# Production efficiency and policy impact of heterogeneous farm households

# in developing countries

by

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B.S., University of Asmara, 2008
M.S., Consortium of European Universities, 2014

AN ABSTRACT OF A DISSERTATION

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**Department of Economics**
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## Abstract

Agricultural development is an essential factor in the economic development of much of the developing world and comprises a significant element of foreign assistance portfolios. Over the last decade, there has seen a renewed interest in more credible estimates of the economic impacts of development programs, such as assistance to extension programs. We compare the estimation of technical efficiency to farm output and income as an outcome variable to evaluate the impact of development programs such as farm education and extension programs. We develop a simple theoretical model which shows that using technical efficiency as an outcome variable could be a viable alternative to more traditionally used outcome variables such as farm output and farm profit. We note that when farmers are capital constrained, extension programs can theoretically have a large *efficiency* effect despite a small or zero change in farm profits.

If farm technical efficiency is used as an outcome variable, then it must be estimated correctly. Mismeasurement of farm technical efficiency leads to misleading extension program evaluations. Farm households face heterogeneous infrastructural constraints (Suri 2011; Ojiem et al. 2006), credit constraints, information barriers and other input market constraints (Duflo, Kremer and Robinson 2011; Jack 201; Suri 2011and Stifel and Minten 2008), labor markets constraints (Henning and Henningsen 2007), socio-economical (Ojiem et al. 2006) and non-farm income opportunities (Chang et al. 2012) and thus have different access to agricultural inputs and outputs. These constraints have a substantial impact on agricultural production decisions of farm households. A key production decision of farm households is the allocation of resource to cash and food crops. Production of cash crops requires relatively higher market involvement in both the purchase of inputs and the selling of output than home-consumed food crops. The heterogeneous constraints across farm households leads to a substantial imbalance in the transaction costs

associated with the production of each crop. Moreover, home-consumed crops may have quality attributes (e.g. color, taste, softness of dough, and suitability for certain dishes) not reflected in market prices. Factors such as transaction costs, crop quality attributes, and other factors such as household characteristics are farmer specific and drive a heterogeneous price wedge between the market prices for household's crop production and the economic value of these crops for the household. These distinctions have important implication for farm productivity analysis, such as technical efficiency measurement.

The standard approach to productivity analysis, such as efficiency estimation, assume that farm households face homogenous price wedges that leads to homogenous set of production and profit functions. However, the price gap created by transaction costs, crop quality attributes, and other factors such as household characteristics generally vary among subsistence, semi-subsistence and commercial farmers and leads to a heterogeneous set of profit and production frontiers. Subsistence and semi-subsistence farmers who produce largely home consumed crops have potentially greater price wedges than commercial farmers. Failing to account for the heterogeneity in price wedges that drive heterogeneity profit and production frontiers is likely to lead to underestimation of the efficiency of subsistence and semi-subsistence farmers. We test if traditional productivity analysis indeed underestimates the efficiency of subsistence and semi-subsistence farmers by employing a conditional Data Envelopment Analysis (DEA) model for household survey data in Uganda. Results confirm that naïve estimates of efficiency understate the efficiency scores of subsistence and semi-subsistence farmers. The results cast doubt on policies, such as extension programs or other information treatments, that interpret low efficiency scores for subsistence and semi-subsistence farmers as a management shortfall.

We demonstrate the use of farm technical efficiency as an outcome measure by analyzing data from 2008-2012 for farm training program in Armenia. In this program, farmers received technical guidance on modern farm techniques.  Two previous evaluations (Schwab and Shanoyan 2016; Fortson et al. 2012) find ambiguous evidence that farm profits increased. The measurement or potential gain from an extension program is captured using farm technical efficiency measures. We find evidence that the program in Armenia increased farm technical efficiency from 2008 to 2012.

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# Copyright

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We demonstrate the use of farm technical efficiency as an outcome measure by analyzing data from 2008-2012 for farm training program in Armenia. In this program, farmers received technical guidance on modern farm techniques.  Two previous evaluations (Schwab and Shanoyan 2016; Fortson et al. 2012) find ambiguous evidence that farm profits increased. The measurement or potential gain from an extension program is captured using farm technical efficiency measures. We find evidence that the program in Armenia increased farm technical efficiency from 2008 to 2012.

# Table of Contents

## List of Figures

## List of Tables

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Above all, I praise God for guiding me through all this including to finish the PhD program successfully.

## Dedication

I am dedicating it in memory of my father: Teklay Embaye and my mother: Zufan Zere.

# Chapter 1. Overall Introduction

## 1.1. Motivation

Agricultural development is the cornerstone of economic development for much of the developing world. As a result, agricultural development programs comprise a significant element of most foreign assistance portfolios. The last decade has seen a renewed interest in more credible estimates of the economic impacts of these agricultural development programs. Development funds for agriculture are frequently funneled to farm education and extension programs. For example, about 70 percent of the Ministry of Agriculture budget in Kenya (Muyanga and Jane 2006), 4 million dollars in Ethiopia (only under Agricultural Transformation Agency in the year 2009), 24.4 million US dollars of the government budget in Uganda (Kuteesa et al. 2018), and 60 million dollars in India (in the year 2010) are used to fund farm education and extension programs. These extensions based programs seek to provide farmers with the most up-to-date information on new farm techniques and technologies, with the goal of alleviating information constraints to profitable technology adoption (Jack 2011).

Birner et al. (2006) defines agricultural extension programs as complete sets of organizations that include: governmental, non-governmental, and producer organizations that assist farmers in obtaining information, skills, and technologies that increase agricultural production and improve income and well-being of farm households. Equipping farmers with new techniques and technologies can increase farm productivity (including farm technical efficiency), which in turn can increase income and well-being. Due to an increasingly limited availability of land, and continual increases in world population (9.7 billion by 2050, a 2.7 billion higher than today's population; United Nation 2015 report) increasing agricultural production and productivity through increases in efficiency and/or innovation is crucial to alleviate future food security issues.

In addition, gains in farm productivity increase the competitiveness of farmers, which ultimately increases market share domestically and at the world stage, as well as help to convince state and federal governments to allocate funds for development programs. Assessing information-based development programs, such as extension program using farm efficiency as an outcome variable is important. The use of farm efficiency and/or innovation directly as an outcome variable for evaluating extension programs has been relatively limited in previous studies. Several studies that assess the impact of extension program use changes in farmers' income, yield or input use as an outcome variable in their evaluation (Cole and Fernando 2014; Wordofa and Sassi 2014; Davis et al. 2012; Fortson et al. 2012). Previous studies that strictly use farm income or yield as an outcome variable seem to forget that depending on the level of input use, extension programs may show different effects.

The theory of most extension programs is that they will affect farmer's knowledge, which then translates into a more efficient allocation of inputs (technical efficiency). Technical efficiency is the ability of the production firm to avoid waste through producing maximum output for a given technology or producing an output level using the minimum amount of input required (Farrell 1957). Increases in technical efficiency thereby can often increase output or yields, which can result in increases in farm income. For the single output case, technical efficiency is defined as average output produced per unit of input, or referred to as average productivity (APP) (Battese and Coelli 1988).

There are three stages of the production process (stage 1 to 3), assuming that some factors of production remain fixed, while other inputs vary. Stage 1 represents the beginning of production up to the point where average productivity (APP) reaches its maximum or is equal to Marginal Physical Production (MPP). MPP is the change in total output per unit of input. Stage 2, ranges from the end of stage 1 to the point where MPP becomes zero or Total Physical Product (TPP), or total output, reaches its maximum. Stage 3 of production is when TPP falls as more input is added to the process or MPP becomes negative. Average productivity (APP) is a measure of technical efficiency and increases throughout stage 1 and decreases throughout stages 2 and 3. Output and profits of a farmer increase with the increase in technical efficiency, keeping input and output prices constant. However, in stage 1, of the production process, per unit changes in technical efficiency exceed the change in profit as input use changes. Profit, which is the difference between total revenue and total cost is lower in magnitude than the change in technical efficiency.

The simple theoretical proof of this is presented in chapter two of this dissertation. Under these conditions, using technical efficiency, which potentially may change in a larger way, as an outcome variable can better capture the treatment effects of extension programs than profit. In this sense, technical efficiency is a more sensitive measure of program effects and increases the likelihood of detecting a true program impact that may otherwise may go undetected. Duflo, Kremer and Robinson (2011); Jack (2011) and Stifel and Minten (2008) note that farmers in developing countries are often faced with several constraints to agricultural production. Credit constraints and input market imperfections, in particular, may prevent farmers from using optimal levels of inputs. Crucially, these constraints suggest underutilization of inputs, which suggests that farmers may choose 'irrational' input levels for reasons other than information constraints. Hence, depending on the stage of the production, technical efficiency may be more viable option than using profit when examining extension program for the above reasons.

## 1.2. Purpose and Objectives

**The overall purpose of this dissertation is to identify the most appropriate methods for evaluation of agricultural development and extension programs in developing countries**. More specifically, this study evaluates the impact of agricultural extension programs on farm productivity and development, but it can also easily be extended and used on impact analyses of other related agricultural development programs. This purpose is achieved by meeting the following objectives:

1. Develop a theoretical framework for the evaluation of extension programs that explicitly identifies the conditions under which farm technical efficiency is complementary to using farm income as an outcome measure;
2. Develop a measure for farm technical efficiency for inseparable production and consumption decisions of farm households; and
3. Demonstrate the use of farm technical efficiency or farm productivity as an outcome measure to evaluate extension program.

## 1.3. Approach

Using a simple theoretical model, we show that that relative desirability of using output, farm profit/income or technical efficiency as a metric to evaluate extension programs depends on the level of input use by the farm. In particular, we note that when farmers produce at input levels whereby marginal physical product (MPP) exceeds average physical product (APP), known as Stage 1 of production, an increase in productive efficiency may not produce a commensurately large change in profit as compared to farm technical efficiency on relative basis. While this stage of production is often ignored, as rational producers would not 'choose' to produce in this region, the population targeted by extension programs are often beset by binding constraints, such as credit, that can prevent farmers from taking advantage of increasing returns to investment (Jack 2011) and constraining them to operate in the 1st stage of production. Thus, an extension program targeting farmers that shows no or little impact on profit may still have resulted in more efficient production behavior. As a result, in the case of a null effect of profit or income, using an outcome measure for efficiency can allow program evaluators to determine if the extension program provided no positive production effects or if farmer efficiency improved but was beset by other binding constraints.

To use farm technical efficiency as an outcome variable, it must be estimated correctly. If we do not measure it correctly, then using farm technical efficiency as an outcome variable will lead to misleading extension program evaluations. Farm households face heterogeneous infrastructural constraints (Suri 2011; Ojiem et al. 2006), credit constraints, information barriers and other input market constraints (Duflo, Kremer and Robinson 2011; Jack 201; Suri 2011and Stifel and Minten 2008), labor markets constraints (Henning and Henningsen 2007), socio-economical (Ojiem et al. 2006) and non-farm income opportunities (Chang et al. 2012) which leads to different access to agricultural inputs and outputs choices. This affects the farm household's agricultural production decisions.

Generally, production decisions of farm households are broadly classified in to cash and food crops. Production of cash crops requires relatively higher market involvement in both the purchase of inputs and the selling of output than home-consumed food crops (Henning and Henningsen 2007; Masanjala 2006; Key et al 2000; Jayne 1994). The heterogeneous constraints across farm households leads to a substantial imbalance in the transaction costs associated with the production of each crop. Moreover, home-consumed crops may have quality attributes (e.g. color, taste, softness of dough, and suitability for certain dishes) not reflected in market prices (Arslan 2011;

Arslan and Taylor 2009). Transaction costs, crop quality attributes, and other factors, such as household characteristics, are farmer specific and drive a heterogeneous price wedge between the market prices for a household's crop production and the economic value of these crops for the household. These distinctions have important implication for farm productivity analysis, such as efficiency measurement.

The standard approach to measure productivity analysis, such as efficiency, assumes that farm households face homogenous price wedges that leads to homogenous sets of production and profit frontiers. However, the price gap created by transaction costs, crop quality attributes, and other factors such as household characteristics generally varies and differs between subsistence, semi-subsistence and commercial farmers and leads to a heterogeneous set of profit and production frontiers. Subsistence and semi-subsistence farmers who produce largely home consumed crops have potentially greater price wedges than commercial farmers. Failing to account for the heterogeneity in price wedges that drive heterogeneous profit and production frontiers is likely to lead to underestimation of the efficiency for subsistence and semi-subsistence farmers. We test if traditional productivity analysis indeed underestimates the efficiency of subsistence and semi-subsistence farmers by employing a Conditional Data Envelopment Analysis (CDEA) using household survey data from Uganda. Results confirm that naïve estimates of efficiency understate the efficiency scores of subsistence and semi-subsistence farmers. The results cast doubt on policies, such as extension programs or other information treatments, that are interpret low efficiency scores for subsistence and semi-subsistence farmers as a management shortfall.

We demonstrate the use of farm technical efficiency as an outcome measure by analyzing data from 2008-2012 for farm training program in Armenia. In this program, farmers received technical guidance on modern farm techniques. Two previous evaluations (Schwab and Shanoyan 2016;

Fortson et al. 2012) find ambiguous evidence that farm profits increased as a result of the training program. The measurement or potential gain from an extension program is captured using farm technical efficiency measures instead. We find evidence that the program in Armenia increased farm technical efficiency from 2008 to 2012.

### 1.4. Contribution

The dissertation contributes to the literature on agricultural research evaluation and farm productivity in three ways. First, we demonstrate theoretically why measures of farm efficiency may be useful outcome measures for extension programs, particularly those in developing countries. Second, we demonstrate measures of efficiency for farmers that account for inseparable production and consumption decisions. Third, we show the use of farm efficiency as an outcome measure using a randomized control trial (RCT) of a farm training program in Armenia, whereas most previous literature assesses the impact of treatment on farm households' profit, yield, and input use (Wordofa and Sassi 2014; Davis et al. 2012; Fortson et al. 2012). While the dissertation deals specifically with agricultural extension programs, the framework can be easily extended for impact analyses of other related agricultural development programs.

### 1.5. Organization

The rest of the dissertation is presented as follows. Chapter 2, presents the comparison of farm technical efficiency versus output and income as outcome variables to evaluate development programs such as agricultural extension. Chapter 3, presents the demonstration of modeling farm productivity, such as technical efficiency for farmers that are heterogeneous in transaction costs, quality of crops and other factors, applied especially, to farmers in developing countries, using farm household data from Uganda. Chapter 4, presents the evaluation of an extension program using an impact of randomized control trial (RCT) farm training on technical efficiency and farm productivity in Armenia. Chapter 5, presents the overall conclusion.

# Chapter 2. Modeling the Impact of an Extension Program on Profit and Efficiency

## 2.1. Abstract

We show the comparison of estimating technical efficiency versus farm output and income as an outcome variable to evaluate the impact of farm education and extension programs. We develop a simple theoretical model which shows that using technical efficiency as an outcome variable for assessing effectiveness of farm education and extension program, could be a viable alternative to more traditionally used outcome variables such as farm output and farm profit. We note that when farmers are capital constrained, extension programs can theoretically have a large *efficiency* effect on technical efficiency despite little change in farm profits.

## 2.2. Introduction

Governments and Non-Governmental Organizations (NGOs) heavily invest in agricultural extension programs that assist farmers in obtaining information, skills, and technologies that increase agricultural production and improve income and well-being of farm households. Agricultural extension programs that provide farmers with the most updated information on new techniques and technologies can help to increase farmers' income through increases in technical efficiency or management (Cole and Fernando 2014). Information plays a key role in adoption and integration of new technologies. Duflo, Kremer and Rabinson (2008) note that a lack of information can constrain farmers from adopting profitable technologies. Extension programs provide information to farmers directly (through training, printed documents, demonstrations), such as in Fortson et al. 2012, or via mobile-based technologies (Cole and Fernando 2014).

Agricultural researchers are frequently asked to evaluate the effectiveness of agricultural extension programs. In most impact evaluation studies, the availability of data is a common challenge (Athey and Imbens 2017; Davis et al. 2012). Thus, researchers tend to rely on methodological improvements, new tools and approaches for enhancing their ability to fully and accurately capture program impact (Davis et al. 2012). The improved ability to accurately and credibly evaluate the impact of extension programs can result in more efficient allocation of limited funds and resources (Moyo et al. 2007). With increasing demand and declining supply of development funds, the need for more innovative and rigorous impact evaluation methods is becoming critical for international development in general and for extension and technology transfer programs. Similarly, if the full impact of a development program is not adequately captured and some key benefits go undetected, the case for allocating funds for such programs may weaken unnecessarily.

To our knowledge, there are only a few studies that assess the effectiveness of extension program using credible research designs. These studies assessed programs by analyzing changes in farmer's income, and output (Cole and Fernando 2014; Wordofa and Sassi 2014; Davis et al. 2012; Fortson et al. 2012). The results are mixed. For example, Cole and Fernando (2014), examined the impact of mobile-based extension programs on cumin and cotton output between 2012 and 2013 in India using a randomized control trial and found the program increased output of both crops. Wordofa and Sassi (2014) also assessed the impact of extension programs on farmers' income in 2013 using cross sectional data in Ethiopia using propensity score matching method. They showed that the extension program increased farmer's income.

