Detailed farming information includes crops planted, area planted, crop production, value of the crop, and agricultural assets. These data will be useful in estimating direct effect indicators from Table 3-1. Agricultural asset data are typically most important because these data can be used as proxy signals for technology adoption rates by gender of the household head and crop. An estimated adoption rate for women or female-headed households would mean that we could now draw from step 3b indicators in Table 3-1 compared to step 3a using only EPHPM data, given we have other technology-specific parameters.[19]

By combining the Honduran ENCOVI, EPHPM, and Trifinio datasets, national indicators for direct and indirect effects can be estimated through step 3a for onions, tomatoes, and peppers because household-level adoption rates and specific technology characteristics have been obtained from experts. However, step 3b indicators cannot be estimated for these crops because no gender-

[19] Or the adoption propensity could be "transferred" from this data set to one of the others.

specific adoption data are available. For this example, we compute step 3a indicators for four technologies used on tomatoes, peppers, and onions to identify women's crop-technology pairings. For maize, only direct and indirect effects indicators through step 2 can be estimated because no technologies on maize are being developed by FHIA. Because we have household composition data, we can analyze effects on women--assuming intra-household equity--and on female-headed households. The exchange rate used to convert Honduran lempiras (HNL) to US dollars (USD) is 1HNL = 0.0531USD. Formulae for step 2 and 3a indicators used in the analysis are found in Table 3-3.

Table 3-3. Step 2 and Step 3a Indicator Formulas Used

Effects		Step 2	Step 3a
Direct	1	Number (#) of FHH producing	
	2	# of females (fem) in hhs producing	
	3	# FHH selling	
	4	# fem in hhs selling	
	5	$tons\ prod\ by\ FHH$	
	6	$\sum_{i=1}^{n}\left(\frac{\#\ fem\ in\ hh\ i}{\#\ peo\ in\ hh\ i} * tons\ prod\ hh\ i\right)$	
	7	$tons\ sold\ by\ FHH$	
	8	$\sum_{i=1}^{k}\left(\frac{\#\ fem\ in\ hh\ i}{\#\ peo\ in\ hh\ i} * tons\ sold\ hh\ i\right)$	
	9	$v\ sold\ by\ FHH$	
	10	$\sum_{i=1}^{k}\left(\frac{\#\ fem\ in\ hh\ i}{\#\ peo\ in\ hh\ i} * v\ sold\ hh\ i\right)$	
Indirect	11	$tons\ con\ by\ FHH$	
	12	$\sum_{i=1}^{m}\left(\frac{\#\ fem\ in\ hh\ i}{\#\ peo\ in\ hh\ i} * tons\ con\ by\ hh\ i\right)$	
	13	$v\ con\ by\ FHH$	
	14	$\sum_{i=1}^{m}\left(\frac{\#\ fem\ in\ hh\ i}{\#\ peo\ in\ hh\ i} * v\ con\ by\ hh\ i\right)$	
	15	$\frac{\#\ FHH\ consuming}{\#\ hhs\ consuming} * \Delta CS$	$\frac{\#\ FHH\ consuming}{\#\ hhs\ consuming} * \Delta CS'$
	16	$\sum_{i=1}^{m}\left(\frac{\#\ fem\ in\ hh\ i}{\#\ peo\ in\ hh\ i}\right) * \Delta CS$	$\sum_{i=1}^{m}\left(\frac{\#\ fem\ in\ hh\ i}{\#\ peo\ in\ hh\ i}\right) * \Delta CS'$
	17	$\frac{q\ con\ by\ FHH}{q\ con\ by\ hhs} * \Delta CS$	$\frac{q\ con\ by\ FHH}{q\ con\ by\ hhs} * \Delta CS'$
	18	$\sum_{i=1}^{m}\left(\frac{\#\ fem\ in\ hh\ i}{\#\ peo\ in\ hh\ i} * q\ con\ by\ hh\ i\right) * \Delta CS$	$\sum_{i=1}^{m}\left(\frac{\#\ fem\ in\ hh\ i}{\#\ peo\ in\ hh\ i} * q\ con\ by\ hh\ i\right) * \Delta CS'$

