Three Essays on Productivity, Efficiency,
and the Role of Social Networks

by

Dawit Kelemework Mekonnen

(Under the Direction of Dr. Esendugue Greg Fonsah and Dr. Jeffrey H. Dorfman)

Abstract

In the first chapter of the dissertation, we study the effects of informal labor sharing arrangements and other social interactions on farmers' productivity in a developing country context, testing whether these types of social and work interactions lead to productivity gains through learning, synergy, or both. Using a rich panel data set of Ethiopian subsistence farmers, we estimate a distance function of grains production and find large productivity gains (approximately 20 percent) from labor sharing due to synergy effects that boost labor productivity. We find no learning effects from labor sharing as the productivity gains observed in years with labor sharing disappear in following years if the farmers do not continue to employ labor sharing. The results do not encourage policies based on passive learning, and provide evidence in favor of extension programs and off-farm works.

The second chapter of the dissertation explores the level of technical efficiency of small-scale farmers as well as factors that determine the level of efficiency. We find that the most important factors determining farmers' efficiency are access to the public extension system, participation in off-farm activities, taking advantage of labor sharing arrangements, gender of the household head, and the extent to which farmers are forced to produce on marginal and steeply sloped plots. We find that the average farmer's technical efficiency is less than

60 percent, so bringing farmers toward the production frontier using the successful policies identified could yield large, economically significant productivity gains.

The third chapter examines how different components of an agricultural innovation system interact to determine the level of technical inefficiency of agriculture for a panel of 45 low-income and lower-middle-income countries between 2008 and 2010. Results show that the mean level of relative technical efficiency among the sampled countries is about 97 percent, showing limited potential (approximately 3.1 percent) to increase production at the current level of inputs and technology. This calls for a focus on investments that push the technology frontier outward such as irrigation. High quality education and health expenditure per capita are found to improve the efficiency of agricultural production in these countries.

Index words: Agricultural Innovation Systems, Developing Country Agriculture, Distance Function, Efficiency, Ethiopia, GMM, Labor Sharing, Learning, Productivity, Social Networks, Stochastic Frontier Analysis, Synergy, Technical Efficiency

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by

Dawit Kelemework Mekonnen

B.A., Addis Ababa University, 2001

M.Sc., Addis Ababa University, 2005

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Dawit Kelemework Mekonnen

Approved:

Major Professors: Dr. Esendugue Greg Fonsah
Dr. Jeffrey H. Dorfman

Committee: Dr. Cesar Escalante
Dr. Berna Karali

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
May 2013

Dedication

I dedicate this dissertation to my close, understanding, helping, and friendly God, who made all possible; to my loving wife, Mariamawit, for her selfless support and encouragement; my daughter Misbak, for even the joy of expecting her helps me keep my eyes on the ball; my mother, Bezunesh Abebe, who I always wish to get a bit of her good judgment and wisdom; my sisters Tekuam, Firehywot, Muleye, and Eskedar; and my best friends Michael and Yared.

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Chapter 1

Learning and Synergy in Social Networks: Productivity Impacts of Informal Labor Sharing Arrangements

1.1 Introduction

The influence of social networks on individuals' behavior and success has long been of interest to sociologists, and this interest has recently been picked up by economists. Some countries (and states in the U.S.) have designed agricultural extension programs that target progressive farmers as model or contact farmers, with the expectation that these model farmers will influence other farmers in their networks to follow their lead and adopt new production practices. Similarly, some countries award and recognize successful farmers with the belief that it encourages other farmers to adopt the successful production decisions of the awardees in their immediate surroundings. These policy initiatives are based on the assumption of mutual learning and influence among farmers. We investigate whether even ordinary farmers can be models that others learn from by studying whether different types of social interactions and educational opportunities lead to agricultural productivity gains. Learning more about what forms of learning opportunities boost productivity can help developing countries design better production-increasing policies.

The main type of social networks that we consider in this study are labor sharing arrangements in which a household head invites members of other households in his network to help him with specific agricultural activities. The reasons for calling such a work party include quick completion of tasks, unavailability or expensiveness of hired labor, and completion of tedious agricultural activities in a group. Households respond to such requests not based on wages but in expectation that the household will reciprocate the labor supply when they make a similar request later. Labor sharing in Ethiopia is used in a wide range of agricultural activities including land preparation and ploughing, weeding, harvesting, and threshing. Watching other workers perform the same task provides an obvious opportunity for learning and also may lead to gains from synergy if workers improve their performance when working in front of others. The data set we use also includes other social interactions such as access to extension programs, membership in funeral associations and off-farm work activities which might provide opportunities for learning in different settings.

The objective of this chapter is to analyze the impact of these different interactions and learning opportunities on agricultural productivity using a rich panel data set of Ethiopian subsistence grain farmers. We investigate to what extent involvement in informal labor sharing arrangements affects productivity above and beyond the direct impact of the additional labor to production. In other words, we want to know whether labor sharing means more than an increase in labor supply. This question will be answered affirmatively if labor sharing facilitates mutual learning or if there are increasing returns to working together (synergy). We also examine whether social interactions such as funeral association membership and educational opportunities like extension programs and off-farm work lead to learning that increases agricultural productivity.

Interest in social network studies has been growing in recent years. The economics literature has used social network theories in a wide range of applications such as peer effects among college roommates (Sacerdote, 2001), friendship formation (Marmaros and Sacerdote, 2006), neighborhood peer groups on childhood skill acquisition (Helmers and Patnam, 2011), peers behavioral influences on the choice of college major (De Giorgi, Pellizzari, and Redaelli, 2010), risk-sharing networks to deal with income and expenditure shocks, and illness (Fafchamps and Lund, 2003; De Weerdt and Dercon, 2006), on what makes students popular among high school peers and the economic gains from popularity later in life (Conti et al., 2009), social influence on risky behavior by adolescents such as the consumption of alcohol, tobacco, and marijuana (Clark and Loheac, 2007), and the role of social networks in welfare participation (Bertrand, Luttmer, and Mullainathan, 2000).

The social network studies in agriculture have mainly focused on the impact of networks on technology adoption and diffusion (Liverpool-Tasie and Winter-Nelson, 2012; Maertens and Barrett, 2012; Conley and Udry, 2010; Bandiera and Rasul, 2006; Munshi, 2004; Foster and Rosenzweig, 1995). In addition, Santos and Barrett (2010) applied social network theories on the role of identity in farmers' search for information while Krishnan and Sciubba (2009) analyzed the role of the number of links and network architecture in determining the impact of social networks on outcomes.

There has been only few studies on the impact of peer effects on individual productivity in work or work-like settings. Bandiera, Barankay, and Rasul (2010) combined personnel records on individual worker productivity with a survey of worker's social networks of friends and find that presence of friends affects worker's performance as friends conform to a common productivity norm. Using grocery scanner data on workers' productivity, Mas and Moretti (2009) find evidence of strong peer effects associated with the introduction of high-productivity workers into work groups. Mas and Moretti (2009) claim that they find these positive productivity spillovers even though the data come from a group production process that is particularly prone to free-riding, in a low-skill occupation where the tasks performed by workers are highly standardized. Using a controlled field experiment, Falk and Ichino (2006) present evidence for peer effects in improving workers' performance by comparing the productivity of workers who were asked to fill letters into envelopes at the same time in the same room and alone, with a remuneration independent of output. However, Guryan, Kroft, and Notowidigdo (2009) use the random assignment of playing partners in professional golf tournaments, and state that they find no evidence that the ability or current performance of playing partners affects the performance of professional golfers.

We believe our study will contribute to this growing literature by exploring the effects of informal labor sharing arrangements and other social interactions on farmers' productivity in a developing country context, testing whether these types of social and work interactions lead to productivity gains through learning, synergy, or both. If ordinary interactions with other farmers can boost productivity through the influence and leadership of some farmers, that has implications for the design of production-increasing policies. Alternatively, if observation and interaction is not enough, but rather training and educational opportunities are necessary, then developing countries need to alter policies such as model farmer programs and instead focus more on policies such as extension programs. This study should shed light on such policy questions and could point the way toward important agricultural production improvements.

1.2 Synergy versus Learning Effects

After accounting for the direct impact of labor sharing in production in terms of increased labor supply, we hypothesize that informal labor sharing arrangements affect agricultural productivity and efficiency in two ways: the synergy effect and the learning effect. The synergy effect is the result of the physical presence of the labor sharing partners on the farmer's plot and it refers to productivity gains that come from working together such as speed gains and being less bored by tedious agricultural activities or working harder while observed by the labor sharing partners. The learning effect is the skills learned and information obtained from the labor sharing partners that the household can put into use to improve its productivity and efficiency even on plots and at times when a labor party is not present.

Labor sharing is expected to have an impact on farmers' current level of technical efficiency based on the current and previous period labor sharing status. Farmers are, therefore, grouped into four types as shown in Table 1.1. Type I farmers are those who do not use labor sharing this year, and do not have prior labor sharing experience. Type II farmers refer to those who used labor sharing in the current year, and also have prior labor sharing experience in at least one of the previous survey rounds. Type III farmers are those who do not use labor sharing this year but have prior labor sharing experience. Type IV farmers are those who use labor sharing in the current year but do not have prior labor sharing experience.

Table 1.1: Farmers Classification Based on Labor Sharing Participation

	Labor Sharing Participation		
Farmer Type	Previous Seasons	Current Season	
I	No	No	
II	Yes	Yes	
III	Yes	No	
IV	No	Yes	
Farmer Type	Previous Seasons	Current Season	Future Season
Ia	No	No	No
Ib	No	No	Yes

We have further divided farmers who have never used labor sharing (Type I farmers) into Type Ia and Type Ib based on whether or not they have used labor sharing in a future year. Type Ia refers to farmers who have not used labor sharing this year, who do not have prior labor sharing experience, and who do not use labor sharing in a future period. Type Ib refers to those farmers who do not have labor sharing either in the current year or in the past but who will use labor sharing in a future year. Type Ib farmers are a better control group since they use labor sharing at a future point in time, thus are not inherently different as far as labor sharing is concerned, and may be more similar in other respects to Type II, Type III, and Type IV farmers.

As discussed in the data section below, the empirical application of this study uses the Ethiopian Rural Household Survey (ERHS), which is a longitudinal household data set that covers 15 peasant associations in Ethiopia in 1989, 1994, 1995, 1997, 1999, 2004, and 2009. Even though the estimation in this study is undertaken using only the 1999 and 2004 survey rounds, we have used all but the 1989 and 1997 surveys to classify farmers based on their labor sharing participation. For the 1999 observations, for instance, previous labor sharing experience refers to whether the farmer used labor sharing either in 1994 or 1995 and future labor sharing experience refers to whether the farmer used labor sharing either in 2004 or 2009. For the 2004 observations, prior experience refers to labor sharing participation either in 1994, 1995, or 1999 while future year experience refers to labor sharing participation in 2009. The 1989 survey is not included to classify the farmers into the different labor sharing groups since it covers only 6 of the total 15 villages, as the decision to make the survey panel and to re-randomize the sample to include additional 9 villages was made in 1994. The 1997 survey is not included because labor sharing participation was obtained only for the preceding four months, instead of season by season as is done in the other surveys. After accounting for a host of other factors discussed below that affect productivity, the identification strategy for the presence or absence of productivity improving effects from labor sharing is summarized in Table 1.2.