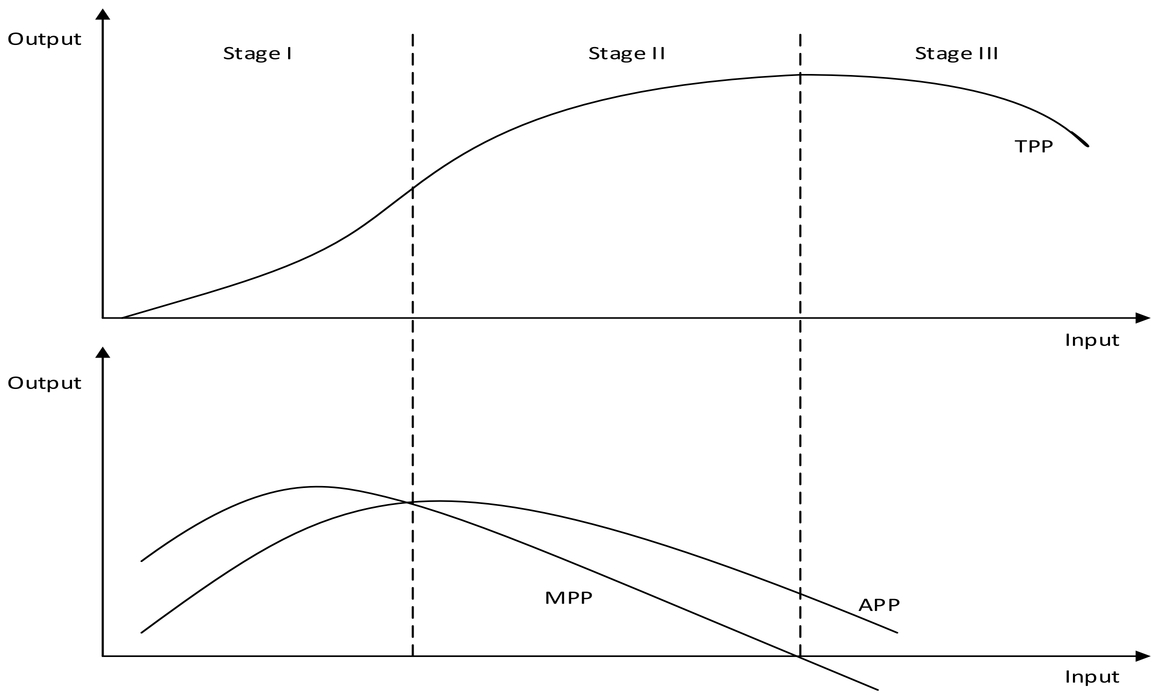
However, Davis et al. (2012), evaluated the impact of extension programs on output and income between 1999 and 2008 across three eastern Africa countries: Kenya, Tanzania and Uganda using propensity score matching and covariate matching methods. Results show that extension programs increased output and income in Kenya and Tanzania, but not in Uganda. Another interesting finding from the Davis et al. (2012) results were that, even in Kenya and Tanzania, land poor farmers didn't benefit as much from the program as compared to their counterparts.

Two other previous studies, Schwab and Shanoyan (2016) and Fortson et al (2012), examined the effectiveness of farm training program between 2007 and 2012 in Armenia. The Millennium Challenge Corporation Compact (MCC) launched a farm training program that increases agricultural performance, which in turn increases farmers' income in 2007/8 in Armenia. The farm training includes: training on farm water management, high value agriculture production, post-harvest management, processing, marketing, and access to credit. Fortson et al 2012, using an intention to treat (ITT) approach, found the program did not change average output, and found positive but not robust or precisely estimated effects on farm income and profits on program effectiveness. Schwab and Shanoyan (2016), using the same data, attempted to correct for two-sided non-compliance in the data by estimating local average treatment effects (LATE), using randomization as an instrument. They find similar results, though the positive impacts on farm profits are larger and slightly more precisely estimated. Overall, the evaluations using traditional outcome measures provide an ambiguous picture of the impact of extension program, and do not provide persuasive evidence for a strong effect at times.

Using technical efficiency as an outcome variable for assessing effectiveness of farm education and extension program could be a viable alternative to the more traditionally used outcome variables. In this paper, we do not consider the level or type of extension programs offered as a choice variable. We assume that program assessment is conducted ex post or after program has taken effect. Another interesting question not address here, is the optimal level or type of extension program that could be offered in a particular situation. An extension program with no or little impact on profit may still have positive impact on technical efficiency for subsistence and semi-subsistence farmers that are often beset by input constraints. Subsistence farmers refers to small scale farming primarily operate to produce food for family consumption. Commercial farmers refer to farming primarily operate to produce food for profit. And semi-subsistence farmers are between the two (refer to farmers that sell less than 50 percent of the total production). Extension programs that provide up-to-date information about farming increases farmer's knowledge, which is translated into a more efficient allocation of inputs (technical efficiency).

The theory underlying the development and usefulness of extension programs is the idea that they affect farmer's knowledge, which should translate into a more efficient allocation of inputs (technical efficiency). Technical efficiency is the ability of a production firm to avoid waste through producing maximum output for a given technology or producing an output level using the minimum level of input required (Farrell 1957). Increases in technical efficiency thereby often increase output, which then may increase farm income. For simplicity, assume that a farmer produces a single output using a single input and technical efficiency is defined as output over input use. The measure is called average productivity (Battese and Coelli 1988). There are three stages of the production process: stage 1, stage 2 and stage 3, assuming that some factors of production remain fixed, while other inputs vary (see figure 1).

**Figure 2.1: Three stage of production function (Stage I to III)**




Stage 1 ranges from the beginning of the production function until the point where average productivity (APP) reaches its maximum and is equal to Marginal Physical Product (MPP). MPP is the change in total output per unit input. Stage 2, ranges from the end of stage 1 until the point where MPP becomes zero or Total Physical Product (TPP) reaches its maximum. TPP is the total output produced. Stage 3 encompasses the remainder of the production function or where TPP falls and MPP is negative. Average productivity (APP), measure of technical efficiency, increases throughout stage 1 and then decreases throughout stages 2 and 3. Output and profit of a farmer increase with an increase in technical efficiency, keeping input and output prices constant. However, in stage 1 of the production process, relative changes (percentage change) in technical efficiency are likely greater than relative changes in a profit. The relative changes in profit, which is equal to the difference between relative changes in total revenue and total cost are lower in magnitude than the relative changes in technical efficiency. For farmers that operate in stage one of the production process, extension programs could theoretically result in lower impacts when using farm income than technical efficiency.

Stage one is commonly referred to as an irrational stage of production, as any input allocation corresponding to this stage will be non-optimal. However, as Duflo, Kremer and Robinson (2011); Jack (2011) and Stifel and Minten (2008) note, farmers in developing countries are often faced with several constraints to agricultural production. Credit constraints and input market imperfections may prevent farmers from using optimal levels of inputs. Crucially, these constraints suggest underutilization of inputs, which implies that farmers may choose 'irrational' input levels for reasons other than information constraints. Hence, depending on the stage of the production, technical efficiency may be a more viable option to income when evaluating extension programs.

However, the use of farm technical efficiency directly as an outcome variable for evaluating extension programs has been relatively limited in previous work. The purpose of this paper is to develop a theoretical framework for the evaluation of extension programs that explains the conditions under which farm technical efficiency is complementary to using farm income or output as an outcome measure.

### 2.3. Theoretical Framework for Extension Program Assessment

#### 2.3.1. Technical Efficiency

in this chapter, when we refer to treatment effect, we are referring to the impact of an extension program. We use the terms "treatment effect(s)" or 'impact of extension program(s)" interchangeably throughout the paper. Treatment effects of the impact of extension programs have been traditionally been estimated using output and profit (income) as outcome variables. Alternatively, technical efficiency (farm productivity) may be used explicitly as an outcome measure to evaluate extension programs. Following Battese and Coelli (1988), we define efficiency as average productivity (APP). For simplicity, assume a single input, single output profit maximizing farmer.

$$(1)\ \mathrm{E(T)} = \frac{Y(X(T))}{X(T)},$$

where E is technical efficiency, T is extension program (T) which we refer to as 'treatment' through the paper, X is inputs, and Y is total output. E, X and Y are all functions of treatment effect.

One can derive the treatment (extension program) effect on technical efficiency using the first order derivative of technical efficiency with respect to T, which is equal to:

$$(2)\ \frac{\partial E}{\partial T} = \frac{\frac{\partial Y}{\partial X} * \frac{\partial X}{\partial T} * X - \frac{\partial X}{\partial T} * Y}{X^2} = \frac{\frac{\partial Y}{\partial T} * X - \frac{\partial X}{\partial T} * Y}{X^2}$$

If treatment does not affect output ( $\frac{\partial Y(X)}{\partial T} = 0$), but improves input allocation ($\frac{\partial X}{\partial T} < 0$), then $\frac{\partial E}{\partial T} > 0$. In this case, the relative change in technical efficiency due to treatment is greater than the relative change in output. When the treatment effect using technical efficiency is higher, then we learn that farmers are operating at stage two of the production function, that they decrease input use and still produce the same level of output. For farmers who initially produce output at the point where marginal revenue is less than marginal cost, extension programs may advise them to reduce their input use and produce the same level or more output.

### 2.3.2. Profit and Technical Efficiency

In this section, we discuss the importance of using profit and technical efficiency as outcome variables to evaluate extension programs. The equation for profit (π) is given by the following:

$$(3)\ \pi(T) = PY(X(T)) - WX(T)$$

where P and W are output and input prices, respectively. Assume prices are exogenous and the profit function is continuous and differentiable, such that $\frac{\partial \pi}{\partial T} > 0$, and $\frac{\partial^2 \pi}{\partial T^2} < 0$ (or concave in T).

This assumption is valid if markets are complete, where prices (output and input) are determined by the market. However, this may not be valid for thin or incomplete markets, where farm households consume all of their output. If farm households use their output produced for home consumption, then prices are endogenously determined (Dillon and Barrett 2017, Lafave and Thomas 2016; Chang, Huang, Chen 2012; Binam et al. 2004; Jayne 1994; De Janvry, Fafchamps and Sadoulet 1991). For the time being, though, our model excludes farmers who don't participate in the market, we will return to this case in Chapter 3 of the dissertation.

The first order derivatives of the profit function with respect to treatment give:

$$(4)\ \frac{\partial \pi}{\partial T} = \frac{\partial Y(X)}{\partial T} P - \frac{\partial X}{\partial T} W$$

recognizing that $\frac{\partial Y(X)}{\partial T} = \frac{\partial Y}{\partial X} * \frac{\partial X}{\partial T}$.

Substituting $\frac{\partial Y(X)}{\partial T} = \frac{\partial E}{\partial T}X + \frac{\partial X}{\partial T}E$ derived from equation (2) into equation (4) and recognizing that where $E = APP$, as in equation (1),

we get:

$$(5)\ \frac{\partial \pi}{\partial T} = \frac{\partial E}{\partial T}PX + \frac{\partial X}{\partial T}(PE - W)$$

Assuming the market is competitive, input prices are equal to the MVP (marginal value product) of the input (P*MPP). MVP refers to the value of the output resulting due to an additional unit of input. We can then rewrite equation (5) as:

$$(6)\ \frac{\partial \pi}{\partial T} = \frac{\partial E}{\partial T}PX + \frac{\partial X}{\partial T} * P(APP - MPP)$$

Equation (6) then allows us to examine when the use of APP or technical efficiency may be equivalent to or relatively better than using farm profit or income as an outcome measure to evaluate extension programs.

When $APP = MPP$, there is no distinction between using farm profit (income) or technical efficiency as an outcome variable. The measures are only different by scale and are relatively the same. Disparities occur when $APP \neq MPP$.

When $APP > MPP$, we see that the effect of a program on relative profit incorporates both the scaled efficiency effect (the first term on the RHS), as well as the relative value of the difference between average and marginal products (second term on the RHS). This case corresponds to the familiar second stage of production, where farmers increase their use of input X to the point where marginal revenue (MR) is equal to marginal cost. In this case, using farm profit to examine may be relatively better than using farm technical efficiency as an outcome measure to evaluate extension programs.

However, when $APP < MPP$, a farmer is in the first stage of production. If $\frac{\partial X}{\partial T} > 0$, the second term on the RHS becomes negative, which means that an increase in farm efficiency due to the program may not necessarily be reflected in profits. For large gaps between APP and MPP, which occur close to the inflection point of the marginal product curve in the canonical production process, the differential effects of treatment on a technical efficiency may be relatively large. Stage one of the production process therefore permits the case that increases in farm efficiency may correspond to zero or little changes in profit. In this stage, increase in relative average productivity of inputs exceeds the increase in relative profit (a difference between marginal revenue and cost) on a relative basis (e.g. percentage change). This could be common in developing countries where farmers often face input constraints (Jack 2011), which potentially lead them to operate in the first stage of the production function. Hence, depending on the scenario, technical efficiency is a viable alternative to output (such as case 1), or profit (such as in case 2) when examining impact of treatment effects, as extension programs could positively affect farmers with constrained input use.

We compared output and profit (income) with technical efficiency derived from single input and single output as outcome variables to evaluate extension programs. We recommend a future research that compare output and profit (income) with technical efficiency derived from multiple inputs and multiple outputs as outcome variables to evaluate extension programs.

**Conclusion**:

Extension programs that provide farmers with the most up-to-date information can potentially increase farm output and income through increasing farm technical efficiency. In this paper, we show that farm efficiency can be used as a complementary outcome variable to farm output and/or profit/income to evaluate extension programs. We develop a simple model that shows that an extension program with no or little impact on profit may still have resulted in more efficient production behavior for farmers that operate in stage one of the production process. Subsistence and semi-subsistence farmers are often beset by input constraints, which potentially leads them to operate in the first stage of the production function. We note that when farmers are capital constrained, extension programs can theoretically have a large *efficiency* effect despite little or no change in farm profits/income. Alternative methods to evaluate extension programs, such as using farm technical efficiency instead of farm income or output as outcome variables can helps to identify program impacts that may have otherwise gone undetected.

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# Chapter 3. Modeling Farm Productivity for Heterogeneous Farm Households in Developing Countries

## 3.1. Abstract:

Relative to home-consumed crops, production of cash crops requires relatively higher market involvement in both the purchase of inputs and the selling of output. This difference leads to a substantial imbalance in the transaction costs associated with the production of each crop. Moreover, home-consumed crops may have quality attributes (e.g. color, taste, softness of dough, and suitability for certain dishes) not reflected in market prices. Factors such as transaction costs, crop quality attributes, and household characteristics are farmer specific and drive a heterogeneous price wedge between the market prices for household crop production and the economic value of these crops for the household. These distinctions have important implication for farm productivity analysis, such as efficiency measurement. The standard approach to measure productivity analysis, such as efficiency, assumes that farm households face homogenous price wedges that lead to a homogenous set of production and profit functions. However, the price gap created by transaction costs, crop quality attributes, and other household characteristics generally varies among subsistence, semi-subsistence and commercial farmers and leads to a heterogeneous set of production frontiers. Subsistence and semi-subsistence farmers, who produce largely home consumed crops, have potentially greater price wedges than commercial farmers. Failing to account for the heterogeneity in price wedges that drive heterogeneity in production frontiers is likely to lead to underestimation of the efficiency of subsistence and semi-subsistence farmers. We test if traditional productivity analysis indeed underestimates the efficiency of such farmers by employing a conditional Data Envelopment Analysis (DEA) model for household survey data in Uganda. Results confirm that naïve estimates of efficiency understate the efficiency scores of subsistence and semi-subsistence farmers. The results cast doubt on policies, such as extension programs or other information treatments, that are promised on interpreting low efficiency scores for subsistence and semi-subsistence farmers as a management shortfall.

**Key words**: joint production and consumption decisions, Data Envelopment Analysis, efficiency

### 3.2. Introduction

In most developing countries, improving agricultural productivity growth is considered an important strategy for reducing high poverty levels. Agriculture remains a key sector in terms of output and source of employment. For example, more than 60% of the African population depends on agriculture for their livelihood (Elias et al. 2013). The World Development Report (2008) identifies improving agricultural productivity and development as a key pathway to escape poverty. Farm households that face different infrastructural constraints (Suri 2011; Ojiem et al. 2006), credit constraints, information barriers, input market constraints (Duflo, Kremer and Robinson 2011; Jack 201; Suri 2011and Stifel and Minten 2008), labor market constraints (Henning and Henningsen 2007), socio-economic factors (Ojiem et al. 2006) and non-farm income opportunities (Chang et al. 2012) have different access to agricultural inputs and outputs. This has a big impact on farm households' agricultural production decisions.

Agricultural production in developing countries can be broadly classified into cash versus home consumed crops. Cash crops are produced for market sale, while some food commodities are often produced solely for home consumption. Production of cash and marketed crops (excess of consumption) have relatively higher degrees of market involvement for both the purchase of inputs and selling of outputs. As such, transaction costs associated with cash and marketed crops exceed those for home-consumed crops.[1] Transaction costs include search costs associated with finding the best price and quality, transportation costs, negotiations, commissions, cost of screening and supervision necessary due to asymmetric information, governmental fees, etc (Henning and Henningsen 2007; Masanjala 2006; Key et al 2000; Jayne 1994). The heterogeneous constraints such as infrastructure, credit, non-farm income and others across farm households leads to a

[1] Transaction costs may be fixed, proportional and variable (see Henning and Henningsen 2007; Key et al. 2000).

substantial imbalance in the transaction costs associated with the production of each crop. Moreover, farm households who produce cash and marketed crops must also purchase food for consumption. Transaction costs reduce the profitability of cash and marketed crops and increase the cost of buying home consumed crops from market. Farmers who produce home consumed crops do not incur such costs. Moreover, production of home consumed crops may have quality attributes (e.g. ease of shelling and processing, color, taste, softness of dough, and suitability for certain dishes) that market prices may not reflect (Arslan 2011; Arslan and Taylor 2009).