Table 3-3. Continued

Effects		Step 2	Step 3a
Direct & Indirect	**19**	$\frac{\#\ FHH\ selling}{\#\ hhs\ selling} * \Delta PS$	$\frac{\#\ FHH\ selling}{\#\ hhs\ selling} * \Delta PS'$
	20	$\sum_{i=1}^{k}\left(\frac{\#\ fem\ in\ hh\ i}{\#\ peo\ in\ hh\ i}\right) * \Delta PS$	$\sum_{i=1}^{k}\left(\frac{\#\ fem\ in\ hh\ i}{\#\ peo\ in\ hh\ i}\right) * \Delta PS'$
	21	$\frac{q\ sold\ by\ FHH}{q\ sold\ by\ hhs} * \Delta PS$	$\frac{q\ sold\ by\ FHH}{q\ sold\ by\ hhs} * \Delta PS'$
	22	$\sum_{i=1}^{k}\left(\frac{\#\ fem\ in\ hh\ i}{\#\ peo\ in\ hh\ i} * q\ sold\ hh\ i\right) * \Delta PS$	$\sum_{i=1}^{k}\left(\frac{\#\ fem\ in\ hh\ i}{\#\ peo\ in\ hh\ i} * q\ sold\ hh\ i\right) * \Delta PS'$
	23	$\Delta TS = 19 + 15$	$\Delta TS' = 19 + 15$
	24	$\Delta TS = 20 + 16$	$\Delta TS' = 20 + 16$
	25	$\Delta TS = 21 + 17$	$\Delta TS' = 21 + 17$
	26	$\Delta TS = 22 + 18$	$\Delta TS' = 22 + 18$

Notes:

1. Abbreviations are same as in Table 1.

3.7. Results

Indicators from Step 1 and 2 show that maize is the most important women's crop with tomatoes second. Results also indicate that peppers and onions are third and fourth most important, with peppers being third using female indicators and onions being third using female-headed household indicators. Step 3a indicators indicate that the tomatoes-solarization crop-technology pair is best because it is associated with the highest total surplus change.

3.7.1. Step 1

3.7.1.a. Crop size indicators. Consumption data from the ENCOVI survey show that maize is the most important consumer crop of the four analyzed. Onions are consumed by the greatest number of households (996,257) followed by tomatoes (925,635), peppers (764,162), and maize (691,325). However, Hondurans consume 510,239 tons of maize, compared to only 62,315 tons of tomatoes, 26,537 tons of onions, and 5,943 tons of peppers. The value of consumption by households follows the same pattern: maize (USD 7,212,748), tomatoes (USD 2,128,159), onions (USD 1,500,610), and peppers (USD 1,083,334). The estimated number of households consuming maize is low because processed maize (corn tortillas, cornmeal, etc.) is not included; these estimates constitute a lower bound of true maize consumption.

Of the crops considered, maize is by far the most important crop; 435,101 households grew maize, compared to 5,675 with tomatoes, 2,659 with peppers, and 2,016 with onions. These households grew 578,400 tons of maize, 59,381 of tomatoes, 12,440 of peppers, and 6,928 of onions. However, only 41.7% of households growing maize sell their maize production, while 86.6%, 78.0%, and 62.5% sold their tomato, pepper, and onion production, respectively. The percentages of tons sold are even more striking. 40.5% of maize production was sold, but over 98% of tomato and pepper production was sold.[20] This shows that much maize is grown for own consumption, while tomatoes, peppers, and onions are almost entirely grown for income generation.

However, even with the large differences in percent of production sold, the value of maize production sold (USD 50,878,560) is over 4 times larger than the next closest crop (tomatoes, 11,785,166). About USD 3.98 million of peppers and USD 2.84 million of onions were sold. These step 1 direct and indirect crop size indicators are shown in Table 3-4.

A research-induced reduction in cost of production of maize will have the biggest overall impact in Honduras, but other factors affect the distribution of these benefits.

[20] Amount sold by onion producers is larger than amount produced, which is most likely due to the timing of production and marketing relative to the survey because onions may be stored for several months before they are sold.