If the technical efficiency of Type III farmers is greater than that of Type Ib farmers, then labor sharing has a learning effect. This is because neither type of household uses labor sharing in the given year. Thus, there will be no synergy effect and the only difference in the levels of efficiency should come from the learning effect.

Table 1.2: Identification of Learning and Synergy Effects

Technical Efficiency		Effect of Labor Sharing
III > Ib	$\Rightarrow$	Learning
II > III > Ib	$\Rightarrow$	Both learning and synergy
II > III = Ib	$\Rightarrow$	Synergy but not learning
II = III > Ib	$\Rightarrow$	Learning but not synergy
II = III = Ib	$\Rightarrow$	Neither learning nor synergy
II > III > Ib & IV = III	$\Rightarrow$	Learning and synergy; Synergy=Learning
II > III > Ib & IV > III	$\Rightarrow$	Learning and synergy; Synergy > Learning

Ib, II, III, and IV refer to the type of farmers as defined in Table 1.1

If the technical efficiency of Type II farmers is greater than that of Type III farmers, and if the technical efficiency of Type III farmers, in turn, is greater than that of Type Ib farmers, then labor sharing has both learning and synergy effects. This is because if there were only learning effects, the technical efficiency of households who have used labor sharing both in the current year and in the past (Type II farmers) would be the same as those who did not use labor sharing that year but have used it in a previous year (Type III farmers).

If there were only a synergy effect, there would be no difference in the efficiency of Type III and Type Ib farmers because neither used labor sharing for that year.

Likewise, if the technical efficiency of Type II farmers is greater than that of Type III farmers, and if the technical efficiency of Type III farmers is, in turn, equal to that of Type Ib farmers, then labor sharing has a synergy but not learning effect. If labor sharing provided a learning effect, the efficiency of Type III farmers, who have had a chance to learn from others when using labor sharing in the past, would have been higher than that of farmers without any labor sharing experience as of the current year (Type Ib farmers). If there is no learning, then the difference in the efficiency of Type II and Type III farmers must have come from the synergy effect.

Following the same reasoning, if the technical efficiency of Type II farmers equals that of Type III farmers, and if the technical efficiency of Type III farmers is greater than that of Type Ib farmers, then labor sharing has a learning but not a synergy effect. Finally, if the technical efficiency of Type II, Type III, and Type Ib are equal, then labor sharing has neither learning nor synergy effects.

In addition, if the technical efficiency of Type II is greater than that of Type III, which, in turn, is greater than that of Type Ib; and the technical efficiency of Type III equals that of Type IV, then labor sharing has both learning and synergy effects, and the synergy effect is equal in magnitude to the learning effect since Type IV farmers enjoy only synergy and Type III only learning effects. However, if the technical efficiency of Type II >Type IV > Type III > Type Ib, the synergy effect is stronger than the learning effect, giving Type IV farmers an edge over the cumulative learning of Type III farmers.

1.3 Theoretical Framework

The theoretical framework below draws heavily on Gilligan's (2004) model of labor exchange and is used to guide our empirical model. Consider a farmer that produces output, Q, using land, labor, fertilizer, oxen and other purchased inputs. Let us represent land, fertilizer, oxen, and other purchased inputs by the vector X to be able to focus our attention on labor (N). Farm labor days, N, is comprised of family labor (N_f) defined as the number of family members who work on the farm multiplied by the number of days worked, hired labor (N_h) defined as number of hired labor multiplied by the number of days hired labor is used, and shared labor (N_s) defined as number of labor sharing partners multiplied by the number of labor sharing days. Thus, the technological possibilities can be summarized using the transformation function

$$Q_{max} = f(X, N_f + N_h + N_s) \tag{1.1}$$

where $f(.)$ is non-negative, non-decreasing, and concave in its arguments. If we subtract from the transformation function a non-negative random variable, U, associated with technical inefficiency and add a stochastic term, V, for remaining randomness, then the actual production, Q, can be re-written as

$$Q = f(X, N_f + N_h + N_s) - U + V. \tag{1.2}$$

Since farmers have to reciprocate the shared labor of their partners in a more or less equivalent amount and quality, they will engage in labor sharing only if there is productivity gain from working together in labor sharing parties. Thus, if labor sharing impacts efficiency, a farmer's inefficiency, U, will be a function of whether the farmer is engaged in labor sharing along with a vector of other household and farm characteristics, K, that determine technical inefficiency:

$$U = g(N_s, K). \tag{1.3}$$

Though labor sharing does not involve cash payments, there is a per-head per-day search and transaction cost of organizing a labor sharing party, c_s. The search and transaction cost (c_s) is perceived in terms of labor days lost to organize the labor sharing party, rather than in monetary terms. Since we assumed a full or near full reciprocity, c_s is assumed to be more or less similar across labor sharing partners of a given household. However, c_s can be different across different households who organize labor sharing parties depending on their history of labor sharing participation. For instance, households who have been using labor sharing for a long time can potentially have lower average c_s than those who use labor sharing for the first time this season. In addition, full or near full reciprocity reduces labor supply on one's own farm by the amount of labor days on the partners' farms, N_s.

If we represent the initial family labor endowment of the household by $\overline{N}_F$, leisure time by R, labor days spent on off-farm activities by N_o, then the household time constraint can be shown as

$$\overline{N}_F - R - N_f - N_s - N_o - c_s N_s \geq 0. \tag{1.4}$$

The first N_s in equation 1.4 refers to labor days spent on others' farms to reciprocate labor received from partners while the second N_s is multiplied by c_s to get the total search and transaction cost of organizing a labor sharing party since c_s is defined in per-head per-day terms. Hired labor (N_h) is not part of the household's time constraint because hired labor is not part of the initial time endowment of the family, even though it indirectly affects family labor (N_f) through the liquidity constraint defined below and the production function.

In addition to the time constraint, there is also a liquidity constraint as farmers have to pay for hired labor. Labor sharing enters the liquidity constraint because it is customary in many labor sharing parties that the person calling for such a work party has to provide food and drink. The per-head per-day cost of providing food and drink to the partners is given as c_f. Farmers' initial financial endowment is represented by $\overline{M}$, and their off-farm income by $w_o N_o$ where w_o and N_o are the wage rate and labor days associated with off-farm activities. As Gilligan (2004) explained, farm income does not enter as a source of liquidity because it is not earned until the end of the season. If we define the wage rate per labor day for the amount of labor hired-in by w, then the liquidity constraint is given as

$$\overline{M} + w_o N_o \geq w N_h + c_f N_s. \tag{1.5}$$

We also follow Gilligan (2004) in assuming that households have identical preferences over income, y, and leisure, R, and that utility, Ψ, is additive in income and the utility derived from leisure,

$$\Psi(Y,R) = y + \psi(R) \tag{1.6}$$

where $\Psi' > 0$, $\Psi'' < 0$, and $\psi'(0)$ is infinite. The assumption of constant marginal utility of income in equation 1.6 is reasonable within the sample of subsistence farmers being studied here as the farmers do not earn much to reach the point at which marginal utility of income declines. We normalize the price of agricultural product to one. The farmer, then, maximizes his household utility subject to the time constraint, the liquidity constraint, and the non-negativity constraints on the choice variables.

$$\underset{X,R,N_o,N_f,N_s,N_h}{\arg\mathrm{Max}} \quad f(X, N_f + N_h + N_s) + w_o N_o - w N_h - c_f N_s + \psi(R) - g(N_s, K) + V \tag{1.7}$$

s.t. $\overline{N}_F - R - N_s(1 + c_s) - N_o \geq 0$

$\overline{M} + w_o N_o \geq w N_h + c_f N_s$

$R > 0, X > 0, N_o \geq 0, N_h \geq 0, N_s \geq 0.$

Leisure, R, is assumed strictly positive because $\psi'(0)$ is infinite, implying that some leisure is always reserved as its marginal utility is infinite at $R = 0$. This ensures the time constraint in 1.4 is always binding[1] as the household can increase R if N_f can fall, allowing us to treat family labor on farm, N_f, as a residual of the household's other time uses. Thus, the time constraint in 1.7 is a non-negativity constraint on N_f. This also allows for the substitution of the time constraint into the actual production function in equation 1.2 and for N_f to be determined during optimization by the selection of the other choice variables. [2]

The Lagrangian for this optimization problem becomes

$$\begin{aligned} \ell_{R,N_o,X,N_h,N_s,\beta,\alpha} = f(X, \overline{N}_F - R - N_s c_s - N_o + N_h) \\ + w_o N_o - w N_h - c_f N_s + \psi(R) - g(N_s, K) + V \\ + \beta[\overline{N}_F - R - N_s(1 + c_s) - N_o] \\ + \alpha[\overline{M} + w_o N_o - w N_h - c_f N_s]. \end{aligned} \tag{1.8}$$

[1] $\overline{N}_F - R - N_f - N_s - N_o - c_s N_s = 0$

[2] We owe this trick to Gilligan (2004).

The Kuhn-Tucker first order conditions are as follows.

$$\frac{\partial \ell}{\partial N_s} = f'_{N_s} - c_f - g'_{N_s} - \beta(1+c_s) - \alpha c_f, \qquad N_s \geq 0, \qquad N_s \frac{\partial \ell}{\partial N_s} = 0. \tag{1.9}$$

$$\frac{\partial \ell}{\partial N_h} = f'_{N_h} - w(1+\alpha), \qquad N_h \geq 0, \qquad N_h \frac{\partial \ell}{\partial N_h} = 0. \tag{1.10}$$

$$\frac{\partial \ell}{\partial R} = f'_R + \psi'(R) - \beta, \qquad R > 0, \qquad R \frac{\partial \ell}{\partial R} = 0. \tag{1.11}$$

$$\frac{\partial \ell}{\partial X} = f'_X, \qquad X > 0, \qquad X \frac{\partial \ell}{\partial X} = 0. \tag{1.12}$$

$$\frac{\partial \ell}{\partial N_o} = f'_{N_o} + w_o(1+\alpha) - \beta, \qquad N_o \geq 0, \qquad N_0 \frac{\partial \ell}{\partial N_o} = 0. \tag{1.13}$$

$$\frac{\partial \ell}{\partial \beta} = \overline{N_f} - R - N_s(1+c_s) - N_o, \qquad \beta \geq 0, \qquad \beta \frac{\partial \ell}{\partial \beta} = 0. \tag{1.14}$$

$$\frac{\partial \ell}{\partial \alpha} = \overline{M} + w_o N_o - w N_h + c_f N_s, \qquad \alpha \geq 0, \qquad \alpha \frac{\partial \ell}{\partial \alpha} = 0. \tag{1.15}$$

If a farmer is involved in a labor sharing party ($N_s > 0$), the complementarity conditions of the Khun-Tucker first order conditions in (1.9) imply that $\frac{\partial \ell}{\partial N_s} = 0$. Thus

$$-g'_{N_s} = c_f + \beta(1+c_s) + \alpha c_f - f'_{N_s} \tag{1.16}$$

where g'_{N_s} is the marginal impact of labor sharing on farmers' technical inefficiency. c_f and c_s are both non-negative as they refer to per-head per-day costs of transaction and food provision while organizing labor sharing. β and α are also non-negative since they are Lagrange multipliers, which will be strictly positive if the respective time and liquidity constraints that they refer to are binding. Labor sharing enters the function f only in two ways. The first is through affecting the amount of family labor to be dedicated to own farms as farmers have to reciprocate on their partners' plots. The second is by taking away the farmers' time towards search and transaction to organize labor sharing. Thus, both have negative effects on farmers output ($f'_{N_s} < 0$). Therefore, the right-hand-side of equation 1.16 is greater than zero. This implies that, if a farmer is engaged in a labor sharing party, then labor sharing improves the farmer's efficiency, i.e, $g'_{N_s} = \frac{\partial g}{\partial N_s} < 0$.