Transaction costs and crop quality attributes not embedded in the market price, as well as other factors such as household characteristics can drive a price wedges between market prices for household's crop production and the economic value of these crops for households. The price wedge, the difference between the market price and shadow price of home consumed crops can be substantial (Arslan 2011; Arslan and Taylor 2009). Arslan and Taylor (2009), for example, estimated the shadow price of local maize in rural Mexico using the marginal productivity of labor as a proxy. They find that the shadow price of local maize consumed at home 210 percent higher than the market price.

Price wedges, generally increase with market interactions. Price wedges are farmer specific and appear in the optimality conditions associated with the farm household's choice of cash and marketed versus home-consumed crops (Suri 2011; Jayne 1994). Heterogeneity in factors that drive price wedges leads to heterogeneity in production frontiers. Farm efficiency measures assumes homogeneous production frontier, which leads to potentially biased efficiency estimates. As a result, consideration of these factors is important for productivity analysis such as efficiency estimation. Productivity analysis of farm households that face potentially significant price differences may be difficult to assess if these factors are not explicitly addressed.

Some farm household models have incorporated price wedges in their analysis (Suri 2011; Arslan and Taylor 2009; Henning and Henningsen 2007; Masanjala 2006; Key et al 2000; Jayne 1994). However, to our knowledge, research focused on farm households' productivity measurement, especially efficiency analysis, have not considered potential biases arising from price wedges (Ghebru and Holden 2015; Peterman et al. 2011: Balcombe et al. 2008; Chavas, Petrie and Roth, 2005; Rahman, 2003; Wang, Cramer and Wailes, 1996 etc). Such analyses implicitly assume failure to produce at the frontier (i.e. 'inefficiency') stems from managerial failure (i.e. shortfalls in choosing the optimal mix of inputs for a given production technologies), but may in fact arise due to the presence of large price wedges (e.g. high transaction costs).

The standard approach to measuring productivity analysis assumes that farm households face homogenous price wedges and homogenous production frontiers. Price wedges created due to heterogeneous transaction costs, crop quality attributes and other factors such as household characteristics leads to heterogeneous production frontiers (Suri 2011; Arslan 2011; Arslan and Taylor 2009; Henning and Henningsen 2007). Because of significant differences in price wedges, subsistence, semi-subsistence and relatively commercial farmers likely have different production frontiers. Failure to account for the price wedges underestimates the value of the production of home consumed crops, which leads to underestimation of efficiency for farmers who produce such crops. If the production frontiers are heterogeneous across farmers, then estimating and comparing efficiency of farms without accounting for these factors is useful only to determine levels of efficiency 'as if' price wedges did not exist. The purpose of this study is to model farm productivity and estimate farm efficiency in a manner that accounts for the influence of heterogeneous price wedges across farm households.

In this paper, we explicitly model the potential impact of price wedges on farm technical efficiency of farmers that make optimal crop choices based on a utility maximizing farm household model. As in previous work, we show that the existence of price wedges discourages production of cash and encourages production of home consumed crops. The optimal production mix varies due to these price wedges. With the increase of such price wedges, a utility maximizing farm household, more typically a subsistence farmer, withdraws inputs from cash crops and allocates them toward home consumed crop production. All else equal, the magnitude of the price wedges is expected to be higher for relatively subsistence farmers who produce crops predominantly for home consumption than for commercial farmers.

We discuss the implication of performing productivity analysis with and without taking price wedges into account. We focus here only on estimating technical efficiency, as the methods developed here would be similar for estimating other types of efficiency. Infrastructure constraints, credit constraints and other input market imperfections could lead to different access to input and output markets. Which in turn lead to higher transaction costs. Higher transaction costs lead to higher price wedges which may discourage farmers from using some specific agricultural inputs. For instance, farmers located in remote area may have less access to agricultural machinery than farmers located closer to roads. Farmers with better access to credit or non-farm income opportunities could easily afford better agricultural inputs than farmers with low access to credit or non-farm income opportunities.

We measure technical efficiency using unconditional (naïve DEA) and conditional Data Envelopment Analysis (DEA). We use conditional DEA to account for heterogeneity in production frontiers due to price wedges when estimating the technical efficiency of farmers. Conditional DEA measures technical efficiency by grouping farmers who face similar price wedges together and the allowing construction of a separate production frontier for that group. That is, efficiency is estimated comparing relatively subsistence with subsistence farmers and commercial with commercial farmers. Subsistence and semi-subsistence farmers may be better-off by producing home consumed crops over cash and marketed crops. From a profit maximization point of view, subsistence and semi-subsistence farmers appear to choose the "wrong" crop production mix, which includes more home consumed using fewer modern inputs. However, internalizing price wedges into the profit and production analysis may give quite different and more important answers to the puzzle of modern input adoption and commercialization.

We find that naïve estimates of technical efficiency understate the efficiency scores of subsistence and semi-subsistence farmers. The average technical efficiency score using naive and conditional DEA estimators are 0.48 and 0.68, respectively. The average bias, the difference between conditional and unconditional technical efficiency score is about 0.21 (Table 4). This is important for development programs, such as extension and other information based programs to identify the actual efficiency loss due to managerial inefficiency.

### 3.3. Background

Efforts to increase agricultural productivity often focus on promotion of technological change and commercialization (Masanjala 2006; Zeller, Diagne and Mataya 1998; Binswanger and Braun 1991). Agricultural technological advancement increases agricultural production and farmers' income through increases in per unit productivity. Commercialization further improves farm productivity and income via specialization in farm products that farmers may have a comparative advantage in producing (Barrett 2008; Binswanger and Braun 1991). Significant development resources have been invested by both domestic and international agencies in teaching subsistence farmers about modern agricultural inputs and high value, commercial products under the belief that farmers lack awareness and knowledge (Sturdy, Aquino and Molyneaux 2014; Elias et al. 2013; Fortson et al. 2012). Such extension programs often seek to provide farmers with technical and practical information about the management of modern technologies, often with the goal of alleviating information constraints to profitable technology adoption (Jack 2011).

However, adoption of modern agricultural technology, particularly in many parts of sub-Saharan Africa, remains low, and agricultural output and employment continue to be dominated by subsistence and semi-subsistence farmers (Suri 2011; Binam et al. 2004; Zeller, Diagne and Mataya 1998; Jayne 1994; De Janvry, Fafchamps and Sadoulet 1991). These farmers largely produce food crops for home consumption and supply excess to the market. Several studies show that many farmers in developing countries continue to produce a high proportion of home consumed commodities, even though researchers identify higher returns from cash commodities (Suri 2011; Arslan and Taylor 2009; Henning and Henningsen 2007; Masanjala 2006; Key et al 2000; Jayne 1994).

Transaction costs remain a fundamental reason for the lack of market specialization. Key et al. (2000) delineate a clear link between transaction costs and agricultural household market participation. Small holder farmers are often surrounded by thin (few buyers and sellers) and incomplete markets. Thin and incomplete markets increase the cost of exchanging goods and services (Dillon and Barrett 2017; Lafave and Thomas 2016; Chang, Huang, Chen 2012; Henning and Henningsen 2007; Masanjala 2006; Key et al. 2000; Omamo 1998).

In well-functioning markets, input and output prices are exogenously determined by the market, and production and consumption decisions are separable. However, in thin and poorly functioning markets, farm household's input and output prices are endogenously determined by their shadow prices, which differ from the prevailing market prices (Barrett 2008). The difference between the market price and economic value of the crop to the household is called a price wedge. When farm households find it optimal to satisfy family consumption from their own agricultural production, then the shadow price (opportunity cost of consuming the crop) is influenced by both supply and demand factors, leading to inseparable production and consumption decisions (Dillon and Barrett 2017, Lafave and Thomas 2016; Chang, Huang, Chen 2012; Binam et al. 2004; Jayne 1994; De Janvry, Fafchamps and Sadoulet 1991; Singh, Squire and Strauss 1986).

The shadow prices are household specific and are an important determinant of the adoption of modern inputs, high value crops and commercialization. Because of differences between the market price and the shadow price, farm households may find adoption of modern inputs and production of cash (commercial) outputs, such as high value crops, unprofitable (Shamdasani 2016; Suri 2011; Arslan and Taylor 2009). Factors that may contribute to differences in transaction costs for instance and hence to differences between market and shadow prices are variation in credit access, infrastructure settings, biophysical factors, socio-economic factors, and off-farm income opportunities (Zhao and Barry 2014; Chang et al. 2012; Tittonell et al. 2007; Ojiem et al. 2006; Nehring et al. 2005; Zeller et al. 1998; Jayne 1994). Understanding these price wedges is essential to understanding how farm households prioritize the production of cash and versus home consumed crops. Failure to account for such wedges can mislead policy makers into believing that knowledge gaps are the primary barrier to production of cash crops over home consumed crops, as such 'high value' crops appear profitable under market prices.

Profit maximizing farmers intend to produce cash crops over home consumed crops if the market price is high enough to cover the costs of buying home consumed crops (Henning and Henningsen 2007; Key et al 2000; Jayne 1994). If the return from marketed crops is lower than the cost of buying home consumed crops, including any foregone value from non-priced quality attributes of home-produced crops, then it is rational for farmers to choose to produce home consumed over cash crops (Arslan and Taylor 2009). The return for farmers who produce home consumed crops is lower by the amount equal to the price wedges.

Accounting for price wedges, production of high values crops can become unprofitable for subsistence and some of the semi-subsistence farmers. On the other hand, use of modern technologies and production of high value crops are still profitable for other, relatively commercial farmers. Price wedges appear in the optimality conditions of production and play a significant role in the choice of cash and marketed versus home-consumed crops. Price wedges generally vary between subsistence, semi-subsistence and relatively commercial farmers and lead to heterogeneous sets of profit and production frontiers. Hence, the evaluation of farmer's productivity needs to account for these heterogeneous sets of production frontiers between subsistence, semi-subsistence and commercial farmers.

### 3.4. Theory

We present a theoretical model to illustrate the potential influence of price wedges (Arslan and Taylor 2009; Henning and Henningsen 2007; Key et al 2000; and Jayne 1994). Using a farm household model, we explicitly model profit and production decisions that account for price wedges. We explain the implication of price wedges in measuring efficiency. We define two types of crops: cash $(m_i)$ and food crops $(h_i)$. Food crops can be home consumed crops $(o_i)$ and/or marketed (excess of home consumption) $(g_i)$ crops. Farmers may specialize in production of cash crops or food crops or a combination of both. Assume that total output produced $(Q_i)$ is a combination of cash $(m_i)$ and food crops $(h_i)$ produced using a fixed vector of inputs $A_i$, where it is given by: $Q_i = f(h_i;\ m_i;\ A_i)$. To simply the analysis, we assume inputs available for production are fixed (i.e. for land inputs see Arslan and Taylor (2009) and labor inputs see De

Janvry, Fafchamps and Sadoulet (1991). We assume production is separable for cash and home consumed food crops. Thus, we have a separate production functions for cash crops ($m_i$) and home consumed crops ($h_i$). This case may arise when some farmers choose to specialize completely in cash crops; produce specially crops that are only for sale at the market; certain crops are produced communally; among other reasons. Input allocation is still constrained and connects the production process for both types of crops as $A_{mi} + A_{hi} = A_i$, where $A_i$ is the vector of fixed inputs such as family and hired labor (L) and capital (K) available for production, $A_{hi}$ is the vector of inputs allocated to food crop production, $A_{mi}$ is the vector of inputs allocated to cash crop production.

In our model, farm households maximize utility ($U_i$), through production of cash, and/or food crops subject to an income constraint, production technology and availability of inputs. Transaction costs reduce the effective prices received from cash crops and increase the cost of buying home consumed crops. Assume that utility (U) and production functions ($f$) are concave and twice differentiable.

The i<sup>th</sup> farm household's optimization problem is modelled as follows:

(1) $\max_{o_i;\, n_i;\, g_i; A_{hi}, A_{mi}} \mathrm{U} = (o_i; n_i\, ; Z_{ui})$

s.t:

(2) $(p_{mi} - t_{mi})m_i + (p_{gi} - t_{gi})g_i - (p_{ni} + t_{ni})\, n_i + T_i = 0$

(3) $f(A_{hi};\ z_{hi}) = h_i$

(4) $h_i = g_i + o_i$

(5) $f(A_{mi};\ z_{mi}) = m_i$

(6) $A_{mi} + A_{hi} = A_i$

(7) $o_i, g_i, m_i, n_i \geq 0$,

where $h_i$ is the food crop for farm household i, $m_i$ is cash crops, $o_i$ is food crops produced for home consumption, $g_i$ is food crops sold to the market, $n_i$ is purchased items used for home consumption, $p_m$ is the per unit net price (revenue minus cost) for cash crop, $p_g$ is the per unit net price (revenue minus cost) for food crop sold, $p_n$ is the per unit output price for purchased crops, $t_{m_i}$ is the per unit output transaction costs (such as fixed, proportional and variable transaction costs) associated with marketing and selling cash crops, $t_{g_i}$ is the per unit output transaction costs (such as fixed, proportional and variable transaction costs) associated with marketing and selling food crops sold, $t_{n_i}$ is vector of per unit transaction costs (such as fixed, proportional and variable transaction costs) associated with buying consumed items, $Z_{ui}$ is vector of utility shifters (e.g. farm household characteristics), $z_{mi}$ is a vector of production shifters for cash crops, $z_{hi}$ is vector of production shifters for food crops (e.g. improved seed), $T_i$ is other net income such as off-farm, transfers, government payments, and $f_i$ is a production function. Farm households are constrained by income, given by equation (2), production technology, given by equations (3) and (4), and input allocations, given equation (5).

We assume that the marginal return of inputs is positive and subject to diminishing marginal returns. In addition, we assume the production functions are concave in the level of inputs used, implying that the first derivatives are positive and second derivatives are negative.

i.e. $f_{m_i} = \frac{dm_i}{dA_{m_i}} > 0, f_{h_i} = \frac{dh_i}{dA_{h_i}} > 0, f_{m_i m_i} = \frac{d^2 m_i}{dA_{m_i}{}^2} < 0, f_{h_i h_i} = \frac{d^2 h_i}{dA_{h_i}{}^2} < 0.$

Substituting $h_i = f(A_{h_i};\ z_{hi})$ and $m_i = f(A_{m_i};\ z_{mi})$, we have the following Lagrangian function:

(9) $L = \mathrm{U}(o_i; n_i\ ; Z_{ui}) + \lambda_i\big[(P_{m_i} - t_{m_i})\ f(A_{m_i};\ z_{mi}) + (P_{g_i} - t_{g_i})\ (f(A_{h_i};\ z_{hi}) - o_i) -$

$(p_{n_i} + t_{n_i})\ n_i + T_i\big] + r_i[A_i - (A_{m_i} + A_{h_i})]$

Which can be used to determine the optimal level of production of cash and food crops, as well as optimal input allocation that will maximize utility.

From equation (4), $g_i = h_i - o_i$, or the amount of food crops sold is equal to total food crops production minus food crops used for home consumption.

The first order conditions (FOCs) for maximizing equation (9) are:

(i) for home consumed crops: optimal consumption of food crops is governed by:

(10) $\frac{dL}{do_i} = \frac{du}{do_i} - \lambda_i(P_{g_i} - t_{g_i}) = 0 \Rightarrow MU_{oi} - \lambda_i(P_{g_i} - t_{g_i}) = 0;$

(ii) for purchased food crops: optimal consumption of purchased crops is governed by:

(11) $\frac{dL}{dn_i} = \frac{du}{dn_i} - \lambda_i(p_{n_i} + t_{n_i}) = 0\ \Rightarrow MU_{n_i} - \lambda_i(p_{n_i} + t_{n_i}) = 0;$

(iii) for inputs used for food crops: optimal allocation of inputs used for food crops are governed by:

(12) $\frac{dL}{dA_{h_i}} = \lambda_i(P_{g_i} - t_{g_i}) f_{h_i}(A_{h_i}) - r_i = 0$; and

(iv) for inputs used for cash crops: optimal allocation of inputs used for cash crops are governed by:

(13) $\frac{dL}{dA_{mi}} = \lambda_i(P_{m_i} - t_{m_i})f_{m_i}(A_{m_i}) - r_i = 0;$

where $MU_{oi}$ is the marginal utility of consuming food crops, $\lambda_i$ is marginal utility of income, and $MU_{n_i}$ is the marginal utility of consuming purchased goods.

To estimate prices for home consumed crops, we optimize utility with respect to outputs and input allocations. Implicitly, households optimize output by optimally choosing inputs. Using the Karush-Kuhn-Tucker (KKT) conditions, we can derive the optimal conditions, including the corner solution, for producing food versus cash crops.

The optimal decision prices for farm crops sold, consumption crops bought and farm crops consumed are similar to those in Arslan (2011), Arslan and Taylor (2009), Henning and Henningsen (2007), Key et al. (2000), Jayne (1994), and De Janvry, Fafchamps and Sadoulet (1991). The net prices for each potential crop is given by the following:

$$(14)\ P_i = \begin{cases} P_m - t_m\,, & for\ cash\ crops \\ P_g - t_g\,, & food\ crops\ sold \\ P_n + t_n\,, & for\ purchased\ crops \\ \frac{MU_{oi}}{\lambda_i}, & for\ home\ consumed\ crops \end{cases}$$

A detailed derivation of the above prices is provided in the appendix.