Table 3-4. Step 1 Indicator Results

Direct Indicators	***Maize***	***Peppers***	***Tomatoes***	***Onions***
Number of households producing	435,101	2,659	5,675	2,016
Number of households selling	181,624	2,075	4,916	1,261
Number of people producing	2,400,727	13,964	39,120	12,539
Number of people selling	984,650	10,773	31,168	8,007
Tons Produced	578,400	12,440	59,381	6,928
Tons Sold	234,208	12,387	58,323	7,009
Value of harvested production (USD)	127,149,495	3,990,259	11,872,370	2,848,810
Sales value (USD)	50,878,560	3,980,674	11,785,166	2,841,511
Indirect Indicators	***Maize***	***Peppers***	***Tomatoes***	***Onions***
Number of households consuming	691,325	764,162	925,635	996,257
Number of people consuming	3,806,267	3,833,183	4,620,673	5,055,328
Pounds consumed	1,020,478,590	11,885,909	124,630,732	53,073,974
Tons consumed	510,239	5,943	62,315	26,537
Pounds consumed per hh	1,476	16	135	53
Pounds consumed per person	268	3	27	10
Value of consumption (USD)	7,212,748	1,083,334	2,128,159	1,500,610
ΔCS (USD)	25,484,420	0	6,913,054	1,881,357
Direct & Indirect Indicators	***Maize***	***Peppers***	***Tomatoes***	***Onions***
ΔPS (USD)	25,484,420	4,800,669	4,839,138	940,678
ΔTS (USD)	50,968,841	4,800,669	11,752,191	2,822,035

Sources: EPHPM, ENCOVI, and Trifinio data sets

Notes:

1. Amount sold by onions is larger than amount produced, which is most likely due to the production and marketing of onions because the onions may be stored for several months before they are sold.

3.7.1.b. Potential benefit indicators. Using these crop size indicators along with market assumptions and an assumed similar k-shift across crops, we can provide estimates of potential benefits.[21] Table 3-5 displays these market and constant technology assumptions.[22]

[21] A constant k-shift across crops allows us to introduce market characteristics without bringing in technology-specific parameters, while using the easier to calculate change in economic surplus than current economic surplus.

[22] The market assumption for onions implies that the elasticity of demand is small, relatively close to zero. The open market assumption for the peppers market means that the elasticity of demand is infinite. The elasticity of demand for tomatoes will be somewhere between onions and peppers, not infinite, but not small either (Sparger, Alwang, Norton, Rivera, & Breazeale, 2011).

Table 3-5. Market Parameters and Constant Technology Parameters Used In Step 2 Indicator Calculations

Crop	Initial Q (Tons)	Initial P (USD)	Demand Elasticity	Supply Elasticity	Yield Δ per Ha (%)	Input Cost Δ per Ha (%)	Net Yield Δ (%)	Prob of Succ (%)	Max Adpt Rate (%)	Years to Max Adpt
Maize	234,208	217.24	- 1	1.0	9	-6	0.145	100%	75%	3
Peppers	12,387	321.37	- ∞	1.0	9	-6	0.145	100%	75%	3
Tomatoes	58,323	202.07	- 0.5	1.0	9	-6	0.145	100%	75%	3
Onions	7,009	405.44	- 0.7	1.0	9	-6	0.145	100%	75%	3

Sources: EPHPM data set and Sparger et al. (2011)

Notes:

1. Abbreviations
    a. Q = quantity
    b. P = price
    c. Δ = change
    d. Ha = hectare
    e. Prob of Succ = probability of success
    f. Max = maximum
    g. Adpt = adoption

Maize is again the most important crop using any potential benefit indicator. Tomatoes continue to be the second most important crop using any indicator. These crops are first and second because they are "large" crops; both have much larger sales value than onions and peppers. Maize, however, is much more important than any other crop with any measure of its potential benefits being at least 3.6 times as large as tomatoes, while potential benefits for tomato research are only slightly higher than the next crop. Onions are third using the consumer surplus indicator because the pepper market is open, so no consumer surplus change occurs with peppers. However, peppers are third when using producer surplus and total surplus changes because it is a much larger crop than onions. These indicator results can be found in Table 3-4.

3.7.2. Step 2

3.7.2.a. Crop size indicators. Moving from step 1 to step 2, allocating crop size and potential benefits found in step 1 to men and women, maize is still the most important crop overall by a large margin, and in all but one measure, tomatoes are still second (Table 3-6). Generally, peppers are third when using female direct indicators, but peppers are last when using female-headed household direct indicators. This can be found in Table 3-6 by comparing indicators 3 and 4, 5 and 6, 7 and 8, or 9 and 10. Peppers are typically last when considering female-headed household indicators because no female-headed households in the survey sold peppers (indicator 7 and 9) and those that produced them did not produce large amounts (indicator 5). Conversely, onions are the third most important crop according to female-headed household direct indicators, but last according to female direct indicators. Peppers are also last for all indirect indicators because they are not an important consumption crop. The consumption-based rankings do not change from step 1 because the shares of females in households and the shares of female headed-households that consume a crop are only slightly different across crops (all close to 50%), and these differences are not large enough to counter the effect of the initial crop size.