Equation 1.16 reveals that a positive impact of labor sharing on efficiency is a necessary but not sufficient condition for farmers to benefit from labor sharing. The positive impact of labor sharing on efficiency has to be greater than the sum of the transaction cost, the cost of providing food to partners, the reduced level of output due to reciprocity, and the extra pressure it creates on farmers' liquidity and time constraints.

1.4 Empirical Model

Agricultural producers are usually engaged in the production of multiple outputs. When faced with agents producing multiple outputs, many studies resort to the use of monetary aggregates of the outputs so as to be able to apply standard single output mechanisms or use a multi-output dual cost function approach. However, as Coelli and Perelman (2000) have noted, monetary aggregation requires output prices to be observable (and reflect revenue maximizing behavior), while the dual cost approach requires an assumption of cost-minimizing behavior. For a small scale agricultural set-up such as we are considering for this study, monetary aggregation is not a good option due to the technical interdependence of the range of crops farmers cultivate, while the cost minimization assumptions are not likely to hold as agricultural outputs are endogenously determined by the farmers.

Other studies employ non-parametric data envelopment analysis or DEA (see Alene and Zeller (2005)). However, DEA is sensitive to data noise (e.g, measurement error) since it estimates a deterministic frontier where all deviations from the frontier are implicitly assumed to be due to inefficiency (Atkinson, Cornwell, and Honerkamp, 2003; O'Donnell and Coelli, 2005).

On the other hand, Coelli and Perelman (2000) estimated a primal distance function using corrected ordinary least squares (COLS) by choosing one of the outputs to be the dependent variable. The authors estimated the distance function by OLS and, as a second step, adjust the OLS estimate of the intercept by adding the largest negative residual to it for output oriented distance function or by adding the largest positive residual for input oriented distance function. Though this adjustment makes the distance function bound the data points rather than passing through the center, it ignores the presence of the endogenous outputs on the right hand side of the equation, causing biased and inconsistent estimates. Atkinson, Cornwell, and Honerkamp (2003) have shown that generalized method of moments (GMM) can be used to address the possibility of endogeneity of either outputs or inputs with the composite error term inherent in distance functions. The GMM approach has an additional advantage as it does not require distributional assumption on the error term. In a cost minimizing dual approach, Atkinson and Dorfman (2005, 2009) have handled endogeneity in distance function estimations through a limited-information Bayesian system estimator.

The empirical model that we follow adopts the GMM approach of Atkinson, Cornwell, and Honerkamp (2003) aiming to accommodate the multiple output nature of production in the farming system under study through distance functions as well as address the endogeneity inherent in distance function estimation by instrumenting the endogenous right-hand-side outputs.

1.4.1 Distance Function

Let X be a vector of inputs $X = (x_1, \cdots, x_L) \in R_+^L$ and let Y be a vector of outputs denoted by $Y = (y_1, \cdots, y_M) \in R_+^M$. The output distance function is defined as

$$D^o(X, Y, t) = inf_\theta\{\theta > 0 : (X, \frac{Y}{\theta}) \in S(X, Y, t)\} \tag{1.17}$$

where $S(X, Y, t)$ is the technology set such that X can produce Y at time t. $D^o(X, Y, t)$ is the inverse of the factor by which the production of all output quantities could be increased while still remaining within the feasible production set for the given input level (O'Donnell and Coelli, 2005). θ, and hence, the distance function, $D^o(X, Y, t)$, takes a value less than or equal to 1, where a value of 1 means that the farmer is operating at the frontier of the technology set. The output distance function is non-decreasing, linearly homogeneous and convex in outputs, and non-increasing and quasi-convex in inputs (O'Donnell and Coelli, 2005).

An output distance function defined over M outputs and L inputs takes the form

$$D_{it}^o = D^o(x_{1it}, \cdots, x_{Lit}, y_{1it}, \cdots, y_{Mit}) \tag{1.18}$$

where $i = 1,\cdots,N$ represents farmers; $t = 1,\cdots,T$ denotes time; $m = 1,\cdots,r,\cdots,M$ are the different crops produced by the farmer; and $l = 1,\cdots,p,\cdots,L$ are the applied inputs. We have chosen a generalized quadratic Box-Cox model to represent $D^o(.)$:

$$\begin{aligned} D^o_{it} = exp(\gamma^*_o + \sum_m^M \gamma^*_m y^\lambda_{mit} + .5\sum_m^M\sum_r^M \gamma^*_{mr} y^\lambda_{mit} y^\lambda_{rit} + \sum_l^L \gamma^*_l x^\lambda_{lit} \\ +.5\sum_p^L\sum_l^L \gamma^*_{pl} x^\lambda_{pit} x^\lambda_{lit} + \sum_m^M\sum_l^L \gamma^*_{ml} y^\lambda_{mit} x^\lambda_{lit}) exp(v_{it}) \end{aligned} \tag{1.19}$$

where y^λ_{mit} and x^λ_{nit} are the Box-Cox transformations of outputs and inputs, defined by Box and Cox (1964) as $y^\lambda_{mit} = \frac{y^\lambda_{mit}-1}{\lambda}$ and $x^\lambda_{nit} = \frac{x^\lambda_{nit}-1}{\lambda}$, λ is the transformation parameter to be estimated, and v_{it} is the usual two sided error term that captures the noise in production with zero mean and variance σ^2_v. The generalized quadratic Box-Cox distance function has a form similar to a translog distance function but with a Box-Cox, instead of logarithmic, transformation. If $\lambda = 0$, the Box-Cox transformation reduces to a log transformation, and hence the generalized Box-Cox distance function incorporates the translog distance function as a special case. The Box-Cox transformation is continuous around zero and hence allows us to include output and input variables with zero values for which log transformation is not possible. This is an important feature of the model because it is likely that farmers only produce some of the crops or do not use some inputs such as fertilizer.

The actual distance D^o_{it} is equal to θ. If a farm is on the frontier, then $D^o_{it} = \theta = 1$. Otherwise, $D^o_{it} = exp(-u_{it})$, where u_{it} is a non-negative random variable associated with technical inefficiency. Thus, substituting $exp(-u_{it})$ for D^o_{it} in equation 1.19, taking the natural logarithm of both sides, and re-arranging the equation gives

$$\begin{aligned} 0 = \gamma^*_o + \sum_m^M \gamma^*_m y^\lambda_{mit} + .5\sum_m^M\sum_r^M \gamma^*_{mr} y^\lambda_{mit} y^\lambda_{rit} + \sum_l^L \gamma^*_l x^\lambda_{lit} \\ +.5\sum_p^L\sum_l^L \gamma^*_{pl} x^\lambda_{pit} x^\lambda_{lit} + \sum_m^M\sum_l^L \gamma^*_{ml} y^\lambda_{mit} x^\lambda_{lit} + v_{it} + u_{it} \end{aligned} \tag{1.20}$$

Then, we take one of the outputs, y_{1it}, to the left hand side in order to obtain an observable variable on the left hand side (Brummer, Glauben, and Lu, 2006; Coelli and Perelman, 2000), which results in the following empirical model for farm i in period t :

$$\begin{aligned} y_{1it}^{\lambda} = -[\gamma_o + \sum_{m}^{M-1} \gamma_m y_{mit}^{\lambda} + .5 \sum_{m}^{M-1} \sum_{r}^{M-1} \gamma_{mr} y_{mit}^{\lambda} y_{rit}^{\lambda} + \sum_{l}^{L} \gamma_l x_{lit}^{\lambda} \\ +.5 \sum_{p}^{L} \sum_{l}^{L} \gamma_{pl} x_{pit}^{\lambda} x_{lit}^{\lambda} + \sum_{m}^{M-1} \sum_{l}^{L} \gamma_{ml} y_{mit}^{\lambda} x_{lit}^{\lambda} + v_{it}] - u_{it} \end{aligned} \tag{1.21}$$

The coefficients in equation 1.21 are different from 1.20 to note that they are normalized by γ_1^*, the coefficient of the output transferred to the left hand side. The following homogeneity and symmetry restrictions are imposed on the above distance function (O'Donnell and Coelli, 2005).

Symmetry:

$$\begin{aligned} \gamma_{mr} = \gamma_{rm} \ \forall \ m, r; \\ \gamma_{lp} = \gamma_{pl} \ \forall \ l, p; \ \ and \\ \gamma_{ml} = \gamma_{lm} \ \forall \ l, m \end{aligned} \tag{1.22}$$

Linear homogeneity in outputs:

$$\begin{aligned} \sum_{m} \gamma_m = 1; \\ \sum_{m} \gamma_{mr} = 0 \ \forall \ r; \ \ and \\ \sum_{m} \gamma_{ml} = 0 \ \forall \ l. \end{aligned} \tag{1.23}$$

Factors that affect the inefficiency of farmer i are incorporated in the model by defining u_{it} in terms of household specific variables

$$u_{it} = \beta_o + \sum_{j} \beta_j w_{ijt} \tag{1.24}$$

where w_{ijt} refers to *j=1,...,J* different variables for farmer i at time t that are believed to affect the productivity and efficiency of a farmer. The w_{ijt} include informal labor sharing arrangements such as dummy variables on whether the farmer has called for a work party on at least one of his plots, as well as whether he is involved in other informal social networks such as funeral associations (*idir*) and off-farm activities. In addition, w_{ijt} includes other major sources of information and education such as whether the farmer has access to government extension services, the highest level of education among members of the household, the average slope and soil fertility of the farmer's plots, as well as the household head's age, gender, education, marital status, access to irrigation, and soil conservation practices.

Following Atkinson, Cornwell, and Honerkamp (2003) and Atkinson and Dorfman (2005), the non-negativity of the u_{it} is imposed after estimation by adding and subtracting from the fitted model $\hat{u}_t = min_i(\hat{u}_{it})$, which defines the frontier intercept. Letting $\hat{D}_i(Y, X, t)$ denote the part of the fitted distance function other than the composite error term $v_{it} - u_{it}$, adding and subtracting $\hat{u}_t$ yields

$$y^{\lambda}_{1it} = \hat{D}_i(Y, X, t) + \hat{v}_{it} - \hat{u}_{it} + \hat{u}_t - \hat{u}_t = \hat{D}^*_i(Y, X, t) + \hat{v}_{it} - \hat{u}^*_{it} \tag{1.25}$$

where $\hat{D}^*_i(Y, X, t) = \hat{D}_i(Y, X, t) - \hat{u}_t$ is the estimated frontier distance function in period t and $\hat{u}^*_{it} = \hat{u}_{it} - \hat{u}_t \geq 0$.