The shadow price for home consumed crops is given by:

(15) $P_i = \frac{MU_{oi}}{\lambda_i}$,

$MU_{hi}$ and $\lambda_i$ represent the marginal utilities of home consumed crops and income, respectively (see De Janvry, Fafchamps and Sadoulet 1991). Define $\varphi_i$ as the price wedge, or the difference between the shadow ($\frac{MU_{oi}}{\lambda_i}$) and market price ($p_{gi}$). That is,

(16) $\varphi_i = \frac{MU_{oi}}{\lambda_i} - p_g$.

The shadow price can then be written as:

(17) $\frac{MU_{oi}}{\lambda_i} = P_i = P_g + \varphi_i$ .

where $P_g$ is the market price of home consumed crops if it is sold to the market.

Price wedges are functions of several factors. The household saves $t_{gi}$, the amount that would have been paid if the household sold the crop to the market. That is, the market value is higher by $t_{gi}$. Moreover, production of food crops might have embedded quality attributes that are not reflected in the market prices (see Arslan 2011; Arslan and Taylor 2009). Assume that the market values of these quality attributes for the household are equal to $\theta_i$. There could also be other household characteristics (socio-cultural, preferences etc.) and factors that affect price wedges. The price wedges ($\varphi_i$) then is a function of the transaction costs ($t_{gi}$) (Henning and Henningsen 2007; Key et al. 2000), crop quality attributes ($\theta_i$) (Arslan 2011; Suri 2011; Arslan and Taylor 2009) and these other factors (e.g. household characteristics) (Suri 2011; Ojiem et al. 2006 and Jayne 1994).

The objective here is to show that profitability and productivity analysis of farm households explicitly must incorporate price wedges. The next step is to derive the optimal condition for maximizing utility of cash versus food crops accounting for price wedges. We have three cases to determine the optimal solution or product mix; two boundary solutions and one interior solution.

Case 1: interior solution: $m_i \neq 0, h_i \neq 0$.

From equation (10) and (12):

(18) $r_i = MU_{oi}MP_{h_i}$ where $MP_{h_i} = f_{h_i}(A_{h_i})$ is the marginal productivity of inputs used for food crop production.

From equation (13) and (18):

(19) $MU_{oi}MP_{h_i} = \lambda_i(P_{m_i} - t_{m_i})MP_{m_i}$ where $MP_{m_i} = f_{m_i}(A_{m_i})$ is the marginal productivity of inputs used for cash crop production.

At equilibrium:

(20) $\frac{MU_{oi}}{\lambda_i}MP_{h_i} = (P_{m_i} - t_{m_i})MP_{m_i}$

Note that the $\frac{MU_{oi}}{\lambda_i}$ is the shadow price for home consumed crops, which is equal to $P_g + \varphi_i$.

If we replace $\frac{MU_{oi}}{\lambda_i}$ by $P_g + \varphi_i$ in equation (20), then the equilibrium point of production can be written as:

(21) $(P_g + \varphi_i)\ MP_{h_i} = (P_{m_i} - t_{m_i})MP_{m_i}$

If $(P_g + \varphi_i)\ MP_{h_i} \geq (P_{m_i} - t_{m_i})MP_{m_i}$, farmers start to move input/s toward home consumed crops, decreasing marginal productivity for home consumed crops and increasing marginal productivity for cash crops, and vice-versa. At equilibrium, the ratio of marginal physical (MP) products of the crops is equal to their inverse effective price ratio. That is:

(22) $\frac{MP_{m_i}}{MP_{h_i}} = \frac{(P_{gi}+\varphi_i)}{(P_{mi}-t_{m_i})}$.

When the an interior equilibrium is unique, $(p_{gi} + \varphi_i)MP_{h_i}$= $(p_{mi} - t_{m_i})MP_{mi}$, and farmers allocate resource between home consumed and cash crops until the point where the shadow value of the marginal product of allocating the resources to home consume crops is equal to the marginal value of resources allocated to cash crops.

Case 2: Boundary solution:$h_i \neq 0, or\ m_i = 0$.

This occurs when only home consumed crops are profitable for the farmers. A farmer allocates all the inputs to home consumed crop production.

Under this case; $(p_{mi} - t_{m_i})MP_{mi} \leq (p_{gi} + \varphi_i)MP_{h_i}$, which implies that the value of the contribution of allocating one unit to cash crops is always less than the contribution of allocating one unit to home consumed crop. The farmer allocates all the inputs to home consumed crops and zero inputs to cash crops, implying $A_{m_i} = 0$, and $A_{h_i} = A_i$. Case 2 represents the optimal allocation for subsistence farmers.

Case 3: Boundary solution:$m_i \neq 0, h_i = 0$.

This occurs when only cash crops are profitable for the farmers. A farmer allocates all the inputs to cash crop production.

Under this case; $(p_{gi} + \varphi_i)MP_{h_i} \leq (p_{mi} - t_{m_i})MP_{mi}$, which implies that the value of the contribution of allocating one unit to home consumed crops is less than the value of the contribution of allocating one unit to cash crop. The farmer allocates all the inputs to cash crops and zero inputs to food crops, implying $A_{h_i} = 0$, and $A_{m_i} = A_i$. It is more profitable to buy food crops for home consumption than to produce them. Case 3 represents the optimal allocation for commercial farmers. The effects of changes in price wedges on farm household's optimality conditions can be examined using second order derivatives.

### 3.5. Comparative Statistics of the Change in Price Wedge Between Cash and Food Crops Production

From equations (12) and (13),

(24) $(P_{gi} + \varphi_i(t_{gi}))f_{h_i}(A_{h_i}) = r_i$

(25) $(P_{m_i} - t_{m_i})f_{m_i}(A_{m_i}) = r_i$, and

(26) $A_{m_i} + A_{hi} = A_i$

We perform total differential of the system to examine how changes in price wedges due to change in factors of price wedges such as transaction costs affect farm household decisions to allocate inputs toward cash versus home consumed crop production.

From equation (24), (25) and (26), the Hessian determinants or total differential of the system are:

$$\begin{bmatrix} (P_{gi} + \varphi_i(t_{gi}))f_{h_ih_i} & 0 & -1 \\ 0 & (P_{m_i} - t_{m_i})f_{m_im_i} & -1 \\ 1 & 1 & 0 \end{bmatrix} \begin{bmatrix} dA_{h_i} \\ dA_{m_i} \\ dr_i \end{bmatrix} = \begin{bmatrix} -dP_{gi}f_{h_i} - \varphi_{t_{gi}}f_{h_i} \\ -dP_{m_i}f_{m_i} + dt_{m_i}f_{m_i} \\ dA_i \end{bmatrix}$$

where $\varphi_{t_{gi}}$ represents $\frac{d\varphi_i}{dt_{gi}} > 0$

The Jacobian determinant is: $J = (P_{m_i} - t_{m_i})f_{m_im_i} + (P_{g_i} + \varphi_i(t_{gi}))f_{h_ih_i} < 0$

$$dA_{h_i} = -dP_{g_i}f_{h_i} - \varphi_{t_{gi}}f_{h_i} - (-dP_{m_i}f_{m_i} + dt_{m_i}f_{m_i}) + dA_i\ ((P_{m_i} - t_{m_i})f_{m_im_i})$$

$$dA_{m_i} = (P_{gi} + \varphi_i)f_{h_i}(dA_i) + \left(-dP_{g_i}f_{h_i} - \varphi_{t_{gi}}f_{h_i}\right)(-1) - (-dP_{m_i}f_{,} + dt_{m_i}f_{m_i}(-1).$$

This information can be used to show that:

(28) $\frac{dA_{h_i}}{\varphi_{t_{gi}}} = \frac{-f_{h_i}}{J} > 0$

(29) $\frac{dA_{h_i}}{dt_{m_i}} = \frac{-f_{m_i}}{J} > 0$

(30) $\frac{dA_{h_i}}{dA_i} = \frac{\left(P_{m_i} - t_{m_i}\right) f_{m_i m_i}}{J} > 0$

Assuming that $P_{m_i} - t_{m_i} > 0$.

(31) $\frac{dA_{m_i}}{\varphi_{t_{gi}}} = \frac{f_{h_i}}{J} < 0$

(32) $\frac{dA_{h_i}}{dt_{m_i}} = \frac{f_{m_i}}{J} < 0$

(33) $\frac{dA_{m_i}}{dA_i} = \frac{\left(P_{g_i} + \varphi_i\right) f_{h_i h_i}}{J} > 0$

The price wedge is a function of transaction costs, crop quality attributes and household characteristics. Increases in price wedges due to either of these factors affect the cash versus food crop production decision of farmers. For instance, an increase in transaction costs ($t_{gi}$) increases the price wedges ($\varphi_i$), which discourage production of cash crops (equation (31)) and encourages the production of home consumed crops (equation (28)) and vice-versa. A sample of farmers facing heterogeneous transaction costs and other factors that contribute to price wedges will result in a heterogeneous production frontier. Thus, accounting for such heterogeneity in production frontiers is important when measuring efficiency.

### 3.6. Impact on Efficiency Analysis

We have demonstrated theoretically that utility maximizing farmers such as subsistence, semi-subsistence and commercial producers likely have different production frontiers. Following Daraio and Simar (2005), the production attainable set ($\boldsymbol{\Psi}$) that is conditional on price wedges ($\varphi$) is defined as:

(34) $\Psi^{\varphi_i} = \{(A, Q)|\varphi_i, A\ can\ produce\ Q\}$

We note that farmers that have higher price wedges ($\varphi$) allocate more inputs toward production of food crops, implying that their total agricultural production has a greater composition of home consumed crops ($h_i$) relative to cash crops ($m_i$). On the other hand, farmers that have lower price wedges ($\varphi$) allocate more inputs toward cash crops and have agricultural production that has less composition of home consumed crops ($h_i$) and more of cash crops ($m_i$). We also note that if we don't account for price wedges, then we undervalue the return for subsistence and semi-subsistence farmers that dominantly produce home consumed crops (due to higher price wedges). Undervaluing the returns for subsistence and semi-subsistence farmers as compared to commercial farmers, implies that the production set ($\boldsymbol{\Psi}$) for subsistence and semi-subsistence farmers is lower than it would have been, which we interpret it lower efficiency. Estimating efficiency for all farmers ignoring the price wedges implies that one may unnecessarily understate the return and efficiency of subsistence and semi-subsistence farmers who have potentially higher price wedges. However, one could correct this issue by allowing one to set separate production frontiers for farmers that have similar price wedges ($\Psi^{\varphi_i}$). That is, there will be a separate production sets for subsistence, semi-subsistence and commercial farmers which helps to estimate efficiency through a comparison within each group that has similar price wedges, instead of across all farmers. This helps to overcome the efficiency loss due to price wedges and identify true management shortfalls.

### 3.7. Empirical Model

We test the supposition that accounting for price wedges understates technical efficiency for subsistence and semi-subsistence farmers using a conditional Data Envelopment Analysis (DEA) approach. We use DEA for two reasons. First, DEA is widely used and performs well in estimating efficiency for multi-output and multi-input production process. Second, as it constructs production frontiers from the data, mismeasurement of the return to cash versus home consumed crops will likely affect the efficiency estimation. It is well documented that non-parametric efficiency measures such as DEA are sensitive to heterogeneity across decision making units (Dai and Kuosmanen 2014; Charnes, Cooper and Rhodes 1978). Conditional DEA was developed to account for such heterogeneity (Daraio and Simar 2007; Simar and Wilson 2007). Our contribution is to explain the consequences of this characteristic of the DEA method for farm production efficiency in a developing country settings, and demonstrate how conditional DEA techniques offers a potential remedy.

The empirical model is presented as follows: First, we measure technical efficiency using a conditional DEA technique that accounts for heterogeneous price wedges between market and shadow prices ("first-stage"). Second, we examine the impact of various factors on the conditional technical efficiency of farm households ("second stage").

**3.7.1. First Stage of DEA**

Our empirical strategy is to estimate efficiency that accounts for price wedges between market and shadow prices. It is based on a novel approach developed by Daraio and Simar (2007), Simar and Wilson (2007), and further elaborated and applied by Badin, Daraio and Simar (2012). Traditional efficiency measures under DEA are often criticized for not considering environmental variables in the first stage (Daraio and Simar 2007). Environmental variables are variables that do not directly impact or are not directly considered in production decisions. Environmental variables may affect not only the distribution of inefficiency among farmers, but also the production frontier itself. Simar and Wilson (2007) note that ignoring environmental variables in DEA may lead to invalid inferences in any second stage evaluations of efficiency scores. To correct the bias in the first stage, Daraio and Simar (2007) and Simar and Wilson (2007) propose a methodology to implement

DEA conditioned on environmental variables. In the first stage, efficiency calculations are derived from comparing the performance of farmers with similar values of the environmental variables. We test in our model if ignoring environmental variables in the first stage of DEA leads to invalid inferences in the second stage.

The environmental variables considered here are proxies for the factors that drive price wedges, which are often difficult to measure. For example, transport costs may be known only for those households who sell crops, and are likely to systematically differ for non-participants. The value of quality differences may also be unobservable. Instead, we construct a sales index based on the percentage of production sold as a proxy for the factors that contribute to price wedges. We calculate the percentage of total crop production sold to the market. Our assumption is that these factors that drive price wedges are relatively similar among farmers who largely participate in the market. On the other hand, a price wedge is likely to be largely similar for subsistence and semi-subsistence farmers who consume much of their own production. We estimate efficiency conditional on the sales indices. Efficiency of a farmer is estimated based on the production technology constructed from farmers with similar sales indices. Farmers with similar sales indices are assumed to face similar factors that drive price wedges which leads to similar production frontiers.

There could be farmers with identical factors that drive price wedges, but farmers may have a large sales index simply due to wealth. If farmers with a high value of sales index are more technically efficient than those with a low sales index, separately estimating the efficiency of low sales index farms using DEA will artificially increase their efficiency scores. To determine if the sales index is indeed simply proxying for wealth derived from higher efficiency, we test if using another variable correlated with wealth, but not necessarily with any element of the price wedge, impacts efficiency estimation. We use the value of a households' radio and television assets as a placebo variable to test our proposition. The assumption is that if efficiency estimates conditioning on sales index and value of radio and television show similar results, then the sales index is indeed a poor proxy variable for factors that drive a gap between market and shadow prices of farm households.

Conditional DEA estimates technical efficiency within the boundary of farms with similar environmental variable values. Consider, farmer i, uses a vector of inputs A to produce a vector of outputs Q. Let Z be a vector of environmental variables that impacts the production process. Technical efficiency "$\theta$" is estimated through examining the performance of the farmer from the frontier "$\Psi^{z}$", a frontier formed within the bounds of similar farms based on Z.

The conditional DEA production set is given by:

$\Psi^{z}{}_{DEA} = \{(A, Q)|Z = z, A\ can\ produce\ Q\}$

We estimate technical efficiency ($\theta$) using output oriented DEA. The conditional output oriented DEA efficiency measure is given by:

$$Max\ \theta_i|Z$$
$$Subject\ to:$$
$$\sum_{j=1}^{n} v_{ji}\, A_{rji} \leq \theta A_{ri}|\mathrm{Z}$$
$$\sum_{j=1}^{n} v_{ji}\, Q_{sji} \leq Q_{si}\ |\mathrm{Z}$$
$$\sum_{t=1}^{t} v_{ji} = 1, v_{ji} \geq 0$$

where $v$ represents weights for r vectors of inputs and s vectors of outputs and i represents observation.

The efficiency estimation is performed using linear programing (see Badin, Daraio and Simar 2012). To perform the conditional DEA, we first rank farmers from smallest to largest using the value of the environmental variable. For instance, farmers who have the lowest and largest sales index are ranked first and last, respectively. Following Daraio and Simar (2007), and Badin, Daraio and Simar (2012), we estimate efficiency via grouping at intervals of about 140, or at deciles of the sample, which provides sufficient coverage to estimate efficiency within each group. The Sales indices are zero (sells nothing) for group one, 0.10-0.30 percent for group 2, 0.31-0.75 percent for group 3, 0.76-1.33 percent for group 4, 1.34-2.21 percent for group 5, 2.22-3.48 percent for group 6, 3.50-5.37 percent for group 7, 5.38-9.46 percent for group 8 and 9.50-100 percent for group 9.

The total sample size is 1388. The assumption is that farmers in the same groups have similar price wedges. The efficiency is estimated based on the performance among 140 farmers, bootstrapped 1,000 times, which provides confidence intervals in spite of the deterministic nature of DEA (i.e.e DEA does not allow noise). The Bootstrap procedure helps to overcome the bias that stems from uncertainty of sampling variations (see Simar and Wilson 2000).

### 3.7.2. Second Stage of DEA

In the second stage of the DEA analysis, we estimate the effect of factors that impact efficiency using the following steps. First, we whiten the conditional efficiency scores by removing the effect of environmental variable, in this case of the sales index, as in Badin, Daraio and Simar (2012). The effect of the environmental variable on conditional efficiency is estimated using a non-parametric regression, given in equation (35) and (36).