3.7.2.b. Potential benefit indicators. Using step 2 potential benefit indicators, maize is again the most important women's crop and tomatoes are second for all indicators but two indicators of producer surplus change. Peppers are last, and its female-headed household indicators are zero because no female-headed households sold peppers in our data (indicators 15, 17, 19, 21, 23, 25 from Table 3-6). Similarly, peppers have a value of zero for all indicators of consumer surplus change (indicators 15-18) because the market is assumed to be open. However, when female indicators are used, peppers are second using the producer surplus change indicator and third when using the total surplus change indicator, which can be seen in indicators 20, 22, 24, and 26. Peppers move to second using indicators of female producer surplus change because all benefits from the introduction of a technology accrue to producers and are not split between producers and consumers like all of the other crops. However, research on peppers only provides between $100 and $194 thousand more in benefits to producers compared to tomatoes; and, when consumer surplus changes are added, tomatoes exceed this as evidenced by the indicators of total surplus, 24 and 26. Peppers are third overall in step 3 because they are third when using female indicators of total surplus and because they provide no consumer surplus benefits. Providing no consumer surplus benefits are especially detrimental because women are often in control of food purchases or food production. Onions are again last when using female indicators of potential benefits and third when using female-headed indicators of potential benefits. As before, onion's small "size" is its limiting factor.

Table 3-6. Step 2 Indicator Results

Direct Indicators	***Maize***	***Peppers***	***Tomatoes***	***Onions***
1 Number of FHH growing crop	50,039	500	380	170
2 Number of females growing crop	1,163,856	7,095	18,905	7,900
3 Number of FHH selling crop	15,524	0	341	170
4 Number of females selling crop	467,754	5,794	15,988	4,123
5 Tons produced by FHH	49,535	17	909	421
6 Tons produced by females	273,865	6,166	26,891	3,222
7 Tons sold by FHH	16,263	0	867	420
8 Tons sold by females	108,351	6,132	26,304	3,277
9 FHH value of sales (USD)	3,360,215	0	419,840	180,377
10 Female's value of sales (USD)	23,679,183	1,770,499	5,608,235	1,405,328
Indirect Indicators	***Maize***	***Peppers***	***Tomatoes***	***Onions***
11 Tons consumed by FHH	87,143	1,571	15,323	6,458
12 Tons consumed by females	252,414	3,164	32,759	14,021
13 FHH value of consumption (USD)	1,287,993	301,811	515,913	352,918
14 Female value of consumption (USD)	3,584,073	576,985	1,121,527	780,793
15 FHH ΔCS (USD)	5,179,974	0	1,809,238	473,049
16 Female ΔCS (USD)	12,651,009	0	6,112,859	972,287
17 FHH ΔCS (USD)	4,353,486	0	1,699,888	457,935
18 Female ΔCS (USD)	12,607,097	0	3,634,171	994,040
Direct & Indirect Indicators	***Maize***	***Peppers***	***Tomatoes***	***Onions***
19 FHH ΔPS (USD)	2,178,186	0	335,205	127,031
20 Female ΔPS (USD)	12,106,265	2,582,170	2,482,307	484,393
21 FHH ΔPS (USD)	1,769,646	0	71,963	56,306
22 Female ΔPS (USD)	11,789,784	2,376,521	2,182,519	439,863
23 FHH ΔTS (USD)	7,358,159	0	2,144,443	600,080
24 Female ΔTS (USD)	24,757,274	2,582,170	8,595,166	1,456,680
25 FHH ΔTS (USD)	6,123,132	0	1,771,852	514,241
26 Female ΔTS (USD)	24,396,881	2,376,521	5,816,690	1,433,903

Sources: ENCOVI, EPHPM, and Trifinio data sets

Notes:

1. Amount sold by onions is larger than amount produced, which is most likely due to the production and marketing of onions because the onions may be stored for several months before they are sold.

3.7.3. Step 3a indicators

Step 3a introduces crop specific technology refinements. The top three crop-technology mixes are tomatoes-biological control, tomatoes-solarization, and onions-pressure valve (Table 3-7).[23] By introducing key crop- and technology-specific parameters, onions have now moved from near last or last in all of the other indicators to first using indicators 18 and 26 because the pressure valve technology provides a large k-shift, more than 2.3 times larger than the next best crop-technology pair.