Given these estimates, Atkinson and Dorfman (2005) also showed that technical efficiency (TE_{it}), efficiency change (EC_{it}), technical change (TC_{it}), and productivity change (PC_{it}) can be computed as follows.

Farmer i's level of technical efficiency in period t is TE_{it}:

$$TE_{it} = exp(-\hat{u}^*_{it}) \tag{1.26}$$

where the normalization of $\hat{u}^*_{it}$ guarantees that $0 < TE_{it} \leq 1$.

Efficiency change is the change in the technical efficiency over time, so

$$EC_{it} = \triangle TE_{it} = TE_{it} - TE_{i,t-1}. \tag{1.27}$$

Technical change is measured as the difference between the estimated frontier distance function in periods t and *t - 1* holding output and input quantities constant:

$$TC_{it} = \hat{D}^*_i(Y, X, t) - \hat{D}^*_i(Y, X, t - 1). \tag{1.28}$$

Finally, productivity change is defined as the sum of technical change and efficiency change:

$$PC_{it} = TC_{it} + EC_{it}. \tag{1.29}$$

1.4.2 Instruments

In the final estimated model, teff is the output used as the dependent variable while barley, wheat, maize, and sorghum are the endogenous outputs on the right-hand-side of the equation. Weather related events such as the amount and distribution of rainfall are the initial candidates to be used as instruments of the endogenous outputs because of their strong relationships with the amount of output produced of these crops and because they are exogenous to the farmer. However, there is a need to be cautious in the use of these instruments because the excluded weather-related instruments may simultaneously affect the dependent variable, teff. However, the Ethiopian crop calendar (Figure 1.1) indicates legitimate weather-related variables as instruments of the endogenous output variables. Teff is sown between the end of June and end of July (FAO, 2012) and for better productivity it is advisable to sow teff during the last two weeks of July (Seifu, 2004). However, the months in which maize and sorghum are sown correspond to the previous small showers (*belg*) season which span between February and May. Seifu (2004) noted that sowing for maize should take place in the first two weeks of May or as early as possible after the onset of the main rainy season (end of May or early June). Bewket (2009) stated that maize appears to require a more even distribution of rainfall throughout the *belg* season and the main rainy season. Sorghum production is particularly related to the *belg* rains because sorghum is sown in early May or even late April, which makes the *belg* rainfall critically important (Bewket, 2009).

In the ERHS data set, farmers were asked if *belg* crops were adversely affected by weather. We used this variable and its interactions with other exogenous variables as instruments for maize and sorghum production. That is, *belg* rains affect maize and sorghum production because the sowing of these two crops and part of their growing season correspond with the

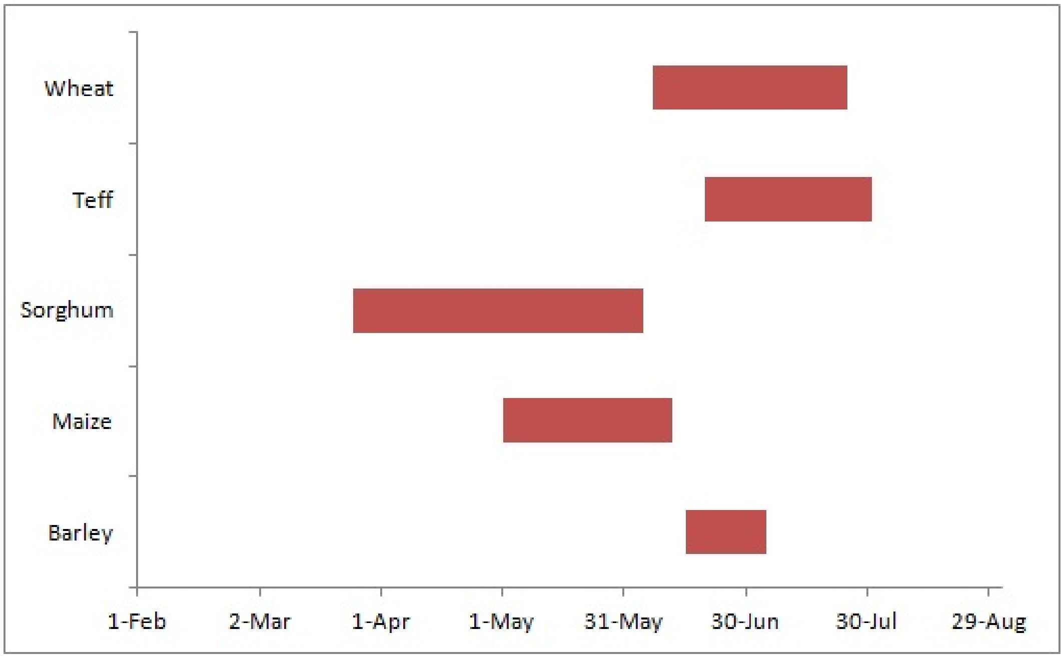


Figure 1.1: Sowing Periods for the Main Rainy Season for the Sub-moist Agro-ecological Zone in Ethiopia.
Source: Extracted from FAO's (2012) Crop Calendar.

belg season but *belg* rains do not simultaneously affect teff production because sowing for teff begins at the end of July, making the instrument relevant as well as legitimate.

The sowing time for wheat is the end of June and the early days of July while sowing for barley should take place soon after the main rainy season begins in June (Seifu, 2004; FAO, 2012). Thus, the performance of the rain at the beginning of the main rainy season (late May and early June) is important both for wheat and barley (as well as sorghum and maize which are in their growing stage at this time) but is not directly related with teff, which is sown after two weeks into July (i.e., the middle of the main rainy season). The ERHS data set is helpful in this regard because farmers were asked if the first rains of the main rainy season came on time and if there was enough rain on the farmer's plot at the beginning of the rainy season. These two variables, along with their interactions with other exogenous variables, are used to instrument for wheat and barley because they are related to the endogenous variables but not directly related to the left-hand-side variable, making them pass the legitimacy and relevance criteria for good instruments.

As shown below in the results section, these instruments passed the Sargan-Hansen or J-test of overidentification. Though formal tests of weak identification for a non-linear-in-parameters GMM are not yet available in the econometric literature, we have shown that the instruments have passed the pathologies that GMM estimators exhibit in the presence of weak identification as suggested by Stock, Wright, and Yogo (2002).

1.5 Data

We use the Ethiopian Rural Household Survey (ERHS) data, which is a longitudinal household data set covering households in 15 peasant associations in rural Ethiopia. Data collection started in 1989 while the decision to make the data panel was made in 1994. The survey was expanded and redesigned, and samples re-randomized to encompass 15 peasant associations across the country, yielding a sample of 1,477 households. A new round was conducted in late 1994, with further rounds in 1995, 1997, 1999, 2004, and 2009. These surveys have been supervised by the Economics Department at Addis Ababa University, the Center for the Study of African Economies (CSAE) at the University of Oxford and the International Food Policy Research Institute (IFPRI).

We focus on the five major cereals in Ethiopia: teff (both white and black mixed), maize, wheat, barley, and sorghum. The choice of these crops is due to their critical importance in food security efforts in Ethiopia and their high share in total land area harvested and amount of production. According to Taffesse, Dorosh, and Gemessa (2012), teff, wheat, maize, sorghum, and barley account for 3/4th of total area cultivated, 14% of GDP, and 64% of calories consumed in Ethiopia in 2005/06.

Ethiopia has two rainy seasons: the main (*Meher*) rains between June and September and the second small showers (*Belg* rains) between February and May (Seifu, 2004). Our study focuses on the main rainy season. This helps to reduce the noise in the data as the agricultural production system in terms of crops in the field, intensity of the rain, and utilization of inputs are markedly different in the two seasons. In addition, the five cereals that are the focus of this study are mainly produced during the main rainy season. According to data from the Central Statistical Agency of Ethiopia, between 1995 and 2008, close to 99% of teff production, 98% of wheat production, 90% of barley production, and 89% of maize production was done during the main rainy season (CSA, 2009). Further, some variables are only available for the main rainy season in the ERHS (2011) data set. For instance, the data do not contain family and hired labor for the *belg* season, the fertilizer data for this season do not report the crop on which it was applied, and variables related to major events during the *belg* season are highly aggregated while they are detailed for the main season.

Labor sharing is a prevalent practice in rural Ethiopia. In our sample, 56% of households in 1999 and 43% in 2004 and 2009 called for labor sharing work parties on their farming plots. Despite being called by different names in different parts of the country, labor sharing arrangements usually follow two types of structures: *debo* and *wonfel*, as they are called in the Amhara region. *Wonfel* refers to a labor sharing group that works in rotation for each group member and reciprocity is within the same season while *debo* refers to a labor sharing group in which reciprocity to members is upon demand either within the same season or in the future (Debebe, 2010; Krishnan and Sciubba, 2009). In this study, we refer to a household head being engaged in labor sharing if he or she participates in either of the two labor sharing arrangements. The 2004 survey round of the ERHS data set shows an 86% reciprocity in labor sharing parties. Of the total farmers who participated in labor sharing in 2004, 78% have either already reciprocated or will reciprocate in the same season and 8% will reciprocate in the future, while 14% said they do not have to reciprocate - perhaps indicating other social aspects of participation in labor sharing.

Reasons for calling such work parties in the 2004 survey round include quick completion of task (47.8%), group work being the best way of completing the tasks (18.3%), only way to get large amount of labor (15.3%), and because it was customary for the task (10.2%).

Based on farmers' responses, labor market failure in terms of unavailability of paid labor accounts for only 2.6% of the reasons for farmers to engage in labor sharing. However, 5.4% of the farmers get into labor sharing partly because they can not afford paid labor. See Table 1.3 for details.

Table 1.3: Why Labor Sharing?

Reasons for calling a work party	Frequency	Percent	Cumulative
Quick completion of task	961	47.8	47.8
Group is the best way of completing task	368	18.3	66.1
Only way to get large amount of labor	308	15.3	81.4
Customary for this task	206	10.2	91.6
Cannot afford paid labor	109	5.4	97.0
No paid labor available	53	2.6	99.6
Others	6	0.3	100.0

Results are based on the 2004 survey only.
The question was asked for each activity labor sharing was called for.
Source: Authors' computation from ERHS

According to subjective assessments of the labor sharing partners by the person who called the labor sharing party, 57% of the partners they called for the work party are as good a farmer as they are while 27% are better farmers and 16% are worse. The fact that about 84% of the farmers they called for a work party are either as good a farmer or better than they are suggests an opportunity for potential productivity gains from learning or synergy by working with others.

As shown in Table 1.4, there is a fair distribution of farmers among the different types based on their labor sharing experiences. Access to irrigation among the sampled farmers increased from about 6 percent in 1999 to about 29 percent in 2004. The share of farmers with access to the public extension system has almost doubled in the five years between 1999 and 2004. More than three quarters of the household heads are male and less than 10 percent completed primary school. More than three quarters of the household heads are members of *idir* (funeral associations), and 23 to 37 percent of the farmers are engaged in off-farm activities in 1999 and 2004. About three quarters of the household heads are married.