(35) $\widehat{\theta^{z}}_i = \mu(Z)_i + \sigma(Z)\delta_i$

(36) $\hat{\delta}_i = \frac{\widehat{\theta^{z}}_i - \mu(Z)_i}{\sigma(Z)_i}$

where $\mu(Z)$ is the average effect of the sales index on technical efficiency, $\sigma(Z)$ is the dispersion of efficiency scores due to the sales index, and $\delta$ is the unexplained (managerial) part of conditional efficiency. Average effects of sales index on efficiency, $\mu(Z)$ are estimated using local polynomial (nonparametric) regression as suggested by Badin, Daraio and Simar (2012). Similarly, dispersion, $\sigma(Z)$ is measured by regressing the square of the residuals from equation (35) on sales index using local polynomial regression. Once we get the estimates for $\mu(Z)$ and $\sigma(Z)$, we calculated the whitened efficiency (pure efficiency) using equation (36). These pure efficiency (managerial efficiency) values range between 0 and 1. Farms with large $\delta$ values have lower efficiency levels, while farms with small $\delta$ values have higher efficiency levels (see Badin, Daraio and Simar 2012).

Finally, we estimate the impact of factors on the whitened efficiency score using OLS.

(37) $\delta_f = \alpha_f G_f + \varepsilon_f$

where $G_f$ are explanatory variables that may impact farm technical efficiency, $\alpha_f$ is a vector of parameter, and $\varepsilon_f$ is a mean 0 IID error term.

Simar and Wilson (2007) indicate that if environmental variables affect the production frontier then, naïve technical efficiency scores will lead to an incorrect inference about the factors that impact efficiency in the second stage. To test this proposition in our case, we directly compare the naïve and conditional DEA estimates.

Factors that affect farm technical efficiency, which is measured by equation (36) are non-farm income, age, family size, extension, education, and gender.[2]

[2] *Factors such as non-farm income, age, family size, extension, education, and gender that affect farm technical efficiency (see Tiruneh and Geta 2016; Muange et al. 2015; Abebe 2014; Karimov et al. 2014; Kitila and Alemu 2014; Thibbotuwa et al. 2013; Beshir et al. 2012; Makombe et al. 2011; Aye and Mungatana 2010; Speelman et al. 2008)*

### 3.8. Data

Table 3.1 presents the summary statistics of key variables used in the study. We use the World Bank's nationally representative Living Standards Measurement Study (LSMS) household survey of 2010/2011 from Uganda. Information from survey households pertaining to crop production and other variables of interest were extracted from the survey data. The total sample size is 1,388. In our sample, the average household head's age is 56, and the average household has nine members. Sixty-seven percent of the households are male headed. Twenty-two percent of farm households have a father who completed elementary school.

Efficiency estimates using DEA require data on multiple outputs and inputs. In our sample, farmers grow a variety of crops such as rice, soybean, maize, beans, cassava, coffee, millet, banana food crop, sweet potato, groundnut and sorghum. We categorize inputs into six categories: fertilizer costs, pesticide costs, hired labor costs, machinery costs, family labor (measured in hours) and land (measured in acres). Crop outputs are converted to revenue using own price for those who sell to the market and using average regional prices for farm households who do not sell.

Farm households earn about 919, 449 Ugandan Shillings of non-farm income per year. On average, maize contribute the highest farm household crop revenue share (21%), followed by beans (14%), banana food crop (12%), groundnuts (10%), sweet potato (9%), coffee (8%), millet (4%), rice (4%), cassava (2%), sorghum (1%) and soybeans, (0.6%). Similarly, farm households incur the highest expense for crop production from hired labor (59,263), followed by fertilizer (44, 853), pesticide (5,764), and machinery (2,169) Ugandan Shillings per year. Farm households use an average of 219 hours of family labor per year. The average land holding, an important farm asset, is 4 acres per farm household. Only 30% of the farm households visit extension centers each year. On average, farmers sold approximately 27 percent of their crop. Percentage of sales ranges from

0 to 100 percent, assuming that farmers with low percentage of sales have high price wedges and farmers with higher percentage of sales have lower or zero price wedges.

## 3.9. Results and Discussion

We test if accounting for price wedges impacts the DEA technical efficiency estimation. We estimate technical efficiency conditional on a sales index, a proxy variable for price wedges in the first stage and determine the factors that affect technical efficiency in the second stage.

### 3.9.1. First Stage of DEA

Technical efficiency is estimated using a double bootstrapped conditional DEA. To determine the extent of bias from ignoring the potential differences between the market and shadow price of agricultural output, we estimate technical efficiency twice: once using unconditional DEA (naïve) and conditional DEA conditioned on sales index. We calculate efficiency ratios by driving conditional efficiency scores by the naive technical efficiency scores. If efficiency of a farmer is the same using conditional and naive DEA, then the ratio is equal to 1. A ratio of unity on average across the sample implies that factors that drive a price wedge have no role in the calculated efficiency level of farmers. If measured efficiency is higher under conditional DEA relative to unconditional, then the ratio is larger than 1. A ratio greater than one, implies that the conditioning variable of price wedges do in fact impact efficiency measurement. In the case analyzed here, a ratio greater than one indicates that estimating efficiency without accounting for the price wedge, possibly underestimates the efficiency of farmers with high price wedges.

Figure 3.1 plots the efficiency ratios of conditional over unconditional DEA with the efficiency ratio on the vertical axis and sales index on the horizontal axis. We estimate the relationship between the efficiency ratio and sales index using a local-linear non-parametric estimator. The effect of sales index on the efficiency ratio is about -4.34 and statistically significant (Table 2).

This shows that the efficiency ratio decreases as we move from a lower sales index to large sales index, which is evidenced by the fact that efficiency ratios are larger than two at lower levels of sales index and eventually approach one when we move toward higher levels of sales index. Thus, estimating efficiency without accounting for sales index (price wedges) understates the efficiency score of lower sales index farmers (i.e. subsistence and semi-subsistence farmers). Underestimation of technical efficiency decreases as we move toward higher values of sales index, that is, toward more commercial producers. We learned that conditional efficiency is larger than the unconditional efficiency for subsistence and semi-subsistence, while it is relatively the same for commercial farmers. This implies that we fail to reject the hypothesis that unconditional efficiency estimation understates the technical efficiency of subsistence and semi-subsistence farmers.

We assume that wealthier farmers have similar price wedges as poorer farmers and simply have larger sales index due to large production. If these wealthier farmers with larger sales index are technically more efficient, estimating efficiency of these poorer farmers with lower sales index separately may increase their technical efficiency unnecessarily. To account for these issues, we test if using another variable correlated with land size or wealth, but not necessarily with the sales index impacts efficiency estimation. We use value of a households' radio and television as a variable to test our proposition. The correlation between land size and value of radio and television is 0.56. However, the correlation between radio and television and sales index is about 0.07, which is very weak. The assumption is that if efficiency estimates conditioned on sales index and value of radio and television, show the same pattern of underestimation, that would cast doubt on our interpretation that the results in figure 3.1, stem from failing to account for the price wedge in household optimality conditions. Instead, we may simply be artificially inducing the pattern by grouping households according to a variable, like wealth, correlated with true efficiency.

We present the results calculating the efficiency ratio conditioning on the value of radio and television is in figure 3.2. The effect of radio and television index on efficiency ratio is -0.03 and statistically insignificant (Table 3.3). The efficiency ratio for lower value of radio and television farmers is below two and doesn't decline when we move toward higher values of radios and television. Unlike the use of sales index as a condition variable, there is no clear pattern as the value of household assets increase. This suggests that the pattern of bias detected by conditioning on sales index is not induced by a spurious relationship with wealth, and is, instead, likely a result of price wedge factors.

Unconditional and conditional on sales index mean efficiency estimates are reported in Table 3.4. The average efficiency using unconditional (naïve) and conditional DEA are 0.48 and 0.68, respectively. The average bias (conditional minus unconditional efficiency) across the sample is approximately 0.21 (Table 3.4). The efficiency conditional on sales index is 44 percent more than the efficiency estimated using unconditional DEA. Efficiency estimation using unconditional DEA may be misleading for information based development programs such as extension programs that interpret the low efficiency score completely as management shortfall.

Previous studies that measure farm technical efficiency using unconditional DEA (Mugabe and Etienne 2016; Ghebru and Holden 2015; Peterman et al. 2011: Balcombe et al. 2008; Chavas, Petrie and Roth, 2005; Rahman, 2003; Wang, Cramer and Wailes, 1996 etc) likely underestimate the efficiency of subsistence farmers which could lead to biased inferences. Conditional DEA to measure efficiency has been applied in other areas such as health science (Halkos and Tzeremes 2011), environmental sciences (Halkos and Tzeremes 2014) and public services (Zschille 2015).

For instances, Halkos and Tzeremes (2014) examined the impact of Kyoto protocol agreement on countries environmental efficiency using conditional DEA. They found that unconditional efficiency was biased as high as 24 percent in some countries.

### 3.9.2. Second Stage of DEA

To examine factors that affect efficiency in the second stage, we whitened the conditional efficiency as suggested by Badin, Daraio and Simar (2012). Whitened technical efficiency is calculated using equations (35) and (36). Examining the effect of factors on the whitened technical efficiency gives more correct inferences (Daraio and Simar 2007; Simar and Wilson 2007). We present factors that affect unconditional efficiency (Table 3.5) and conditional efficiency (Table 3.6). However, we interpret only factors that affect whitened technical efficiency (estimated from conditional efficiency) as our unconditional technical efficiency is biased. Results indicate that factors that affect whitened technical efficiency at a 5 percent level of significance are gender, extension program use and region of residence (Table 3.6). Gender and Extension have a positive effect on whitened technical efficiency. Male farmers are technically more efficient than female farmers. Farmers who visit extension services are technically more efficiency than farmers who don't visit. Region 2 has a negative effect on technical efficiency, implies that farmers located in region 2 are less efficient than other regions.

## 3.10. Summary and Conclusion

Factors such as transaction costs, crop quality (e.g. color, taste, softness of dough, and suitability for certain dishes) and other household characteristics drive price wedges between market and shadow prices for crops produced for home consumption. Price wedges are heterogeneous across farmers and appear in the optimality conditions associated with the farm household's choice of cash and marketed versus home-consumed crops. Consideration of price wedges is important for measuring efficiency such as technical efficiency.

The standard approach to measure efficiency is that farm households face homogenous prices wedges that lead to homogenous production and profit frontiers. However, heterogeneous price wedges lead to heterogeneous profit and production frontiers. Subsistence, semi-subsistence and relatively commercial farmers face difference price wedges and have different profitability and productivity frontiers. Failing to account for this heterogeneity due to price wedges across subsistence, semi-subsistence and commercial farmers can lead to biased efficiency estimation and misleading conclusions.

In this paper, we explicitly model the potential impact of price wedges on optimal crop choices for utility maximizing farm households. We show that the existence of price wedges discourages production of cash crops and encourages production of home consumed crops. With the increase of price wedges, a utility maximizing farm household, more typically subsistence farmers, withdraws inputs from cash crops and allocates them toward home consumed crop production. Because of significant price wedges, use of modern technologies, and production of high values crops may be unprofitable for subsistence and some of the semi-subsistence farmers.

Modeling farm productivity that accounts the price wedge helps to have better understanding about the lack of use of modern agricultural inputs and producing cash (high value) crops by subsistence farmers. Many development programs may invest in teaching farmers such as subsistence and semi-subsistence farmers as if they have a lack of knowledge about the modern agricultural inputs and high value crops. However, higher price wedges could be the reason behind farmers' low use of modern agricultural inputs and producing cash crops.

We measure technical efficiency using unconditional (naïve) and conditional Data Envelopment Analysis (DEA). Conditional DEA helps account for heterogeneity due to price wedges when estimating technical efficiency of farmers. In Uganda, we find that naïve estimates of technical efficiency understate the efficiency scores of subsistence and semi-subsistence farmers. This is important for development programs, such as extension and other information-based programs to identify the actual efficiency loss due to managerial inefficiency. Moreover, this helps on designing appropriate extension programs such as teaching about the most profitable inputs (modern or traditional) and crops (cash versus food) to the farmers. This also in turn increase the effectiveness of the extension program. Under high price wedges, designing development policies that consider price wedges is important for the overall effectiveness of the programs. E.g. development programs such as extension programs should consider the transaction costs such as cost of finding best prices for inputs and outputs, transportation costs, commission costs and etc. that drive price wedges when advising farmers to produce cash crops.

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## 3.12. Tables and Figures

**Table 3.1: Summary Statistics of Sample Households' Characteristics (N=1388)**

| Variable | Definitions | Mean | Stand error |
|---|---|---|---|
| Age | Age of head of household in years | 56.27 | 14.56 |
| Family size | Number of household size | 8.66 | 3.43 |
| Gender | 1 if head of household male, 0 otherwise | 0.67 | 0.43 |
| Nonfarm income | Amount of nonfarm income in dollar | 919,449.2 | 2,956,320.30 |
| Father Education | 1 if farmer completed elementary and 0 otherwise | 0.22 | 0.40 |
| Rice | Revenue from rice | 41,551.21 | 443,162.3 |
| Soybean | Revenue from soybean | 5,808.476 | 29,634.71 |
| Maize | Revenue from maize | 210,735.1 | 451,398.5 |
| Beans | Revenue from beans | 142,810.3 | 207,651.2 |
| Cassava | Revenue from cassava | 156,769.7 | 302,190.1 |
| Coffee | Revenue from coffee | 83,830.29 | 294,418.40 |
| Millet | Revenue from millet | 41,576.44 | 109,496.20 |
| Banana home consumed | Revenue from banana home consumed | 124,531.40 | 352,141.00 |
| Sweet Potato | Revenue from sweet potato | 85,743.03 | 135,266.50 |
| Groundnut | Revenue from groundnut | 95,865.24 | 226,057.1 |
| Sorghum | Revenue from sorghum | 12,571.16 | 32,888.79 |
| Fertilizer | Total cost of fertilizer | 44,853.53 | 187,096.00 |
| Pesticide | Total cost of pesticide | 5,764.87 | 22,350.99 |
| Hired labor | Total cost of hired labor | 59,263.29 | 111,715.50 |
| Family labor | Total number of family labor in hours | 219.88 | 119.40 |
| Machinery | Total machinery cost | 2,169.85 | 8,206.92 |
| Land | Land owned in acres | 4.01 | 3.37 |
| Livestock | 1 if farmer own it, 0 otherwise | 0.97 | 0.16 |
| Extension | 1 if farmer visited extension, 0 otherwise | 0.36 | 0.48 |
| Sales | Percent of production sold to the market | 0.27 | 0.31 |
| observations | 1388 | | |

Monetary values are per year in Ugandan Shilling.

**Table 3.2: Association of Efficiency Ratio and Sales using Kernel Local-Linear Estimator**

| | coefficients | Std.error | P-values |
|---|---|---|---|
| Constant | 2.07 | 0.03 | 0.00 |
| Sales index | -4.34 | 0.12 | 0.00 |
| R2 | | | 0.05 |

**Table 3.3: Association of Efficiency Ratio and Radio using Kernel Local-Linear Estimator**

| | coefficients | Std.error | P-values |
|---|---|---|---|
| Constant | 1.57 | 0.02 | 0.00 |
| Radio and television | -0.03 | 0.32 | 0.10 |
| R2 | | | 0.06 |

**Table 3.4: Technical Efficiency (TE) of Farm Households**

| Type of farms | Technical efficiency |
|---|---|
| Unconditional | 0.48 |
| Conditional | 0.68 |
| Average bias (conditional-unconditional) | 0.21 |

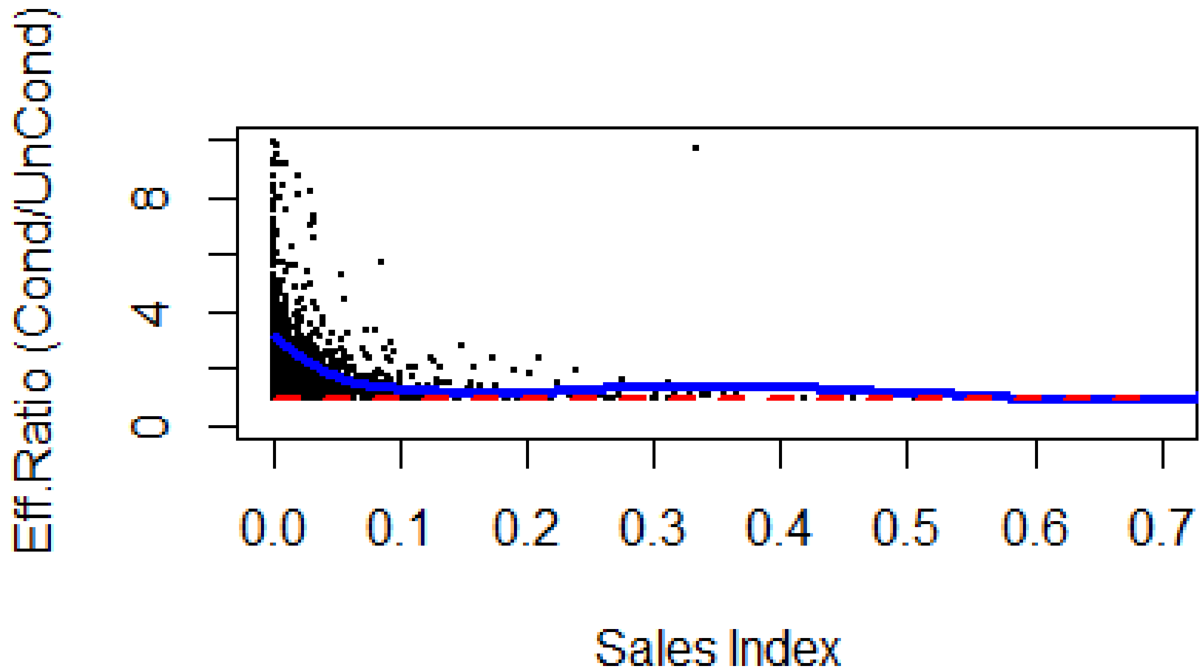
**Table 3.5: Factors that Affect Naive Technical Efficiency Estimated using Tobit Model**

| Variable | Mean | St. Error | P-Value |
|---|---|---|---|
| Constant | 0.358 | 0.090 | 0.000 |
| Age | -0.001 | 0.001 | 0.729 |
| Family size | 0.014 | 0.002 | 0.000 |
| Gender | 0.065 | 0.019 | 0.001 |
| Father education | -0.030 | 0.023 | 0.200 |
| Extension | 0.082 | 0.019 | 0.000 |
| Livestock ownership | 0.049 | 0.079 | 0.540 |
| Region1 | -0.073 | 0.025 | 0.004 |
| Region2 | -0.125 | 0.024 | 0.000 |
| Region3 | -0.147 | 0.024 | 0.000 |