Using indicators from step 2, the three tomato-technology pairings would be chosen as the crop-technology pairings to research because tomatoes would be considered the women's crop. However, step 3a illustrates that further refinements to the estimates are gained by incorporating crop-specific technologies and technology parameter values. Such incorporation leads to a slightly different ordering of the top three crop-technology mixes because each technology is associated with crop-specific impacts and differences in these impacts across crops and technologies can overcome initial crop size disadvantages.

[23] Recall that maize is no longer included.

Table 3-7. Step 3a Indicator Results

Peppers: Indirect Indicators	***Solarization***	***Bio Control***	***Cowpea***	***Press Valve***
15 FHH ΔCS (USD)	0	0	N/A	N/A
16 Female ΔCS (USD)	0	0	N/A	N/A
17 FHH ΔCS (USD)	0	0	N/A	N/A
18 Female ΔCS (USD)	0	0	N/A	N/A
Peppers: Direct & Indirect Indicators	***Solarization***	***Bio Control***	***Cowpea***	***Press Valve***
19 FHH ΔPS (USD)	0	0	N/A	N/A
20 Female ΔPS (USD)	1,250,890	1,802,209	N/A	N/A
21 FHH ΔPS (USD)	0	0	N/A	N/A
22 Female ΔPS (USD)	1,151,266	1,658,677	N/A	N/A
23 FHH ΔTS (USD)	0	0	N/A	N/A
24 Female ΔTS (USD)	1,250,890	1,802,209	N/A	N/A
25 FHH ΔTS (USD)	0	0	N/A	N/A
26 Female ΔTS (USD)	1,151,266	1,658,677	N/A	N/A
Tomatoes: Indirect Indicators	***Solarization***	***Bio Control***	***Cowpea***	***Press Valve***
15 FHH ΔCS (USD)	867,485	1,222,730	146,542	N/A
16 Female ΔCS (USD)	1,724,097	2,430,135	291,248	N/A
17 FHH ΔCS (USD)	814,848	1,148,829	137,685	N/A
18 Female ΔCS (USD)	294,356	294,356	294,356	N/A
Tomatoes: Direct & Indirect Indicators	***Solarization***	***Bio Control***	***Cowpea***	***Press Valve***
19 FHH ΔPS (USD)	160,722	226,540	27,150	N/A
20 Female ΔPS (USD)	1,190,205	1,677,607	201,059	N/A
21 FHH ΔPS (USD)	34,505	48,635	5,829	N/A
22 Female ΔPS (USD)	1,046,464	1,475,003	176,777	N/A
23 FHH ΔTS (USD)	1,028,208	1,449,270	173,693	N/A
24 Female ΔTS (USD)	2,914,303	4,107,742	492,307	N/A
25 FHH ΔTS (USD)	849,353	1,197,464	143,514	N/A
26 Female ΔTS (USD)	1,340,820	1,769,359	471,133	N/A
Onions: Indirect Indicators	***Solarization***	***Bio Control***	***Cowpea***	***Press Valve***
15 FHH ΔCS (USD)	254,306	10,405	N/A	759,925
16 Female ΔCS (USD)	522,691	21,386	N/A	1,561,922
17 FHH ΔCS (USD)	246,180	10,073	N/A	735,645
18 Female ΔCS (USD)	534,384	21,865	N/A	1,596,866
Onions: Direct & Indirect Indicators	***Solarization***	***Bio Control***	***Cowpea***	***Press Valve***
19 FHH ΔPS (USD)	68,231	2,779	N/A	204,008
20 Female ΔPS (USD)	260,176	10,596	N/A	777,920
21 FHH ΔPS (USD)	30,243	1,232	N/A	90,426
22 Female ΔPS (USD)	236,258	9,622	N/A	706,408
23 FHH ΔTS (USD)	322,536	13,184	N/A	963,933
24 Female ΔTS (USD)	782,866	31,983	N/A	2,339,843
25 FHH ΔTS (USD)	276,423	11,304	N/A	826,071
26 Female ΔTS (USD)	770,643	31,487	N/A	2,303,274

Sources: ENCOVI, EPHPM, and Trifinio data sets

3.8. Conclusions

One way of increasing the benefits accruing to women from agricultural research is by performing research in women's crops and technologies for women. However, these crops and specific technologies that could benefit women are difficult to identify. We have developed and tested a framework for identifying these crops and technologies. The application to Honduras shows that the most important and informative indicators are step 1 and step 2 indicators. In particular, crop size is one of the largest factors affecting the flow of research-induced benefits to women. This finding is consistent with Alston et al. (1995) who advocate focusing research on "large" crops. However, gains can be made if accurate technology parameters (e.g. expected k-shifts, propensity of women to adopt) are available for specific crop-technology pairings.