All the output variables (teff, wheat, barley, maize, and sorghum) as well as the two most used chemical fertilizers (urea and DAP) are measured in kilograms. Table 1.4 shows that average production is the highest for teff and the lowest for sorghum but the averages would obviously be higher if we consider only the farmers that produce the specific crop. Average DAP use is approximately three times more than that of urea. The highest level of education in the household is around 4 years on average and it is expected to capture intra-household schooling externality. The average age of a household head is about 50 years. Soil fertility is measured in a 1 to 3 scale where 1 refers to fertile, 2 medium fertile, and 3 infertile soil, and it is averaged among the different plots of the farmer. Labor is measured in labor days and it includes family, hired, and shared labor. Thus, the direct impact of labor sharing on production in terms of increased labor supply has been accounted for in the deterministic part of the production function. While computing labor days, we follow Mulugeta (2009) to account for the physical hardship in crop production by giving adult men a weight of 1, adult women a weight of 0.8, and child labor a weight of 0.35.

1.6 Results

The model is estimated using heteroscedasticity and autocorrelation consistent iterated GMM and it fits the data well with an overall R^2 of 0.691. Using the Sargen-Hansen or J-test of overidentification (Baum, Schaffer, and Stillman, 2003; Wooldridge, 2002), we fail to reject the validity of the over-identifying restrictions. The J-test resulted in a GMM criterion function value of 40.60 which has a χ^2 distribution with 43 degrees of freedom, resulting in a p-value of 0.576. A rejection of this test would have cast a doubt on the validity of our instruments.

Other than the validity of instruments, the other pillar in GMM estimation is that the instruments are sufficiently related to the endogenous variables. When instruments are weak, the orthogonality conditions hold even at non-optimal values of the estimated parameters when in fact they should hold or get close to zero only at the optimal values. That is why

Stock, Wright, and Yogo (2002) suggested that in non-linear GMM, the problem is better termed as the weak identification problem than the weak instruments problem. As discussed in the empirical section, Ethiopia's crop calendar and the literature on crop responses to rainfall variation show that the performance of the *belg* rainfall and rainfall at the beginning of the main rainy season are related with the performance of the endogenous crops (maize, sorghum, wheat, and barley) which are sown before or immediately after the main rainy season begins while not being directly related to the dependent variable, teff, which is sown late in the main rainy season. In addition, the instruments have passed the pathologies that GMM estimators exhibit in the presence of weak identification as suggested by Stock, Wright, and Yogo (2002), since a formal test of weak identification for a non-linear-in-parameters GMM is not yet available in the econometric literature. For instance, two-step GMM estimators and iterated GMM point estimators can be quite different and can yield quite different confidence sets in the presence of weak identification. As shown in Table 1.7 and Table 1.8, the two step GMM and the iterated GMM estimators are almost identical in our case, which differ only after two digits for almost all of the coefficients.

We have presented the variables that explain farmers' inefficiency in Table 1.5 even though they were estimated simultaneously in one step with the full set of the distance function variables presented in Table 1.7. As shown in equation 1.24, these variables are explaining farmers' inefficiency and hence negative signs show that technical efficiency increases as the explanatory variable increases and positive signs are associated with efficiency reducing effects. We have included dummy variables for Type Ia, Type Ib, Type II, and Type IV farmers in the estimation and used Type III as a base group against which the efficiency of the other types of farmers are to be compared.

The results show that the efficiency of Type III farmers is not different from the efficiency of Type Ia and Type Ib farmers. This implies the absence of a learning effect from labor sharing. As discussed earlier, Type Ib is a better control group, and yet this group's efficiency scores are not any different than those of Type III farmers.

Type II farmers, on the other hand, are more technically efficient than Type III farmers, indicating the presence of a synergy effect from labor sharing. That is, labor sharing improves the productivity and efficiency of farmers but the source of this productivity gain is synergy from working together. As made clear below, these gains from synergy are not trivial, but amount to an approximate 20 percent gain in output in 2004.

In addition, the efficiency of Type II farmers is not different from that of Type IV farmers. This is consistent with the finding for only synergy but not learning effects. Both Type II and Type IV farmers are using labor sharing in the current year and hence both are set to benefit from the synergy effect, which is a contemporaneous effect. Since labor sharing does not have cumulative learning effects, the fact that Type II farmers have used labor sharing in the past does not give them a learning edge over Type IV farmers, who are using labor sharing for the first time in the current harvest season. However, the transaction cost of organizing labor sharing is likely to be higher for Type IV farmers as these farmers are using labor sharing for the first time and may have to exert extra effort or care to get labor sharing partners. This explains why the efficiency of Type IV farmers, unlike that of Type II farmers, is not different from that of Type III farmers, though it has the expected negative sign due to the presence of synergy effect.

The negative signs on Type Ia and Type Ib farmers are also consistent with our finding of only a synergy effect. If there is only synergy but not learning, then Type Ia and Type Ib farmers are expected to be more efficient than Type III farmers though all the three types of farmers did not use labor sharing in that specific season. This is because, Type III farmers, due to their involvement in labor sharing in previous seasons, are likely to spend some of their time in the current season on others' plots to reciprocate the labor days they received previously or in anticipation that they will be reciprocated in the future. In the ERHS data set for example, eight percent of the farmers who used labor sharing in 2004 responded that they are expected to reciprocate labor sharing in a future season since they did not do it in the season in which they received labor days. Type Ia and Type Ib farmers, on the other hand, have no obligation to reciprocate as they have never been involved in any labor sharing before.

A possible explanation for the lack of learning effects is the limited possibility for labor sharing partners to transfer new skills either because of a lack of heterogeneity among labor sharing partners or because they are related in a number of other ways that give them an opportunity to learn from each other in those venues, hence decreasing the importance of labor sharing as a venue for learning. The 2004 round of the ERHS survey shows that about 91% of the people invited to the labor-sharing were invited before for the same purpose by the same household and the farmers who called for the work party have worked before for 86% of the people they invited as part of a working party. In addition, 55% of labor sharing partners are relatives, 68% are neighbors, 69% belong to the same funeral association, 27% have plots next to each other, 27% are partners in oxen sharing or similar arrangements, and another 27% are members of the same religious association.

Though we did not find cumulative learning effects that affect productivity at times when a labor party is not present, it is possible for the synergy effect to contain contemporaneous learning such as information exchanges that do not transcend current harvest period to affect future period productivity.

Farmers with access to the public extension system are found to be more efficient than those that do not have access to extension. This gives support to the Government of Ethiopia's effort in increasing the number of public extension staff almost three-fold in the five years preceding 2008 and to the claim that agricultural extension services are what tie improved seed, chemical fertilizers, and credit together for the Ethiopian smallholder (Spielman, Kelemework, and Alemu, 2011).

We did not find evidence for productivity improvement as a result of other village level social interactions such as *idir*. However, we find that farmers exposed to external information through off-farm activities are more efficient than those that do not have such exposures. The most important kind of off-farm activities among the sampled households is food-for-work, which accounts for 39% and 54.4% of all off-farm activities in 1999 and 2004. The food-for-work program in Ethiopia is a welfare safety net for food insecure areas and instead of distributing food aid to those in need, the program involves able-bodied people performing public work in exchange for a food wage. The food-for-work program focuses on rehabilitation of forest, grazing, and agricultural lands as well as construction of wells, ponds, dams, terraces, and roads. The efficiency-enhancing effects of off-farm activities suggests that farmers involved in the food-for-work program have taken home productivity-improving methods from the public works to their individual plots.

Farmers with access to irrigation water are found to be more efficient. Though only marginally significant, the average fertility of the farmers' plot plays a role in determining the technical efficiency of farmers. The soil fertility variable was measured in such a way that higher values refer to less fertility and hence the positive coefficient in Table 1.5 shows that farmers with plots of inferior quality are less efficient than farmers whose plots are more fertile. Similarly, farmers with steeper plots are found to be less efficient.

1.6.1 Technical Efficiency

The average technical efficiency of the 815 farmers included in the final estimation was found to be 56.1% in 1999 and 52.4% in 2004 (Table 1.6). These figures imply that at the current levels of inputs, farmers are producing, on average, only about half of the output of the most efficient farmer in the sample. Thus, there is room to increase farmers' production by about 100 percent through better management. The evidence in Table 1.5 suggests the government needs to intensify efficiency-enhancing investments such as extension, irrigation, and off-farm activities, as well as facilitating venues for farmers to work together. In 2004, farmers using labor sharing in the current year with previous labor sharing experience (Type II farmers) are found to be 9.7 percentage points more efficient than those who do not use labor sharing in the current year but have used it in the past (Type III farmers). Thus, the synergy from labor sharing is not just statistically significant, but economically significant as well, able to boost output by approximately 20 percent.

Average technical efficiency in 2004 has decreased from its 1999 level consistently across all types of farmers except Type II farmers.

As described in the specification of the empirical model, technical change is measured as the difference between the estimated frontier distance function in 1999 and 2004 holding output and input quantities constant, and it is found to be 13.5% between 1999 and 2004 or about 2.6 % per year. The productivity change, which is the sum of the efficiency change and the technical change is also presented in Table 1.6. We found evidence for productivity improvement across all types of farmers. However, farmers who were using labor sharing in 1999 but did not use it in 2004 (Type III farmers) have the smallest improvement in productivity, possibly because they no longer enjoy the synergy effect. Farmers who have continued using labor sharing (Type II farmers) have the highest productivity improvement during the two periods.

The positive values for productivity change reflect the rapid outward shift of the frontier. Farmers display negative efficiency change because while productivity is rising on average, average farmers cannot keep up with the best farmers who are pushing the production frontier outward at 2.6% per year. Thus, these results suggest an increasing dispersion to the distribution of farmer efficiency in Ethiopia. So falling average technical efficiency is not as dismal as it first seems since it is explained by the strong performance of the best farmers.

1.7 Conclusion

Informal labor sharing arrangements, other social interactions, and educational opportunities provide possible avenues for gains in farmers' productivity. In a sample of Ethiopian subsistence farmers, we estimate a distance function of grain production to test for agricultural productivity gains from labor sharing, social club memberships, off-farm work, and exposure to agricultural extension programs. We control for the endogeneity among the multiple outputs and identify the learning and synergy effects from labor sharing by segmenting the farmers into past, current, and future participants in labor sharing parties. We find large gains (approximately 20 percent) from labor sharing, with the gains due to synergy effects that boost labor productivity. Extension education programs and performing off-farm work are found to lead to learning that increases the farmers' productivity. However, labor sharing does not lead to learning as the productivity gains observed in years with labor sharing disappear in following years if the farmers do not continue to employ labor sharing.