**Table 3.6: Factors that Affect Conditional Technical Efficiency using Tobit Model**

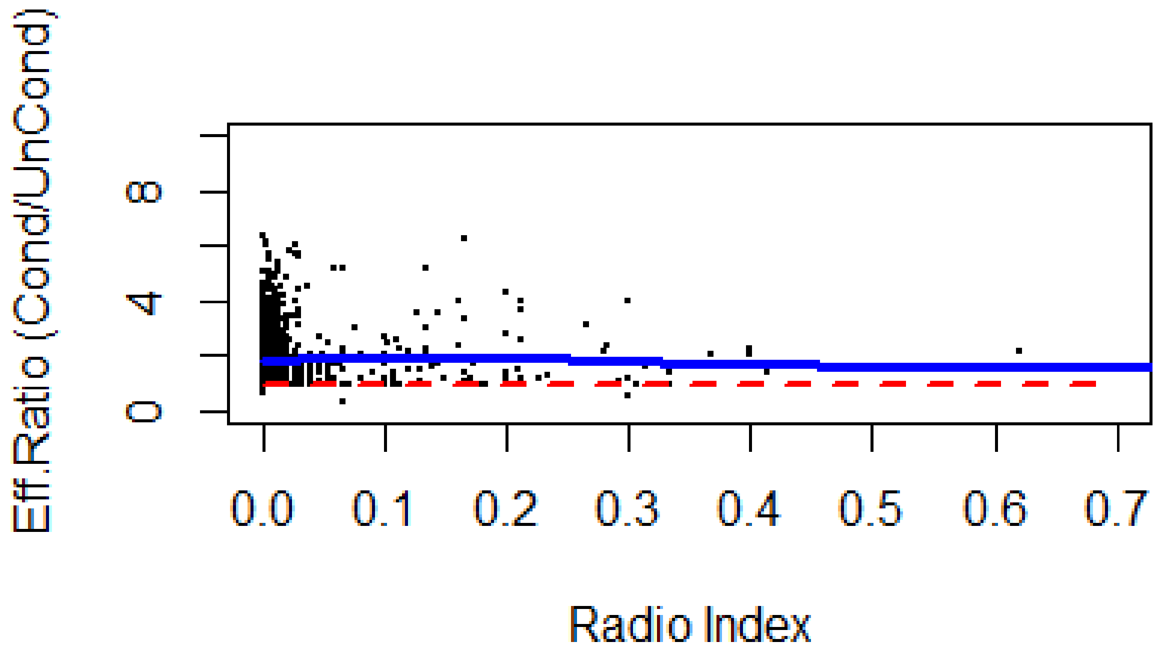
| Variable | Mean | St. Error | P-Value |
|---|---|---|---|
| Constant | 0.223 | 0.033 | 0.000 |
| Age | -0.001 | 0.001 | 0.796 |
| Family size | -0.001 | 0.001 | 0.191 |
| Gender | 0.016 | 0.007 | 0.033 |
| Father education | 0.006 | 0.008 | 0.474 |
| Extension | 0.015 | 0.007 | 0.045 |
| Livestock ownership | -0.037 | 0.029 | 0.203 |
| Region1 | -0.009 | 0.009 | 0.336 |
| Region2 | -0.026 | 0.009 | 0.004 |
| Region3 | -0.006 | 0.009 | 0.485 |

**Figure 3.1: Plotting Efficiency Ratios versus Sales using Local Polynomial Smoothing[3]**




[3] Blue line indicates the non-parametric relationship between efficiency ratio and sales index, and Red line indicates efficiency ratio equal to 1.

**Figure 3.2: Plotting Efficiency Ratios versus Radio using Local Polynomial Smoothing**[4]




[4] Blue line indicates the non-parametric relationship between efficiency ratio and sales index, and Red line indicates efficiency ratio equal to 1

### 3.13. Appendix

The i[th] farm household's optimization problem is modelled as follows:

(1) $\max_{o_i;\, n_i;\, g_i, A_{hi}, A_{mi}} \mathrm{U} = (o_i; n_i\,; Z_{ui})$

s.t:

(2) $(p_{mi} - t_{mi})m_i + (p_{gi} - t_{gi})g_i - (p_{ni} + t_{ni})\, n_i + T_i = 0$

(3) $f(A_{hi};\, z_{hi}) = h_i$

(4) $h_i = g_i + o_i$

(5) $f(A_{mi};\, z_{mi}) = m_i$

(6) $Q_i = m_i + h_i$

(7) $A_{mi} + A_{hi} = A_i$

(8) $o_i, g_i, m_i, n_i \geq 0,$

*One can replace $g_i = h_i - o_i$, i.e. food crops sold is equal to total food crops produced minus food crops used for home consumption.*

Substituting $h_i = f\left(A_{h_i}\right)$ and $m_i = f\left(A_{m_i}\right)$, we have the following Lagrangian function:

(9) $L = \mathrm{U}(o_i; n_i\,; Z_{ui}) + \lambda_i\left[(P_{m_i} - t_{m_i})\, f\left(A_{m_i}\right) + (P_{g_i} - t_{g_i})\,(f\left(A_{h_i}\right) - o_i) - (p_{n_i} + t_{n_i})\, n_i + T_i\right] + r_i[A_i - (A_{m_i} + A_{h_i})]$

The first order conditions (FOCs) for maximizing equation (9) are:

(i) home consumed crops: optimal consumption of food crops is governed by:

(10) $\frac{dL}{do_i} = \frac{du}{do_i} - \lambda_i(P_{g_i} - t_{g_i}) = 0 \Rightarrow MU_{oi} - \lambda_i(P_{g_i} - t_{g_i}) = 0;$

If food crop is sold to the market (g), its price $(P_i) = \frac{MU_{oi}}{\lambda_i} = P_{g_i} - t_{g_i}$.

Farmers are willing to sell the crop at a price of $P_{g_i} - t_{g_i}$.

However, if the food crop is consumed at home (o), its price $(P_i) = \frac{MU_{oi}}{\lambda_i}$.

$P_i = \frac{MU_{oi}}{\lambda_i}$, represents the shadow price for home consumed crop.

(ii) purchased crops: optimal consumption of purchased crops is governed by:

(11) $\frac{dL}{dn_i} = \frac{du}{dn_i} - \lambda_i(p_{n_i} + t_{n_i}) = 0 \Rightarrow MU_{n_i} - \lambda_i(p_{n_i} + t_{n_i}) = 0;$

If food crop is purchased from the market (n), its price $(P_i) = \frac{MU_{ni}}{\lambda_i} = p_{n_i} + t_{n_i}$.

Farmers are willing to buy the crop at a price of $p_{n_i} + t_{n_i}$.

(iv) optimal sell of cash crops is governed by:

(13) $\frac{dL}{dm_i} = \lambda_i(P_{m_i} - t_{m_i}) - \omega_i = 0$; where $\omega_i$ represents the marginal utility of producing cash crop.

If cash crop is sold to the market (m), its price $(P_i) = \frac{\omega_i}{\lambda_i} = P_{m_i} - t_{m_i}$.

Farmers are willing to sell the crop at a price of $P_{m_i} - t_{m_i}$.

# Chapter 4. Examining Effectiveness of Agricultural Extension Program in Armenia

## 4.1. Abstract

We evaluate the impact of a farm education and extension program on technical efficiency and farm productivity in Armenia. Farm productivity and technical efficiency can be used as an outcome measures to evaluate extension programs. Two previous studies, Fortson et al. 2012, and Schwab and Shanoyan (2016), examined the effect of a farm training program on farm income and found no robust farm training treatment effect. The purpose of this study is to examine the effectiveness of the farm training program using another complementary outcome variable such as farm technical efficiency and farm productivity. Controlling for other variables (e.g. non-farm income, education, etc.), the training program had a statistically significant and positive effect on catch-up (change in technical efficiency). However, results indicate that farm training had no effect on the frontier technical efficiency (innovation) and overall farm productivity (Malmquist index).

## 4.2. Introduction

Armenia, a former Soviet Union Republic is a land locked country, located in the mountains of the Caucasus region between Europe and Asia. The topography of Armenia has a diversity of soil types and is fragmented by various systems of ravines. Climatic conditions are equally heterogeneous as a result of the level of the mountains. Climatic zones include: arid, semi-arid and temperate zones (Tumanian, 2001). Based on the Armenian economy report (2015), services contribute the most to GDP (51.9%), followed by industry (27.7%) and agriculture (19.4%). The Armenian economy has undergone a profound transformation after independence in 1991, which caused a sharp decline in GDP through the mid and late 90s (World Bank, 2001).

After independence, significant privatization of the public economy took place. Many state-owned firms were sold to local buyers (FAO, 2000). State-owned agricultural land was distributed to individual farmers. The government redistributed about 70 percent of farmland as small plots to private farmers and retained about 30 percent for state owned large scale farming operations (Fortson et al., 2012). However, after the transformation, economic progress did not proceed as expected. Firms frequently faced a shortage of capital needed to procure inputs and encountered market constraints to selling their output (Shanoyan et al., 2014). Agricultural land was often given to inexperienced and resource constrained farmers, which resulted in a dramatic decline in agricultural production. Through the 1990s and early 2000s, economic stability remained a key challenge in Armenia. To address the challenge, the government, supported by non-governmental agencies, initiated various development projects focusing on key investments in the country. One of the more recent and largest of these was the Millennium Challenge Corporation's (MCC).

To enhance agricultural production and farmers' income, MCC signed an agreement with Armenia in 2006. One aim of the project was to increase agricultural performance by offering farm training. The training offered by the program included: training on farm water management, high value agriculture production, post-harvest management, processing, marketing, and access to credit. Most of the targeted beneficiaries of the project were identified to have limited farming knowledge and poor irrigation systems (Fortson et al., 2012). By offering training to farmers, the project's aim was to improve management practices, which in turn could increase farm efficiency and farm household income. A companion credit program did not develop past a small pilot during the evaluation period, and hence only a handful of farmers were provided access.

Two previous studies examined the impact of the training program and found ambiguous effects. Fortson et al (2012), using an intention to treat (ITT) approach, found the program did not change average input use or yield, and found positive but not robust or precisely estimated effects on farm income and profits. Schwab and Shanoyan (2016), using the same data, attempted to correct for two-sided non-compliance in the data by estimating local average treatment effects (LATE), using the randomization as an instrument. They find similar results, though the positive impacts on farm profits are larger and slightly more precisely estimated (but not robust). Overall, the evaluations using traditional outcome measures of output and income provide an ambiguous picture of the program, and do not provide persuasive evidence for a strong effect. However, for farmers who are beset by capital constraints such as credit, treatment effects using farm efficiency as outcome measure could be more revealing than the treatment effect using farm profit as an outcome measure.

When farmers produce at input levels where marginal physical product (MPP) exceeds average physical product (APP), known as Stage 1 of production, treatment effects may produce a commensurately large change in farm productivity as compared to farm profit (see chapter 1). While this stage of production is often ignored, as rational producers would not ‘choose’ to produce in this region, the population targeted by extension programs are often beset by binding constraints, such as credit, that prevent farmers from taking advantage of increasing returns to investment (Jack 2011), that constrain them to this stage of production.

In Armenia, firms frequently faced a shortage of capital needed to procure inputs and encountered market constraints to selling their output (Shanoyan et al., 2014). Schwab and Shanoyan (2016) note that credit was the most effective tool to attract farmers to the training participation in Armenia. This implies that farmers may potentially be beset by financial constraints and produce sub-optimally in stage 1 of production. Thus, an extension program targeting such farmers that shows no or little impact on profit may still have resulted in positive changes in terms of efficient production behavior. As a result, using farm technical efficiency and productivity as an outcome measure may allow program evaluators to determine if the extension program provided no positive productive effects or if farmer efficiency improved, but was beset by other binding constraints reducing or failing to impact farm household income.

Examining the impact of farm education and extension program on farm technical efficiency and farm productivity may help to identify program impacts that farm profit estimates may fail to detect. In this study, we assess whether or not the farm training program in Armenia increased farm technical efficiency and farm productivity. We use an Armenian panel survey data set collected in 2007/2008 and 2010/2011 by Millennium Challenge Corporation’s Compact, USIAD project. We investigate the effect of treatment on the catch-up effect (change in technical efficiency), frontier shift (change in technology) and Malmquist index (overall farm productivity) using conditional DEA. We find that the training program had a significant effect on catch-up and no effect on the frontier technical efficiency and overall farm productivity.

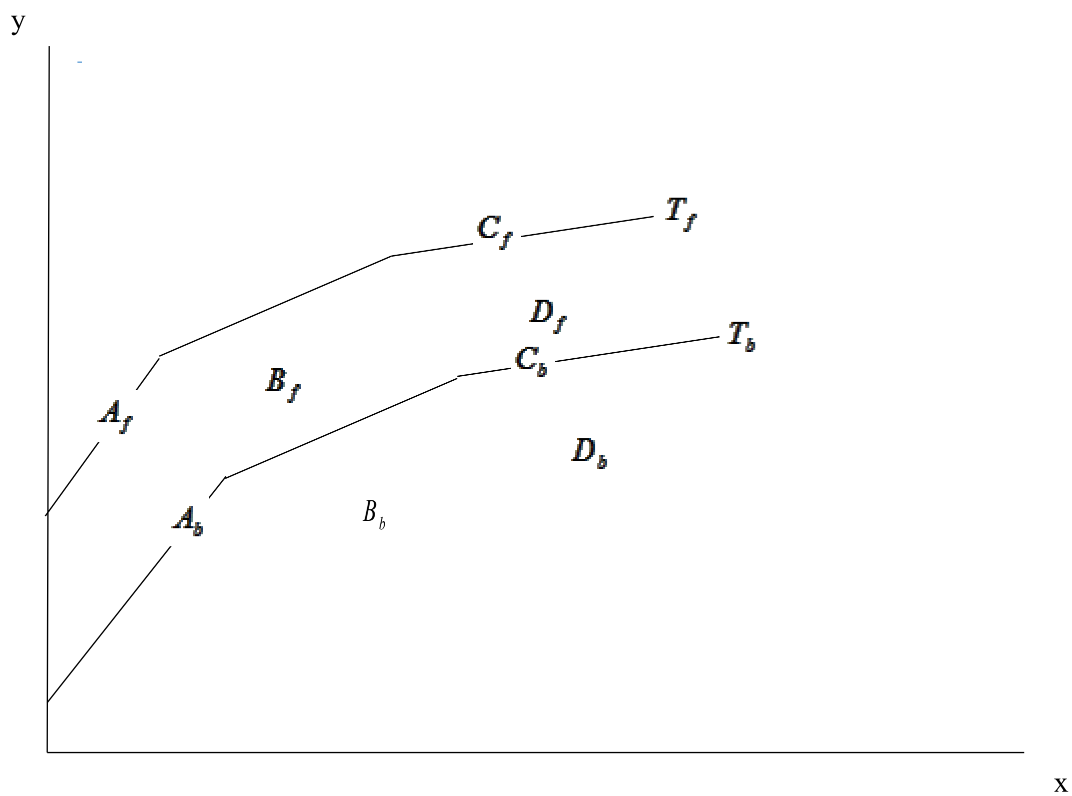
## 4.3. Theory

We discussed the importance of using farm technical efficiency as outcome variables to assess the effectiveness of farm training and extension programs in chapter 2. We noted that farmers in developing countries face input constraints and as a result, operate sub-optimally in stage 1 of the production process. For farmers that operate in stage 1 of the production process, using farm technical efficiency directly as an outcome variable for evaluating extension programs may be more informative than farm income. In stage 1 of the production process, treatment effects (impact of extension program) on technical efficiency are likely larger than treatment effects on profit. Here, we are exploring whether or not a farm training program increases farm productivity in Armenia.

The purpose of this paper is to assess the impact of farm training on changes in technical efficiency as an outcome variable. Training improves knowledge, which can make farmers technically more efficient and innovative. The most appropriate method to measure this potential gains from farm training is the Malmquist index (farm productivity). Farm productivity can be decomposed in to two components, a catch-up effect (capture change in technical efficiency) and a frontier shift effect (capture gain in innovation) (see Cooper, Seiford and Tone, 2007).