This implies that available data matters. While secondary data provide much of the needed information, primary data allow calculation of more refined indicators. Deeper datasets allow more accurate predictions of potential benefits flowing to women and female headed households, but good approximations can be made with currently and readily available data.

A key parameter in these estimates is the propensity of women to adopt technologies. Such parameters are difficult to find, and propensity transfer schemes such as that employed by Moyo et al. (2007) may not be appropriate because adoption of management techniques is likely to exhibit more heterogeneity than variety adoption. Sensitivity analyses could be conducted to determine the difference in men's and women's adoption rates needed to reorder crop-technology pairings. However, this is beyond the scope of this paper. An area for future research is to determine the importance of gender-specific adoption rates in identifying women's crops and technologies.

Finally, we note that women's crops cannot be identified without some reference to policy goals. One policy goal, such as having the largest overall impact on women's well-being, might imply use of one indicator. A different goal might point toward use of another.

3.9. References

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Chapter 4: Conclusions

4.1. Summary

The first paper, *An Evaluation Design for the Onion ipmPIPE*, was unable to provide an estimate of impact for the Onion ipmPIPE, but it constructed an evaluation design for it. The instrumental variables approach was determined to be the most appropriate method, selected over the Bayesian Decision Theoretic and randomization approaches. The actual evaluation must still be performed, and high-speed internet access must be verified as an appropriate instrument. Furthermore, obtaining or creating a comprehensive onion grower list would provide an avenue to integrate randomization and strengthen evaluation results. Additionally, it would provide an example of a way to include randomization in an ethical way for researchers in other projects and crops.

In the second paper, *Identifying Women's Crops and Agricultural Technologies*, a framework to estimate these benefits and disaggregate them by population sub-group using secondary data was developed. This framework was then applied to identify women's crops and technologies in Honduras. The application showed that crop size was the largest determinant in identifying women's crops and technologies. However, incorporating technology-specific and gendered crop data re-prioritized the research mix that would benefit women most. Further research in this area is to determine the importance of gendered adoption rates in estimating the benefits accruing to each gender.

4.2. Constraints of the Evaluation Environment

The unifying theme of both, *An Evaluation Design for the Onion ipmPIPE* and *Identifying Women's Crops and Agricultural Technologies*, is the importance of considering all constraints in the process of evaluating a shock. Both papers, though different in context, faced similar challenges: how to create or select the most appropriate method to estimate a shock given the particular evaluation environment. There were three main constraints in the Onion ipmPIPE evaluation. One was methodological, in which the Bayesian Decision Theoretic approach might not accurately portray reality. The other two, logistical and political, prevented randomization from being utilized. No comprehensive list of onion growers was available to randomize, and the project director did not want to restrict access to the website.

Data and resource constraint were the main constraints in developing the framework to identify women's crops and technologies. Agricultural statistics are often unavailable at an individual level. Therefore, the method utilized must be able to integrate household level data that is readily available to estimate benefits accruing to individuals at the sub-household level. Furthermore, data at the individual level is both time consuming and material intensive to obtain. Research managers in developing countries are often limited in both of these resource areas. Therefore, using readily available data was crucial in creating a framework that was practical and usable in the field.

In the short-run, constraints cannot often be lifted; the researcher must work within them. However, in the long-run, constraints can be overcome or mitigated. More research should be done in developing tools or methods that can work within common constraints that are difficult to overcome, and research should be done to overcome these constraints. A constraint common in both is data collection. Developing methods for working in less-than-ideal data environments is not new, but developing these methods is indispensible work because data collection is so resource (time, money, skills) intensive. At the same time, new methods of collecting data should be developed. In particular, how can more detailed data be obtained at a low cost, while maintaining the rights of those being researched? Developing techniques that mitigate and/or work within constraints of the real-world are the main areas for future research.

Chapter 5: References

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