It appears from the empirical results that casual interaction and observation alone are not enough to produce learning that leads to productivity gains. Rather, training and educational activities such as extension programs and off-farm work are required to produce learning and associated productivity gains. This has implications for policy design in developing countries in which increases in agricultural productivity are crucial to the successful development of the country. Without directly testing such programs, these results suggest that policies designed to improve productivity through the influence or leadership of "model" farmers are not likely to succeed. The lack of learning from labor sharing suggests that, at least in our Ethiopian application, farmers already know most or all of what they might learn simply by observing other farmers. The results suggest that countries can increase the chances of securing gains in productivity by the inclusion of training or educational activities such as farmers get from attending extension programs or being trained to perform off-farm work.

In fact, the negative efficiency change we estimate shows that for our application the best farmers are increasing the gap between themselves and other farmers who are, on average, falling farther behind the production frontier. Farmers are improving on average but not as fast as the best farmers are pushing the frontier outward. Clearly these top farmers could be learned from, but having other farmers present as part of a labor sharing party does not lead to any productivity gains that we can verify. Either the observation and interaction that takes place during labor sharing is insufficient to produce learning or the farmers that participate in labor sharing are not the ones from whom the others should be learning.

Future work might investigate exactly what types of educational or training opportunities can and do boost agricultural productivity. These results do not encourage policies based on passive learning, and provide some evidence in favor of extension programs and off-farm work, but more research is needed to pinpoint exactly which policies should be encouraged.

Table 1.4: Descriptive Statistics of Variables Used in Estimation

	1999		2004	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Type II (1/0)	0.43	0.50	0.43	0.49
Type III (1/0)	0.16	0.36	0.38	0.48
Type IV (1/0)	0.21	0.41	0.05	0.22
Type Ia (1/0)	0.12	0.32	0.12	0.32
Type Ib (1/0)	0.08	0.27	0.03	0.17
Irrigation (1/0)	0.06	0.23	0.29	0.45
Conservation (1/0)	0.35	0.48	0.56	0.50
Male head (1/0)	0.79	0.40	0.76	0.43
Head completed primary school (1/0)	0.03	0.18	0.09	0.29
Off-farm income (1/0)	0.23	0.42	0.37	0.48
Idir membership (1/0)	0.76	0.43	0.80	0.40
Married (1/0)	0.76	0.43	0.71	0.45
Single (1/0)	0.03	0.17	0.02	0.13
Divorced (1/0)	0.04	0.21	0.05	0.22
Widowed (1/0)	0.12	0.33	0.18	0.38
Separated (1/0)	0.01	0.11	0.01	0.11
>1 Spouse (1/0)	0.04	0.19	0.03	0.17
Flat plots (1/0)	0.74	0.44	0.74	0.44
Steep plots (1/0)	0.22	0.42	0.23	0.42
Steeper plots (1/0)	0.04	0.20	0.03	0.17
Extension (1/0)	0.10	0.30	0.18	0.38
Teff (Kg)	226.93	487.35	219.27	484.01
Wheat (Kg)	162.90	328.14	163.38	328.55
Barley (Kg)	190.47	396.54	188.93	392.54
Maize (Kg)	131.92	320.27	178.84	439.90
Sorghum (Kg)	70.38	200.87	43.61	257.68
Land (Ha)	0.92	0.82	1.23	2.51
Oxen (Number)	1.29	1.05	1.06	1.00
Inputs (Ethiopian Birr)	63.46	114.31	86.12	225.26
Urea (Kg)	15.22	30.08	12.81	38.08
DAP (Kg)	43.35	56.85	32.63	64.89
Labor (labor days)	202.18	201.61	146.16	157.70
Age of household head (years)	49.11	15.05	50.94	14.89
Highest years of schooling (all members)	3.78	3.26	3.98	3.44
Average Soil Fertility (1 to 3 scale)	1.68	0.67	1.69	0.69

Number of observations=815;
Units of measurement are given in parenthesis; Kg≡Kilograms; Ha≡Hectares;
Soil fertility decreases from 1 to 3; Inputs ≡ Purchased inputs other than fertilizer;
Source: Authors' Computation from ERHS

Table 1.5: Inefficiency Effects

Parameter	Estimate	Std. Error	t-stat
Age of household head	-0.014	0.120	-0.115
Male head	-0.114	0.093	-1.223
Type II	-0.155	0.079	-1.953
Type IV	-0.073	0.094	-0.777
Type Ia	-0.038	0.113	-0.341
Type Ib	-0.061	0.121	-0.509
Poor quality soil	0.072	0.047	1.529
Irrigation	-0.166	0.100	-1.662
Conservation	0.017	0.077	0.222
Extension	-0.254	0.101	-2.509
Head completed primary school	-0.002	0.165	-0.010
Household members' highest education	-0.045	0.047	-0.963
Steep plots	0.031	0.070	0.439
Steeper plots	0.228	0.123	1.857
Off-farm income	-0.141	0.057	-2.464
Idir membership	0.006	0.108	0.051
Single	-0.101	0.158	-0.642
Divorced	-0.085	0.147	-0.577
Widowed	-0.071	0.084	-0.843
Separated	0.057	0.180	0.314
> 1 Spouse	-0.113	0.226	-0.498

Table 1.6: Mean Technical Efficiency and Average Annual Efficiency, Technical, and Productivity Changes

	TE (%)		Average Annual Changes		
	1999	2004	EC (%)	TC (%)	PC (%)
Full Sample	56.1	52.4	-0.75	2.56	1.88
Type II	57.8	58.3	0.09	2.56	2.65
Type III	56.0	48.6	-1.52	2.56	1.19
Type IV	56.4	49.1	-1.50	2.56	1.21
Type Ia	50.9	44.9	-1.23	2.56	1.45
Type Ib	52.2	50.2	-0.40	2.56	2.20

TE ≡ technical efficiency, EC ≡ efficiency change,
TC ≡ technical change, PC ≡ productivity change;
The types refer to farmers' labor sharing status in 2004

Table 1.7: Full Set of Coefficients for Production and Inefficiency Effects (Iterated GMM)

Dep. Var. = teff; Overid. test = 40.60, p-value = 0.576, degrees of freedom= 43; R^2 = 0.691

	est.	s.e.		est.	s.e.		est.	s.e.		est.	s.e.
λ	0.58	0.07	c	2.59	0.56	pa1	-0.46	0.35	Age	-0.01	0.12
b_lab	0.19	0.08	land	-0.77	0.19	pa2	-0.31	0.39	Male	-0.11	0.09
m_lab	0.01	0.05	oxen	-0.08	0.09	pa3	-0.40	0.62	Type II	-0.15	0.08
s_lab	-0.07	0.05	input	0.05	0.07	pa4	-3.34	0.61	Type IV	-0.07	0.09
b_d	-0.03	0.06	urea	0.02	0.08	pa5	-1.15	0.52	Type Ia	-0.04	0.11
m_d	0.10	0.08	dap	-0.04	0.11	pa6	-2.71	0.53	Type Ib	-0.06	0.12
s_d	-0.13	0.08	labor	-0.31	0.14	pa7	0.44	0.59	Soil	0.07	0.05
b_u	0.02	0.05	l_o	-0.11	0.11	pa8	-0.84	0.56	Irrigation	-0.17	0.10
m__u	0.00	0.04	l_i	-0.04	0.11	pa9	-1.64	0.64	Conserv.	0.02	0.08
s_u	0.04	0.07	l_u	-0.15	0.11	pa10	-0.80	0.46	Extension	-0.25	0.10
b_i	-0.06	0.04	l_d	-0.06	0.11	pa11	-0.69	0.45	Education	-0.002	0.17
m_i	-0.05	0.03	l_lab	-0.06	0.12	pa12	0.19	0.52	Mem Educ	-0.04	0.05
s_i	0.11	0.05	l_sq	0.22	0.06	pa13	-0.15	0.23	Steep	0.03	0.07
b_o	0.09	0.09	o_i	0.02	0.07	pa14	0.04	0.31	Steeper	0.23	0.12
m_o	0.04	0.05	o_u	0.10	0.10	pa15	0.10	0.26	Off-farm	-0.14	0.06
s_o	0.07	0.07	o_d	0.02	0.11	t_d	-0.10	0.09	*Idir*	0.01	0.11
b_l	-0.03	0.12	o_lab	-0.08	0.14	w_sq	0.02	0.09	Single	-0.10	0.16
m_l	-0.12	0.08	o_sq	-0.05	0.13	b_sq	-0.01	0.06	Divorced	-0.08	0.15
s_l	0.14	0.08	i_u	-0.05	0.05	m_sq	-0.11	0.07	Widowed	-0.07	0.08
w_s	-0.06	0.09	i_d	0.18	0.07	s_sq	0.02	0.02	Separated	0.06	0.18
b_s	0.03	0.06	i_lab	-0.05	0.09	w_l	0.02	0.11	> 1 Spouse	-0.11	0.23
m_s	0.01	0.05	i_sq	-0.03	0.03	w_o	-0.20	0.09			
b_m	0.02	0.06	u_d	0.08	0.05	w_i	-0.01	0.04			
w_m	0.08	0.04	u_lab	-0.09	0.08	w_u	-0.06	0.05			
w_b	-0.04	0.06	u_sq	-0.02	0.06	w_d	0.06	0.08			
b	0.39	0.17	d_lab	0.01	0.10	w_lab	-0.13	0.08			
m	0.37	0.16	d_sq	-0.16	0.14	lab_sq	0.00	0.12			
s	-0.06	0.14	w	0.31	0.18						

s ≡ sorghum; m ≡ maize; b ≡ barley; w ≡ wheat; o ≡ oxen; i ≡ purchased inputs;
u ≡ urea; d ≡ dap; lab ≡ labor; l≡ land; _ ≡ interacting with; sq ≡ squared; pa ≡ village
λ ≡ Box-Cox transformation parameter; c ≡ constant; Conserv. ≡ conservation;
Mem Educ ≡ highest years of schooling in the household; steep ≡ average slope of the plots;
soil ≡ average soil fertility (lower values more fertile).