To illustrate the linkage between farm training and technical efficiency of farm households, assume training improves farmer's knowledge by providing new information. As noted by Appleton and Balihutan (1996) and Cotlear (1989), training may have two effects. The first is a cognitive effect where the training increases skills and proficiency of farmers through informational channels. With the increase in skill, farmers can become more creative and do things with fewer resources and in shorter time. The second is a non-cognitive effect, where attitudes, beliefs and habits change in ways that help farmers to adopt productive technology. The effect of farm training on technical efficiency is illustrated in figure1.

**Figure 4.1: Production performance of farmers in two time periods, before ($T_b$) and after ($T_f$) treatment.**




Farm households on the frontier such as A and C are fully efficient while farm households below the frontier such as B and D are less efficient. The indices b and f on farm households B and D show technical efficiency before and after the training respectively. After the training, the technical efficiency of farmer B and D increases from $B_b$ and $D_b$ to $B_f$ and $D_f$, respectivily . The two effects of treatment can be described by the differences before and after training in the figure: technological change, or the frontier shift, is embodied by the change in the frontier (moving from $T_b$ to $T_f$), which is a result of the change in innovation. The second effect, technical efficiency change, or catch-up effect, is embodied by the difference in efficiency before and after the program (e.g. $B_f/B_b$ or $D_f/D_b$) (see Fare et al., 1994). The Malmquist Index measures the overall farm productivity change, which is the combination of catch-up and frontier shift effects. Overall farm productivity could be change due to efficiency and/or innovation.

**Empirical strategies**: We aim to examine impact of farm training on technical efficiency and farm productivity in Armenia. There are two common methods to measure technical efficiency and farm productivity: Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA). DEA is a non-parametric method that does not assume a functional form for the production process, and SFA is a parametric method that incorporates random noise. We choose to measure technical efficiency and farm productivity using the non-parametric, input oriented DEA approach. Since farm households in developing countries have heterogeneous price wedges (See chapter 3), we measure technical efficiency and farm productivity using conditional DEA. We apply conditional input-oriented DEA that accounts for the importance of price wedges on estimating technical efficiency and farm productivity, a method suggested by Daraio and Simar (2007) and Simar and Wilson (2007), who note that traditional DEA does not account for 'environmental variables' that are not directly used in production but still affect the production decision of farmers. Price wedges driven by transaction costs and other farm household factors are such environmental variables. They are not inputs in the production process, but still affect the production decision of farmers (see chapter 3).

Price wedges are often unobservable and are difficult to measure. Instead, we use the probability of sales as a proxy for price wedges. Probability of sales is used to measure the degree of relationship of farmers with the market. We assume that farmers who have low price wedges are highly likely to participate in the market (probability of sales is high) and vice-versa. We estimate technical efficiency and farm productivity based on the production technology constructed from farmers with similar probability of sales. Farmers with similar probability of sales are assumed to face similar factors that drive price wedges, which leads to similar production frontiers. Hence, conditional DEA measures technical efficiency accounting for probability of sales, a proxy for price wedges.

The empirical analysis is structured as follows. First, probability of sales, a proxy for price wedge is estimated. Second, we conduct a two stage Malmquist DEA analysis. The first stage estimates Malmquist farm productivity index using conditional DEA, where efficiency is conditioned on probability of sales. The second stage examines the impact of farm training on the Malmquist farm productivity index recovered from the DEA analysis. Details are outlined in the following subsections.

### 4.3.1. Predicting Probability of Sales using a Logit Model

The objective here is to estimate technical efficiency and farm productivity conditional on the probability of sales, a proxy for factors that drive price wedges (see chapter 3). Probability of sales is predicted using a logit model as follows.

(1) $Z_i = \alpha D_i + v_i, \; Z_i = \begin{cases} 1 \; if \; farm \; sales > 0 \\ 0 \qquad otherwise \end{cases}$

where $D$ is a vector of explanatory variables and $v$ is a mean zero, IID error term.

Explanatory variables are assumed to be linearly related to the probability of sales. The explanatory variables include land, districts (farmer location) and farm household characteristics (gender, family members, age of head of farm household, etc). These variables were selected based on their perceived relationship to probability of sales as supported by economic theory and the applied development literature (Stifel and Minten 2016; Chamberlin and Jayne 2013; Arslan 2011; Vakis, Sadoulet and Janvry 2003; Fafchamps 1992).

### 4.3.2. First Stage of Malmquist Data Envelopment Analysis (DEA)

We use conditional DEA to estimate the Malmquist farm productivity indices. Consider a vectors of inputs A used to produce a vector of outputs Q. Let Z be the environmental variable that impacts the data driven frontier function. We assume that a frontier that can be estimated on the conditional DEA problem is $\Psi^z$, which is given by:

(5) $\Psi^z{}_{DEA} = \{(A, Q)|Z = z, A\ can\ produce\ Q\}$

The conditional input oriented DEA productivity measure is given by:

(6) $\theta^z(A, Q) = \max\{\theta|(A, \theta Q)\ \epsilon\ \Psi^z{}_{DEA}\}$

Malmquist farm productivity index (MI) have four components. $\theta^z(A, Q)$ can be any of the four MI components such as $d^t(Q_t, A_t)$ (efficiency in second period with respect to frontier in the second period), $d^s(Q_s, A_s)$ (efficiency in first period with respect to frontier in the first period), $d^s(Q_t, A_t)$ (efficiency in second period with respect to frontier in the first period) and $d^t(A_s, A_s)$ (efficiency in first period with respect to frontier in the second period), where t and s represents period first and second in the production. We maximize conditional ($\theta^z$) productivity of a single-output and multi-input farmer given input constraints, and production technology.

$\theta^z(A, Q)$ can be obtained using DEA linear programing (see Badin, Daraio and Simar 2012; Coelli and Perelman, 1996) as follows:

$$Max\theta_i|Z$$

$$Subject\ to:$$

$$\sum_{j=1}^{n} v_{ji}\, A_{rji} \leq \theta A_{ri}|\mathrm{Z}$$

$$\sum_{j=1}^{n} v_{ji}\, Q_{sji} \leq Q_{si}\ |\mathrm{Z}$$

$$\sum_{t=1}^{t} v_{ji} = 1, v_{ji} \geq 0$$

where $v$ represents weights, r represents inputs, s represents outputs and i represents observation.

To perform the conditional DEA, we first rank farmers from smallest to largest using the values of the environmental variable. Following Daraio and Simar (2007), Badin, Daraio and Simar (2012), and Simar and Wilson (1998), we estimate efficiency via grouping at intervals of about 100 (10%) farms. The assumption is that farmers in the same groups have similar factors that drive price wedges. Efficiency is estimated based on the performance among these 100 farmers, bootstrapped 1,000 times. The distance from the frontier is interpreted solely as inefficiency. Bootstrap procedures help to overcome the bias that stems from uncertainty of sampling variations. The four components of MI are estimated using input oriented DEA conditional on probability of sales. Farm households are considered as decision making units.

The MI can be decomposed in a frontier shift (FS) (technical change) and catch-up effect (CI) (technical efficiency change) (Fare et al., 1994). That is:

(2) $MI|Z = \frac{d^t(Q_t, A_t)\ |Z}{d^s(Q_s, A_s)\ |Z}\left[\frac{d^s(Q_t, A_t)\ |Z}{d^s(Q_s, A_s)|Z}\frac{d^t(Q_t, A_t)\ |Z}{d^t(Q_s, A_s)|Z}\right]^{0.5}$

(3) $CI|Z = \frac{d^t(Q_t, A_t)\ |Z}{d^s(Q_s, A_s)\ |Z}$

(4) $FS|Z = \left[\frac{d^s(Q_t, A_t)\ |Z}{d^s(Q_s, A_s)|Z}\frac{d^t(Q_t, A_t)\ |Z}{d^t(Q_s, A_s)|Z}\right]^{0.5}$

where Z- represents probability of sales. The Malmquist index, measures productivity changes between two periods, as a distance function that compares farm productivity at period $t$ relative to period s, representing the productivity change (change in the technical efficiency and frontier).

### 4.3.3. Second Stage of Malmquist Data Envelopment Analysis (MDEA)

In the second stage of DEA, we examine the impact of treatment on farm productivity (i.e. catch-up effect, frontier shift and Malmquist index) using the following steps. First, we whiten the conditional productivity measures by removing the effect due to the environmental variable, i.e. probability of sales (See Badin, Daraio and Simar 2012). The whitened farm productivity indices such as MI, CI and FS are estimated using equations (7) and (8).

(7) $\widehat{\Phi^z} = \mu(Z) + \sigma(Z)\delta$

(8) $\hat{\delta} = \frac{\widehat{\theta^z} - \mu(Z)}{\sigma(Z)}$

where $\Phi$ is MI, CI or FS, $\mu(Z)$ is the average effect of probability of sales on the productivity measure, $\sigma(Z)$ is the dispersion of the productivity distribution due to probability of sales, and $\delta$ is the unexplained productivity of the farm. Average effects of probability of sales on productivity, $\mu(Z)$ are measured by regressing probability of sales on productivity using local polynomial (nonparametric) regression as suggested by Badin, Daraio and Simar (2012). Similarly, dispersion, $\sigma(Z)$ is measured by regressing the square of residuals from the equation (7) on probability of sales using local polynomial regression. Once, we get the estimates, $\mu(Z)$ and $\sigma(Z)$, we estimate the whitened productivity using equation (8). $\delta$ is a continuous variable. Productive farmers have smaller $\delta$ values and the less productive farmers have larger $\delta$ values (see Daraio and Simar 2012; Badin, Daraio and Simar 2012).

Training was offered randomly to producers at the level of water use associations (WUA). We measured the impact of the training on farm productivity indices using the following equation.

(9) $\delta_i = \Pi_t T_i + \varepsilon_{ti}$

where T is the intention to treat for observation i, $\Pi_t$ are parameters, and $\varepsilon_{ti}$ is mean 0, IID error term.

However, our data indicate that some farmers from the treated WUA did not attend the training. On the other hand, some farmers from the control WUAs attended and completed the training. There also exists some missing values that can neither be categorized with treatment nor control. The training was completely on a voluntary basis. There was no enforcement to attend the training. To avoid biased results, we considered only those who completed the training. We use a training completion variable, where participants were asked whether or not they completed the training. However, training participation is a farmer specific decision that depends on many factors, which could be endogenous on the system. To overcome this endogeneity problem, an instrumental variable method is used. We use the random assignment of treated and control villages as an instrument for training completion. The IV estimation is implemented using a Two Stage Least Square method (2SLS). The first step involves fitting a binary response model (probit) for training completion ($\hat{h}$) on the instrument, intention to treat (T).

(10) $h_i = \Pi_0 + \Pi_1 T_i + \Pi_2 G_i + \eta_i$

where $h_i$ is the training completion, $G_i$ is a vector of control variables i.e. household characteristics, $\Pi_0, \Pi_1$, $\Pi_2$ are parameters, and $\eta_i$ is mean 0, IID error term.

We also include the results for treatment effect using the original treatment assignment.

The second steps follows by regressing farm productivity measures on $\hat{h}$ and control variables, i.e. household characteristics (G). The second stage is estimated using OLS as follows:

(11) $\delta_i = \alpha G_i + \beta \hat{h}_i + \varepsilon_i$

where $\alpha$ and $\beta$ is parameters, and $\varepsilon_i$ is the mean 0, IID error term.

We test if the unconditional productivity index as compared to conditional productivity index give similar treatment effects. Simar and Wilson (2007) indicate that if environmental variables have significant effects on the production frontier then, unconditional productivity indices in the first stage of DEA leads to wrong inferences in the second stage and recommends that conditional productivity index as an appropriate method to use in the first stage.

We consider non-farm income, age, family size, education, and gender as explanatory variables for the second stage.[5]

## 4.4. Data

We used an Armenian panel survey data set collected in 2007/2008 and 2010/2011 by Millennium Challenge Corporation. The sample was selected from 189 communities out of which 112 were in the treatment group and 77 were in the control group. Communities were randomly assigned to treatment and control groups. Training was offered to famers in the treatment groups, but not to farmers in the control group. The data includes non-farm income sources, household demographics, production, income, household expenditure and other agricultural information.

[5] *Factors such as* non-farm income, age, family size, education, and gender *associated to farm productivity ((see e.g.Tiruneh and Geta 2016; Muange et al. 2015; Abebe 2014; Karimov et al. 2014; Kitila and Alemu 2014; Thibbotuwa et al. 2013; Beshir et al. 2012; Makombe et al. 2011; Aye and Mungatana 2010; Speelman et al. 2008).*

Inputs used are four types namely land (main input), irrigation (main target in the training), labor cost and other costs (total cost-irrigation cost – labor cost) and one output, total crop values.

Table 4.1 presents the summary statistics of key variables for both treatment and control groups. Treatment and control group have similar average values on variables such as age, family size, gender, level of secondary education, irrigation cost, land, other costs, and livestock ownership. However, treatment and control group significantly differ on variables such as non-farm income, total values of crop and labor and equipment costs. Average treatment effect could be biased, when treatment and control group show significantly different baseline information. Instead, we use local treatment effect, measuring treatment effect using control variables.

The average age of the households is around 58 years old. The average number of family members in the household is 5. The percent of households are headed by female members is 14 percent for treated and 13 percent for control group. The number of farm households who completed secondary education is 41 percent for the treatment and 39 percent for the control groups. Irrigation and other costs respectively are 110 and 310 dollars for the control and 109 and 307 US dollars for the treatment group. The treatment group has slightly larger average land (1.51 acres) holdings than the control group (1.46 acres). The number of people from the treatment and control groups that own livestock are 64 and 61 percent, respectively.

Regarding non-income per year, farm households in the treatment group earned higher income (1397 US dollars) than the control group (1246 US dollars). Similarly, farmers in the treatment have higher income from crops and higher labor costs compared to farmers in the control groups. The average crop income per year for farm households under the treatment group is 1520 US dollars as compared to 1379 US dollars for the control group. The average labor costs per year for the treatment and control groups is 281 and 265 US dollars, respectively. The total sample size was 3,996. Due to many zeros across inputs and output, DEA couldn't construct a frontier and estimate technical efficiency in the full sample. After we dropped values with zero total input costs and total value of crops, the sample size was reduced to 1554. Since, DEA is sensitive to outliers (Ahamed et al. 2015; Timmer 1971), we removed outliers that were 3 times the standard deviation above and below the mean. After we remove the outliers, we are left with 1227 number of households. Despite these changes, the proportion of treated and control farmers in the estimation sample mirrors the original sample (treatment, 61% and control, 39%).

## 4.5. Results and Discussion

We perform farm productivity analysis conditional on probability of sales, a proxy for price wedges. Results are structured as follows. First, estimation results for probability of sales, a proxy for price wedge is presented. Second, the first stage of the Malmquist DEA, for estimating farm productivity indicators such as catch-up (change in technical efficiency), frontier shift (change in technology) and Malmquist index conditional probability of sales are presented. Third, the second stage of Malmquist DEA for examining treatment impact on farm productivity measures are presented. Details are outlined in the following subsections.

### 4.5.1. Prediction Probability of Sales

Probability of sales, the proxy for price wedges is presented in Table 4.2. It is estimated using a logit model. Results show that land size, and household size can be used to predict sales. Land has positive association with sales. This matches with Vakis, Sadoulet and Janvry (2003) and Fafchamps (1992) findings that farmers that have larger farm size can produce more output and can sell larger amounts than farmers with a smaller land size. Household size have negative impact on sales. Farm households that have larger households use more crops for consumption than farm households with smaller households. This matches with the theory that as food consumption need increases, farm households allocate more of farm inputs for food crops production than for cash crops production.

### 4.5.2. First Stage of Malmquist Data Envelopment Analysis (MDEA)

We first measure the correlation between farm productivity ratios and baseline probability of sales using local polynomial (non-parametric) regression (Table 4.3). The relationship between these ratios and probability of sales is significant, implying that probability of sales, a proxy for factors that drive price wedges matters when we measure farm productivity in Armenia. The baseline probability of sales has a positive association with catch-up (0.13) and Malmquist index (0.03) and negative association with frontier shift (-0.08). This implies that catch-up and Malmquist index increase in probability of sales and frontier shift decreases in probability of sales. Catch-up and Malmquist index that measure change in efficiency and farm productivity is higher for commercial farmers (high probability of sales) than subsistence farmers (low probability of sales). However, the frontier shift that measures change in innovation is larger for subsistence farmers compared to commercial farmers.

Unconditional and conditional farm productivity estimates are reported in Table 4.4. Probability of sales has a significant effect on farm productivity, implying that farm productivity measures based on unconditional DEA are biased. Hence, we interpret only the conditional farm productivity measures. The average catch-up (change in technical efficiency) using conditional DEA is 1.30. This implies that on average, farmers over the given period have improved their technical efficiency by about 30 percent. The average frontier-shift (technological shift) using conditional DEA is 1.50. This indicates that farmers over the given period have increased their technical efficiency by about 50 percent. Similarly, the average Malmquist index (change on overall productivity) is about 1.71, which shows that farmers improved their overall farm productivity about 71 percent. This is mainly due to improvement in efficiency and innovation.

The average catch-up, frontier shift and Malmquist index using unconditional DEA are 1.76, 0.67 and 1.35. The difference between unconditional and conditional DEA farm productivity measures is substantial. The average bias, the difference between conditional and unconditional DEA for catch-up, frontier and Malmquist indexes is about 0.45, 0.83 and 0.52 respectively.