Table 1.8: Full Set of Coefficients for Production and Inefficiency Effects (Two-step GMM)

Dep. Var. = teff; Overid. test = 44.52, p-value = 0.407, degrees of freedom= 43; R^2 = 0.706

	est.	s.e.		est.	s.e.		est.	s.e.		est.	s.e.
λ	0.56	0.07	c	2.57	0.60	pa1	-0.40	0.36	Age	-0.04	0.12
b_lab	0.23	0.08	land	-0.70	0.19	pa2	-0.27	0.40	Male	-0.14	0.10
m_lab	0.02	0.06	oxen	-0.08	0.10	pa3	-0.41	0.65	Type II	-0.17	0.08
s_lab	-0.09	0.05	input	0.04	0.08	pa4	-3.06	0.63	Type IV	-0.08	0.10
b_d	-0.03	0.06	urea	0.03	0.08	pa5	-1.05	0.53	Type Ia	-0.04	0.11
m_d	0.07	0.08	dap	-0.10	0.11	pa6	-2.48	0.55	Type Ib	-0.09	0.12
s_d	-0.14	0.08	labor	-0.32	0.15	pa7	0.49	0.61	Soil	0.08	0.05
b_u	0.01	0.05	l_o	-0.08	0.10	pa8	-0.81	0.58	Irrigation	-0.23	0.10
m__u	0.03	0.04	l_i	-0.07	0.11	pa9	-1.51	0.66	Conserv.	-0.004	0.08
s_u	0.03	0.07	l_u	-0.10	0.11	pa10	-0.74	0.48	Extension	-0.26	0.10
b_i	-0.07	0.04	l_d	-0.01	0.10	pa11	-0.62	0.46	Education	-0.03	0.17
m_i	-0.05	0.03	l_lab	0.00	0.12	pa12	0.38	0.53	Mem Educ	-0.04	0.05
s_i	0.10	0.05	l_sq	0.15	0.05	pa13	-0.03	0.24	Steep	0.03	0.07
b_o	0.07	0.09	o_i	0.06	0.07	pa14	0.19	0.31	Steeper	0.23	0.13
m_o	0.02	0.05	o_u	0.10	0.11	pa15	0.25	0.27	Off-farm	-0.13	0.06
s_o	0.08	0.07	o_d	0.00	0.11	t_d	-0.12	0.09	*Idir*	-0.01	0.11
b_l	-0.04	0.12	o_lab	-0.16	0.14	w_sq	-0.01	0.09	Single	-0.15	0.16
m_l	-0.03	0.07	o_sq	-0.06	0.13	b_sq	-0.02	0.07	Divorced	-0.13	0.15
s_l	0.10	0.08	i_u	-0.04	0.06	m_sq	-0.13	0.07	Widowed	-0.09	0.09
w_s	-0.08	0.09	i_d	0.16	0.07	s_sq	0.02	0.02	Separated	-0.04	0.17
b_s	0.03	0.07	i_lab	-0.06	0.09	w_l	-0.03	0.11	> 1 Spouse	-0.07	0.23
m_s	0.03	0.05	i_sq	-0.04	0.04	w_o	-0.17	0.09			
b_m	0.00	0.06	u_d	0.06	0.05	w_i	0.02	0.04			
w_m	0.10	0.05	u_lab	-0.09	0.09	w_u	-0.07	0.05			
w_b	-0.01	0.06	u_sq	-0.02	0.06	w_d	0.10	0.08			
b	0.36	0.18	d_lab	0.02	0.11	w_lab	-0.16	0.08			
m	0.42	0.17	d_sq	-0.19	0.14	lab_sq	0.02	0.12			
s	-0.10	0.14	w	0.32	0.18						

s ≡ sorghum; m ≡ maize; b ≡ barley; w ≡ wheat; o ≡ oxen; i ≡ purchased inputs;
u ≡ urea; d ≡ dap; lab ≡ labor; l≡ land; _ ≡ interacting with; sq ≡ squared; pa ≡ village
λ ≡ Box-Cox transformation parameter; c ≡ constant; Conserv. ≡ conservation;
Mem Educ ≡ highest years of schooling in the household; steep ≡ average slope of the plots;
soil ≡ average soil fertility (lower values more fertile).

Chapter 2

Productivity and Efficiency of Small Scale Agriculture in Ethiopia

2.1 Introduction

Agricultural productivity gains in developing country settings can reduce rural poverty by raising real income from farming, keep food prices from increasing excessively, and improve food security. The economic importance of improving agricultural productivity is clearly evident in a country like Ethiopia where agriculture accounts for 47% of its GDP and 85% of its employment. Although Ethiopia successfully increased its crop production in the last decade or so, increasingly binding land and water constraints may make it difficult to achieve continued productivity gains for crops and livestock in the highlands without major investments in productivity-increasing technologies (Dorosh, 2012). Taffesse, Dorosh, and Gemessa (2012) also argue that with little suitable land available for the expansion of crop cultivation, especially in the highlands, future cereal production growth will need to come increasingly from yield improvements, so finding the policies that can deliver productivity growth is important for Ethiopia's future.

Policy recommendations on how to improve agricultural productivity, however, require reliable estimates of the current level of farmers' productivity and efficiency as well as identification of the technologies and policies that lead a farmer to be more productive. Toward this end, it is important to model agricultural production in a manner that allows the identification of beneficial policies while being flexible enough to fit the actual type of production practices of most farmers. Among adopters of improved technology, and with access to the public extension system, Alene and Zeller (2005) found close to 79% technical efficiency in one district in Eastern Ethiopia. Using a more representative data from the Ethiopian Rural Household Survey, Abrar and Morrissey (2006) found average technical efficiency of grain production to be 51% in 1995, 54% in 1997, and 57% in 2000. In this study, we provide reliable efficiency estimates for multiple-output, grain-producing farmers using recent econometric developments in the area. We estimate an output distance function of grains production using generalized method of moments with instruments to enable us to accommodate farmers growing several crops as well as avoid the endogeneity issues that are related to the use of distance functions for multi-output production.

Policies and factors that have been studied previously for their role in boosting productivity include access to extension services, use of fertilizer, farmer education, age and gender of the household head, and family size (Bachewe, 2009; Abrar and Morrissey, 2006; Croppenstedt and Demeke, 1997). Using a panel data set of small-scale, Ethiopian subsistence farmers, we follow the literature and examine a wide range of factors for their role in boosting agricultural productivity including demographics, social networks, education, and public policies. Thanks to the richness of our dataset, the set of factors and policies included in our model are more comprehensive than in many earlier studies. In particular, we look at an important local policy in Ethiopia - access to extension programs - and at the value of several social networking opportunities: labor sharing, funeral associations, and off-farm work.

We find that the most important factors determining farmers' efficiency are access to the public extension system, participation in off-farm activities, taking advantage of labor sharing arrangements, gender of the household head, and the extent to which farmers are forced to produce on marginal and steeply sloped plots. We find that the average farmer's technical efficiency is less than 60 percent, so bringing farmers toward the production frontier using the successful policies identified here could yield large, economically significant productivity gains. Technical change has been slow, at about one percent per year. Combined with the low technical efficiency scores, it appears that productivity gains may be more easily found from boosting farmers' efficiency than from shifting the production frontier outward. The gains could be extremely significant as simply making extension programs accessible to all Ethiopian farmers could increase grain production by about 35 percent.

The rest of the chapter is organized as follows. Section II describes the empirical model, while section III explains the data source as well as descriptive statistics of the variables used in estimation. The findings are presented in section IV, with separate subsections that explain the instruments used, the model estimates, the inefficiency effects, and farmers' technical efficiency scores. Section V concludes and draws on policy implications of the findings.

2.2 Empirical Model

Different representations of the production technologies of multi-output producing agents such as monetary aggregation or the dual cost approaches require behavioral assumptions such as revenue maximization, profit maximization, or cost minimization. At times, any of these behavioral assumptions may not properly represent some producers such as the small scale producers that we are considering in this study. Distance functions, on the other hand, allow one to describe a multi-input, multi-output production technology without the need to specify a behavioral objective such as cost minimization or profit-maximization (Coelli et al., 2005).

As a result, distance functions have been used in a wide range of applications that include technology adoption and farmers' efficiency in Ethiopia (Alene and Zeller, 2005), decomposition of productivity growth in Chinese agriculture (Brummer, Glauben, and Lu, 2006), performance of European railways (Coelli and Perelman, 2000), and measuring students' test performance across public and private-voucher schools in Spain (Perelman and Santin, 2011).

The usual implementation of output distance functions that takes one of the outputs to the left-hand-side of the equation is likely to cause inconsistent estimates as it ignores the presence of the remaining endogenous outputs on the right hand side of the equation (Coelli et al., 2005).[1] Atkinson, Cornwell, and Honerkamp (2003) have shown that Generalized Method of Moments (GMM) can be used to address the possibility of endogeneity of either outputs or inputs with the composite error term inherent in distance functions. The GMM approach has an additional advantage in that it does not require a distributional assumption on the error term. Thus we follow the GMM approach of Atkinson, Cornwell, and Honerkamp (2003) aiming to accommodate the multiple output nature of production in the farming system under study through distance functions as well as to address the endogeneity inherent in distance function estimation by instrumenting the endogenous right-hand-side outputs.

Let X be a vector of inputs $X = (x_1, \cdots, x_L) \in R_+^L$ and let Y be a vector of outputs denoted by $Y = (y_1, \cdots, y_M) \in R_+^M$. The output distance function is defined as

$$D^o(X,Y,t) = inf_\theta\{\theta > 0 : (X, \frac{Y}{\theta}) \in S(X,Y,t)\} \tag{2.1}$$

where $S(X,Y,t)$ is the technology set such that X can produce Y at time t. $D^o(X,Y,t)$ is the inverse of the factor by which the production of all output quantities could be increased while still remaining within the feasible production set for the given input level (O'Donnell and Coelli, 2005). θ, and hence, the distance function, $D^o(X,Y,t)$, takes a value less than or equal to 1, where a value of 1 means that the farmer is operating at the frontier of the technology set. The output distance function is non-decreasing, linearly homogeneous and convex in output, and non-increasing and quasi-convex in inputs (O'Donnell and Coelli, 2005).

Given M outputs and L inputs, we have chosen a generalized quadratic Box-Cox model to represent the distance function, $D^o(.)$, as

$$\begin{aligned} D_{it}^o = exp(\gamma_o^* + \sum_m^M \gamma_m^* y_{mit}^\lambda + .5 \sum_m^M \sum_r^M \gamma_{mr}^* y_{mit}^\lambda y_{rit}^\lambda + \sum_l^L \gamma_l^* x_{lit}^\lambda \\ + .5 \sum_p^L \sum_l^L \gamma_{pl}^* x_{pit}^\lambda x_{lit}^\lambda + \sum_m^M \sum_l^L \gamma_{ml}^* y_{mit}^\lambda x_{lit}^\lambda) exp(v_{it}) \end{aligned} \tag{2.2}$$

[1]The same can be said with input distance functions.

where y^{λ}_{mit} and x^{λ}_{nit} are the Box-Cox transformations of outputs and inputs, defined by Box and Cox (1964) as $y^{\lambda}_{mit} = \frac{y^{\lambda}_{mit}-1}{\lambda}$ and $x^{\lambda}_{nit} = \frac{x^{\lambda}_{nit}-1}{\lambda}$, λ is the transformation parameter to be estimated, and v_{it} is the usual two sided error term with zero mean that captures the noise in production. The generalized quadratic Box-Cox distance function has a form similar to a translog distance function but with a Box-Cox, instead of logarithmic, transformation. If $\lambda = 0$, the Box-Cox transformation reduces to a log transformation, and hence the generalized Box-Cox distance function incorporates the translog distance function as a special case. The Box-Cox transformation is continuous around zero and hence allows us to include output and input variables with zero values for which log transformation is not possible. This is an important feature of the model because it is likely that most farmers only produce some of the crops or do not use some inputs such as fertilizer.