### 4.5.3. Second Stage of Malmquist Data Envelopment Analysis (MDEA)

In order to examine the treatment effect in the second stage, we whitened the conditional farm productivity, as in Badin, Daraio and Simar (2012). Conditional farm productivity measures are calculated using equation (7) and (8). The whitened catch-up effect, frontier shift and Malmquist index are shown in figures (4.1), (4.2) and (4.3). The whitened farm productivity measures are drawn against probability of sales. The whitened farm productivity measures are presented on vertical axis and probability of sales on the horizontal axis. The highest whitened farm productivity value indicates low performance and lowest value shows best performance (see Badin, Daraio and Simar 2012 and Simar and Wilson 2007).

The impact of probability of sales on whitened farm productivity measures is statistically insignificant (Table 4.5). The results agree with the Daraio and Simar (2007) findings, implying that whitened farm productivity measures should have no relationship or should be independent of the environmental variable (probability of sales). After, we remove the effect of probability of sales, a proxy for the price wedge, on farm productivity measures, we can then assess the impact of treatment (farm training) on the whitened farm productivity measures. Examining the effect of treatment on the whitened farm productivity measures provides more meaningful measure of the program's impact (Daraio and Simar 2007; Simar and Wilson 2007). Unconditional farm productivity measures are biased and inference based on these farm productivity measures is likely to be misleading.

The results for the ITT impact estimates of training on unconditional and conditional DEA farm productivity indices is presented in table 4.6 and 4.7 respectively. The impact of training on unconditional farm productivity indices are small and insignificant. Conditional measures are similar, though the impact on the frontier shift is negative and significant at the 10 percent level. However, the ITT estimates potentially underestimates the treatment effect due to two-sided non-compliance, which affected approximately 60 percent of the sample. To overcome this issue, we estimate the local average treatment (LATE) to examine the impact of the program.

The LATE uses instrumental variables to calculate the impact based on the complying sample of farmers, or those in the treatment group that attended training and the control group that did not. In equation (10), training completion is fitted on the treatment assignment variable. The effect of treatment assignment on training completion is positive and statically significant (Table 4.8), implying that treatment assignment is a good instrument. We then estimate of the impact of training completion on the whitened farm productivity measures using equation (11). Results indicate that the LATE estimates on naïve or unconditional and whitened (conditional) farm productivity differ. The LATE across all types of naïve farm productivity is statistically insignificant (Table 4.9). However, the LATE under conditional farm productivity measure has a positive and significant effect on the catch-up effect and an insignificant effect on the frontier-shift (negative) and Malmquist index (positive) (Table 4.10). The Malmquist Index is the product of the catch-up and frontier shift effects. With a statistically insignificant effect of the extension program on the frontier-shift, the impact on productivity is likely to be insignificant as well, given the multiplicative nature of the Malmquist Index. It is likely that the farm training, while providing knowledge to farmers, did not result in a significant adoption in technology to result in a shift in the frontier over the time period. Instead, farmers likely used the information to better allocate their inputs, improving technical efficiency (i.e. the positive catch-up effect), not resulting in an improvement in productivity over the time period.

We find that unlike the naïve (unconditional), the conditional DEA indicates positive and statistically significant impact of agricultural extension program on catch-up effect. Unconditional DEA-based efficiency estimation could not detect the impact and would underestimate the effectiveness of the extension program. The positive and significant impact of agricultural extension program on catch-up effect implies that the training improved the productivity of the inefficient farmers and helps them to approach or equal in the productivity performance of the most efficient farmers.

## 4.6. Conclusion

With increasing demand and declining supply of development funds, the need for innovative and more rigorous impact evaluation methods is important for development programs such as extension programs. Examining the effectiveness of farm education and extension program using farm technical efficiency and innovation as an outcome variable instead of farm income helps to adequately capture the program impacts. Farm education and extension programs are thought to increase farm income through increase in farm technical and/or innovation. In this study, we analyzed the effect farm training on farm productivity of Armenian farmers. We investigate the effect of local treatment on catch-up efficiency, frontier shift and Malmquist index using conditional DEA. Controlling for other variables (e.g. non-farm income, education, etc.), the training program has a statistically significant and positive on catch-up effect and insignificant effect on the frontier shift and Malmquist index.

Fortson et al. (2012) and Schwab and Shanoyan (2016) examined the impact on farm income, and they found no persuasive positive effect. However, using farm productivity as an outcome variable, the training proved to provide a positive and significant effect on changes in technical efficiency over the treatment period. Using alternative methods to evaluate extension program such as using farm productivity instead of farm income as outcome variables helps to identify the impacts that would have gone undetected. Mismeasurement of the impact weaken the program unnecessarily and eventually leads to misallocation of development program funds.

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## 4.8. Tables and Figures

**Table 4.1: Summary Statistics of Sample Households' Characteristics**

| **Variable** | **Definitions** | **Mean for each group** | |
|---|---|---|---|
| | | **Treatment** | **Control** |
| Age | Age of head of household in years | 57.36 | 57.83 |
| Family size | Number of household size | 5.21 | 5.20 |
| Gender | 1 if head of household female, 0 otherwise | 0.14 | 0.13 |
| Secondary education | 1 if farmer completed high school and 0 otherwise | 0.41 | 0.39 |
| Irrigation cost | Amount irrigation cost per year in dollars | 108.51 | 110.14 |
| Other costs | Amount of costs other than irrigation and labor in dollar | 306.92 | 310.19 |
| Land | Land owned in acres | 1.51 | 1.44 |
| Livestock | 1 if farmer own it, 0 otherwise | 0.64 | 0.61 |
| Nonfarm income | Amount of nonfarm income in dollars | 1397.33 | 1246.42* |
| Total value of crops | Total value of crops per year in dollars | 1520.00* | 1378.99 |
| Labor and equipment cost | Amount of hired labor and equipment cost per year in dollars | 280.92* | 264.54 |
| Zone 1 | Number of farmers from zone 1 | 349 | 249 |
| Zone 2 | Number of farmers from zone 2 | 291 | 168 |
| Zone 3 | Number of farmers from zone 3 | 81 | 41 |
| Zone 4 | Number of farmers from zone 4 | 7 | 8 |
| Total observations | 1227 | | |

**Table 4.2: Factors associated with crop sales to the market**

| Variables | Logit model for predicting sales | | |
|---|---|---|---|
| | parameters | | |
| | **estimates** | **Std. error** | **P-value** |
| Land | 0.25 | 0.05 | 0.02 |
| Gender | 0.03 | 0.25 | 0.93 |
| Non-farm income | 0.01 | 0.10 | 0.63 |
| Household size | -0.10 | 0.10 | 0.07 |

* District fixed effect variables are used in the estimation of the logit models and the specific results for these variables are not reported in the Table in the interest of space. There are 166 districts included in the data from Armenia.

**Table 4.3: Association of Farm Productivity and Sales using Generalized Nonparametric Regression**

| | **Catch-up ratio** | **Frontier shift ratio** | **Malmquist index ratio** |
|---|---|---|---|
| Constant | 0.76*** | 1.28*** | 1.00 *** |
| Probability of sales | 0.13*** | -0.08*** | 0.03*** |

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

**Table 4.4: DEA Farm Productivity of Farm Households in Armenia**

| Farm productivity | Unconditional DEA Mean | Conditional DEA Mean | Bias (Cond. DEA-Uncond. DEA) |
|---|---|---|---|
| Catch-up | 1.76 | 1.30 | -0.45 |
| Frontier shift | 0.67 | 1.50 | 0.83 |
| Malmquist Index | 1.35 | 1.71 | 0.57 |

**Table 4.5: Association of Whitened Productivity and Sales using Nonparametric DEA Estimation**

| | Catch-up | Frontier shift | Malmquist index |
|---|---|---|---|
| Constant | 0.05 | -0.08*** | 0.03 |
| Probability of sales | -0.03 | 0.02 | -0.08 |

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

**Table 4.6: Impact of Training on Unconditional DEA Farm Productivity using OLS**

| | catch-up | Frontier | Malmquist index |
|---|---|---|---|
| Constant | 1.74*** | 0.66*** | 1.13*** |
| | (0.05) | (0.01) | (0.04) |
| Treatment | 0.02 | 0.01 | 0.01 |
| | (0.07) | (0.01) | (0.05) |

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

**Table 4.7: Impact of Training (ITT) on Conditional DEA Farm Productivity using OLS**

| | catch-up | Frontier | Malmquist index |
|---|---|---|---|
| Constant | 0.67 | 0.56 | 0.99 |
| | (0.14) | (0.12) | (0.44) |
| Treatment | 0.15 | -0.28* | -0.78 |
| | (0.15) | (0.16) | (0.56) |
| $R^2$ | 0.003 | 0.003 | 0.003 |

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

**Table 4.8: Effect of Treatment Assignment on Training Completion using Probit Model (1st stage)**

| | Training completion |
|---|---|
| Constant | -1.68*** |
| Intention to treat | 1.53*** |

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

**Table 4.9: Impact of Training (LATE) on Unconditional DEA Farm Productivity using 2SLS**

| | catch-up | Frontier | Malmquist index |
|---|---|---|---|
| Constant | 1.38*** | 0.56*** | 0.84*** |
| | (0.21) | (0.05) | (0.14) |
| Treatment | -0.05 | 0.03 | -0.01 |
| | (0.15) | (0.03) | (0.07) |
| nonfarm income | -0.00 | 0.00 | -0.00 |
| | (0.00) | (0.00) | (0.00) |
| family size | 0.01 | -0.01 | -0.00 |
| | (0.02) | (0.01) | (0.02) |
| Livestock ownership | -0.09 | 0.08*** | 0.18*** |
| | (0.08) | (0.01) | (0.05) |
| Secondary education | -0.14 | -0.03** | -0.03 |
| | (0.09) | (0.01) | (0.07) |
| Age | -0.00 | -0.00 | 0.00 |
| | (0.04) | (0.00) | (0.01) |
| Gender | 0.12 | 0.03 | 0.14** |
| | (0.14) | (0.03) | (0.12) |
| $R^2$ | 0.01 | 0.05 | 0.02 |

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

**Table 4.10: Impact of Training (LATE) on Conditional DEA Farm Productivity using 2SLS**

| | catch-up | Frontier | Malmquist index |
|---|---|---|---|
| Constant | 0.32 | 8.74 | 1.25 |
| | (0.47) | (18.74) | (3.16) |
| Treatment | 0.64** | -12.37 | 1.42 |
| | (0.34) | (13.62) | (2.30) |
| nonfarm income | 0.00 | 0.00 | 0.00 |
| | (0.00) | (0.00) | (0.00) |
| Family size | 0.03 | 0.65 | 0.46 |
| | (0.05) | (2.02) | (0.34) |
| Livestock ownership | -0.21 | 8.99 | 2.68*** |
| | (0.17) | (6.96) | (1.17) |
| Secondary education | -0.10 | 5.05 | -0.71 |
| | (0.17) | (6.84) | (1.15) |
| Age | -0.01 | -0.07 | 0.00 |
| | (0.01) | (0.30) | (0.05) |
| Gender | -0.14 | 4.39 | 1.38 |
| | (0.25) | (9.34) | (1.67) |
| $R^2$ | 0.01 | 0.01 | 0.01 |

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.01

Figure 4.2: Plotting Catchup using Local Polynomial Smoothing

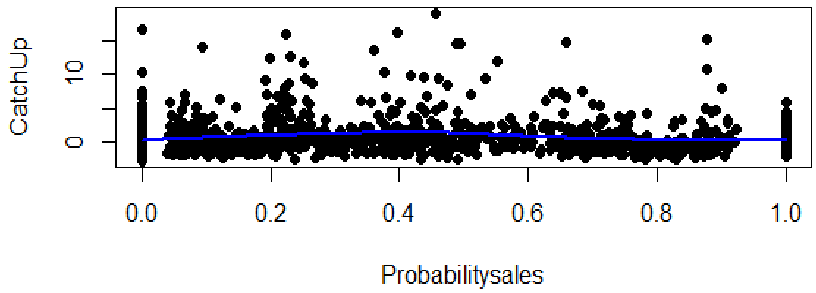



Figure 4.3: Plotting Frontier Shift using Local Polynomial Smoothing

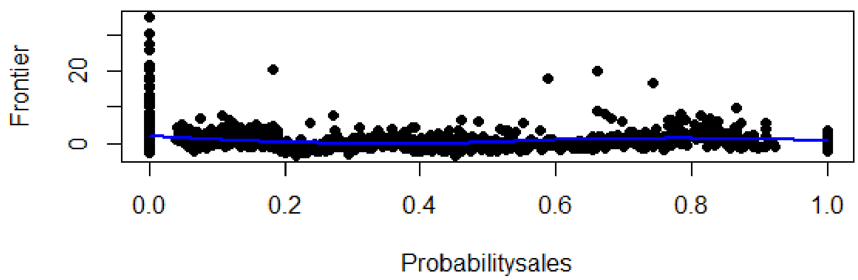
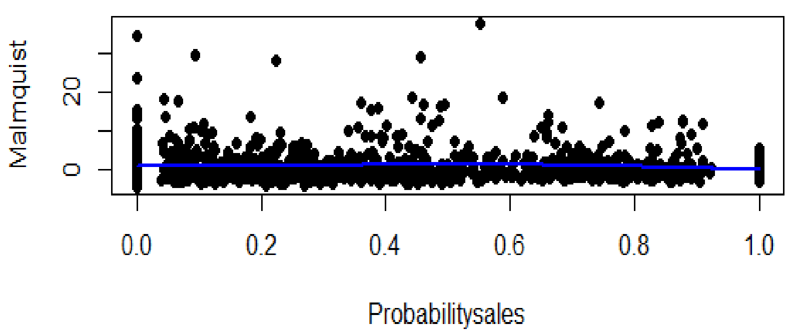



Figure 4.4: Plotting Malmquist using Local Polynomial Smoothing



## Chapter 5. Overall Conclusion

Examining whether or not farm education and extension program increases farm efficiency and/or innovation is important. Due to an increasingly limited availability of land, and continuous increases of world population, increasing agricultural production through increases in efficiency and/or innovation is crucial to alleviate future food security issues. Traditionally, the effect of extension program is evaluated using yield and farm profit, but farm efficiency could also be used as an outcome variable to evaluate the impact such programs.

Using a simple model, we show how farm efficiency could be used as complementary outcome variable to evaluate extension programs. Extension programs are thought to increase income through increases in farm efficiency. An extension program that shows no or little impact on profit may still have resulted in more efficient production behavior for farmers, such as subsistence farmers, that are beset by credit constraints. We note that when farmers are capital constrained, extension programs can theoretically have a large *efficiency* effect despite a small or no change in farm profits.

Assessing the program with alternative methods improves the ability to accurately and credibly evaluate the impact and results in a more efficient allocation of limited funds and resources. If the full impact of a development program is not adequately captured and some key benefits go undetected, the case for allocating funds for such programs may weaken unnecessarily. With increasing demand and declining supply of development funds, the need for innovative and more rigorous impact evaluation methods is becoming more critical for international development community in general and for extension and technology transfer programs in particular.

However, if we are touse farm technical efficiency as outcome variable, then correct way of estimating the metric is crucial. Mismeasurement may counteract the advantages to incorporating efficiency analysis if the analysis is done incorrectly. We demonstrate the measurement of farm efficiency for transaction costs and other factors heterogeneous farmers face in developing countries.

The standard approach to measure productivity analysis such as efficiency assumes that farm households face homogenous prices that leads to homogenous sets of production and profit functions. Transaction costs and crop qualities attributes create a price wedge between the market and shadow price of crops. Transaction costs and other factors are heterogeneous and leads to heterogeneous price wedges among farmers such as subsistence, semi-subsistence and commercial farmers. Subsistence and semi-subsistence farmers who produce largely home consumed crops have potentially higher price wedges than commercial farmers. Failing to account for the heterogeneous set of price wedges that lead to varying profit and production frontiers is likely to lead to underestimation of the efficiency of subsistence and semi-subsistence farmers.

In this paper, we explicitly model the potential impact of price wedges on optimal crop choices for profit maximizing farm household. We show that the existence of price wedges discourages production of cash crops and encourages production of home consumed crops. With the increase of price wedges, a profit maximizing farm household, more typically subsistence farmers, withdraws inputs from cash crops and allocates them toward home consumed crop production. Because of significant price wedges, use of modern technologies, and production of high values crops are unprofitable to subsistence and some of the semi-subsistence farmers. As a result, farmers use the traditional inputs and produce dominantly seemingly low value crops. On the other hand, commercial farmers use modern technologies and produce high value crops as it is still profitable to them at the given market prices.

We test whether or not traditional productivity analysis indeed underestimates the efficiency of subsistence and semi-subsistence farmers by employing a conditional Data Envelopment Analysis (DEA) model for household survey data in Uganda. Results confirm that naïve estimates of efficiency understate the efficiency scores of subsistence and semi-subsistence farmers. The results cast doubt on policies, such as extension programs or other information treatments, based on interpreting low efficiency scores for subsistence and semi-subsistence farmers as a management shortfall.

We examine the efficiency impacts of an extension program within the context of a cluster randomized control trial in Armenia. Fortson et al. (2012) and Schwab and Shanoyan (2016) examined this treatment effect on farm profit and find ambiguous results. We investigate the effect of treatment on catch-up efficiency, frontier shift and Malmquist index using conditional DEA.

Controlling for other variables (e.g. non-farm income, education, etc.), the training program has statistically significant and positive impacts on catch-up. However, our results indicate treatment effect show no significant effect on innovation and Malmquist index. Overall, the demonstration suggests that increasing methods to evaluate extension program helps to identify the impacts that would have gone undetected.