The actual distance D^{o}_{it} is equal to θ. If a farm is on the frontier, then $D^{o}_{it} = \theta = 1$. Otherwise, $D^{o}_{it} = exp(-u_{it})$, where u_{it} is a non-negative random variable associated with technical inefficiency. Thus, substituting $exp(-u_{it})$ for D^{o}_{it} in equation 2.2, taking the natural logarithm of both sides, and re-arranging the equation gives

$$\begin{aligned} 0 = \gamma^{*}_{o} + \sum_{m}^{M} \gamma^{*}_{m} y^{\lambda}_{mit} + .5 \sum_{m}^{M} \sum_{r}^{M} \gamma^{*}_{mr} y^{\lambda}_{mit} y^{\lambda}_{rit} + \sum_{l}^{L} \gamma^{*}_{l} x^{\lambda}_{lit} \\ + .5 \sum_{p}^{L} \sum_{l}^{L} \gamma^{*}_{pl} x^{\lambda}_{pit} x^{\lambda}_{lit} + \sum_{m}^{M} \sum_{l}^{L} \gamma^{*}_{ml} y^{\lambda}_{mit} x^{\lambda}_{lit} + v_{it} + u_{it} \end{aligned} \tag{2.3}$$

Next, take one of the outputs, y_{1it}, to the left hand side in order to obtain an observable variable on the left hand side (Brummer, Glauben, and Lu, 2006; Coelli and Perelman, 2000). In addition, factors that affect the inefficiency of farmer i are incorporated in the model by defining u_{it} in terms of household specific variables that are believed to affect the productivity and efficiency of a farmer. These include whether the farmer has called for labor sharing on at least one of his plots and other informal social networks such as funeral associations (*idir*) and off-farm activities. In addition, these efficiency explaining factors include whether the farmer has access to government extension services, the highest level of education among members of the household, the average slope and soil fertility of the farmer's plots, as well as the household head's age, gender, education, marital status, access to irrigation, and soil conservation practices. Thus, the resulting empirical model for farm i in period t can be written as:

$$\begin{aligned} y_{1it}^{\lambda} = -[\gamma_o + \sum_{m}^{M-1} \gamma_m y_{mit}^{\lambda} + .5 \sum_{m}^{M-1} \sum_{r}^{M-1} \gamma_{mr} y_{mit}^{\lambda} y_{rit}^{\lambda} + \sum_{l}^{L} \gamma_l x_{lit}^{\lambda} \\ +.5 \sum_{p}^{L} \sum_{l}^{L} \gamma_{pl} x_{pit}^{\lambda} x_{lit}^{\lambda} + \sum_{m}^{M-1} \sum_{l}^{L} \gamma_{ml} y_{mit}^{\lambda} x_{lit}^{\lambda} + v_{it}] - [\sum_{j} \beta_j w_{ijt}] \end{aligned} \tag{2.4}$$

where w_{ijt} refers to j=1,...,J efficiency explaining variables for farmer i at time t and β_j refers to their corresponding coefficients.

The coefficients in equation 2.4 are different from 2.3 to note that they are normalized by γ_1^*, the coefficient of the output transferred to the left hand side. We also imposed homogeneity and symmetry restrictions on the above distance function (O'Donnell and Coelli, 2005).

Following Atkinson, Cornwell, and Honerkamp (2003) and Atkinson and Dorfman (2005), the non-negativity of the u_{it} is imposed after estimation by adding and subtracting from the fitted model $\hat{u}_t = min_i(\hat{u}_{it})$, which defines the frontier intercept.

Given these estimates, Atkinson and Dorfman (2005) showed how to compute technical efficiency (TE_{it}), efficiency change (EC_{it}), technical change (TC_{it}), and productivity change (PC_{it}) as follows.

Farmer i's level of technical efficiency in period t is TE_{it}:

$$TE_{it} = exp(-\hat{u}_{it}^*) \tag{2.5}$$

where the normalization of $\hat{u}_{it}^*$ guarantees that $0 < TE_{it} \leq 1$.

Productivity can increase by farmers getting more efficient or by moving the production frontier outward. Thus, productivity change is defined as the sum of technical change and efficiency change:

$$PC = TC_{it} + EC_{it}. \tag{2.6}$$

Efficiency change is the change in the technical efficiency over time, so

$$EC_{it} = \triangle TE_{it} = TE_{it} - TE_{i,t-1}. \tag{2.7}$$

Technical change is measured as the difference between the estimated frontier distance function in periods t and t - 1 holding output and input quantities constant:

$$TC_{it} = \hat{D}_i^*(Y, X, t) - \hat{D}_i^*(Y, X, t-1). \tag{2.8}$$

2.3 Data

For this study, we have used the 1999 and 2004 rounds of the Ethiopian Rural Household Survey (ERHS) data, which is a longitudinal household data set covering households in 15 peasant associations in rural Ethiopia. We focus on the five major cereals - teff, wheat, maize, sorghum, and barley - that according to Taffesse, Dorosh, and Gemessa (2012) occupy almost three-fourths of the total area cultivated and represent almost 70% of the total value-added in recent years.

The study focuses on the main (*Meher*) rainy season that runs between June and September. This helps to reduce the noise in the data as the agricultural production system in terms of crops in the field, intensity of the rain, and utilization of inputs are markedly different from the second small showers (*Belg* rains) season between February and May (Seifu, 2004). In addition, the five cereals that are the focus of this study are mainly produced during the main rainy season. According to data from the Central Statistical Agency of Ethiopia, between 1995 and 2008, close to 99% of teff production, 98% of wheat production, 90% of barley production, and 89% of maize production was done during the main rainy season (CSA, 2009). These qualifications in the data in terms of crops produced and seasons resulted in a sample size of 815 farmers in each of the 1999 and 2004 survey rounds.

There is a regional specialization in the type of cereals farmers produce. For instance, the production of teff and sorghum is not common in Tigray. The farmers in Tigray focus on the production of barley and wheat, and to a lesser extent maize. Barley and sorghum are not commonly produced among the sampled households in the Southern Nations, Nationalities, and Peoples (SNNP) region. There is a fair distribution of farmers producing the five cereal crops in the Amhara and Oromiya regions (Table 2.1). Table 2.1 shows that in the Amhara

Table 2.1: Cereal Production by Region

	Percentage of Farmers Producing					
Region	Teff	Barley	Wheat	Maize	Sorghum	No. of farmers
Tigray	4.3	96.5	33.3	9.2	2.1	141
Amhara	43.1	56.0	44.8	17.6	31.3	364
Oromiya	53.6	14.0	40.7	69.6	28.9	349
SNNPR	67.5	0.6	14.6	33.7	0.0	166

Results are based on the 2004 survey only.
Source: Authors' computation from ERHS (2011)

region, 43% of the farmers in the sample produce teff, 45% produce wheat, 56% produce barely, 31% produce sorghum and less than 18% produce maize. In the Oromiya region, 55% of the sampled households produce teff, about 40% produce wheat, 70% produce maize, 29% produce sorghum but only about 14% produce barley. Among farmers in the SNNP region, 68% of them produce teff, 34% of them produce maize, less than 15% produce wheat and less than 1% produce either barley or sorghum.

Access to irrigation among the sampled farmers increased from about 6 percent in 1999 to about 29 percent in 2004. The share of farmers with access to the public extension system has almost doubled in the five years between 1999 and 2004. More than three quarters of the household heads are male and less than 10 percent completed primary school. More than three quarters of the households heads are members of *idir* (funeral associations), and 23 to 37 % of the farmers are engaged in off-farm activities in 1999 and 2004. About three quarters of the household heads are married.

The ERHS data show significant variation in labor sharing participation among the four regions covered by the study. Labor sharing is not common in the Tigray region where only 13% of the households participate in such type of arrangements. Labor sharing is common in the other three regions with participation rates ranging from 40% to 61% .

All the output variables (teff, wheat, barley, maize, and sorghum) as well as the two most used chemical fertilizers (urea and DAP) are measured in kilograms. Average production is the highest for teff and the lowest for sorghum but the averages would obviously be higher if we consider only the farmers that produce the specific crop. Average DAP use is approximately three times more than that of urea. The highest level of education in the household is around 4 years on average and it is expected to capture intra-household schooling externality. The average age of a household head is about 50 years. Soil fertility is measured in a 1 to 3 scale where 1 refers to fertile, 2 medium fertile, and 3 infertile soil, and it is averaged among the different plots of the farmer. Labor is measured in labor days and it includes family, hired, and shared labor. While computing labor days, we follow Mulugeta (2009) to account for the physical hardship in crop production by giving adult men a weight of 1, adult women a weight of 0.8, and child labor a weight of 0.35. Oromiya has the highest

Table 2.2: Average Input Use on the Selected Cereals (Std. Dev. in brackets)

Region	Land (ha)	Urea (Kg)	DAP (Kg)	Labor days	Livestock (TLUs)	Other Inputs (Br)
Tigray	0.4	2.4	8.6	39.7	8.5	20.5
	(0.3)	(15.0)	(42.5)	(51.8)	(10.1)	(82.8)
Amhara	1.8	65.6	202.2	165.2	23.8	33.5
	(7.1)	(233.8)	(441.8)	(184.3)	(30.0)	(136.9)
Oromiya	4.0	86.8	179.9	190.7	13.1	305.8
	(18.3)	(315.3)	(734.8)	(242.0)	(23.3)	(1461.7)
SNNPR	1.5	4.9	17.1	90.2	3.7	42.8
	(9.9)	(19.0)	(38.2)	(165.4)	(3.5)	(195.7)

Results are based on the 2004 survey only.
TLUs ≡ Tropical livestock Units.
Br ≡ Birr, Ethiopian currency. 1USD= 8.3Br in 2005
Source: Authors' computation from ERHS (2011)

average land holding size under the five crops which was about nine fold higher than Tigray, followed by Amhara and SNNPR (Table 2.2). As one would expect, average labor days used in these crops also follow the same distribution across regions as that of land size under the five crops. Urea and DAP are the two chemical fertilizers commonly used in Ethiopia and farmers in Amhara and Oromiya regions use significantly higher amounts of these fertilizers as compared to the Tigray and SNNP regions.

2.3.1 Instruments

In the final estimated model, teff is the output used as the dependent variable while barley, wheat, maize, and sorghum are the endogenous outputs on the right-hand-side of the equation. Weather-related events such as the amount and distribution of rainfall are the initial candidates to be used as instruments for the endogenous outputs because of their strong relationships with the amount of output produced of these crops and because they are exogenous to the farmer. However, we need to ensure the weather-related instruments do not simultaneously affect the dependent variable, teff. The Ethiopian crop calendar (Figure 2.1) indicates legitimate weather related variables that can be used as instruments for the endogenous output variables. Teff is sown between the end of June and end of July (FAO, 2012) and for better productivity it is advisable to sow teff during the last two weeks of July (Seifu, 2004). Maize and sorghum are sown in the months that correspond to the previous small showers (*belg*) season which spans between February and May. Seifu (2004) noted that sowing for maize should take place in the first two weeks of May or as early as possible after the onset of the main rainy season (end of May or early June). Bewket (2009) stated that maize appears to require a more even distribution of rainfall throughout the *belg* season and the main rainy season. Sorghum production is particularly related to the *belg* rains because sorghum is sown in early May or even late April, which makes the *belg* rainfall critically important (Bewket, 2009).

In the ERHS data set, farmers were asked if *belg* crops were adversely affected by weather. We used this variable and its interactions with other exogenous variables as instruments for maize and sorghum production. That is, *belg* rains affect maize and sorghum production because the sowing of these two crops and part of their growing season correspond with the

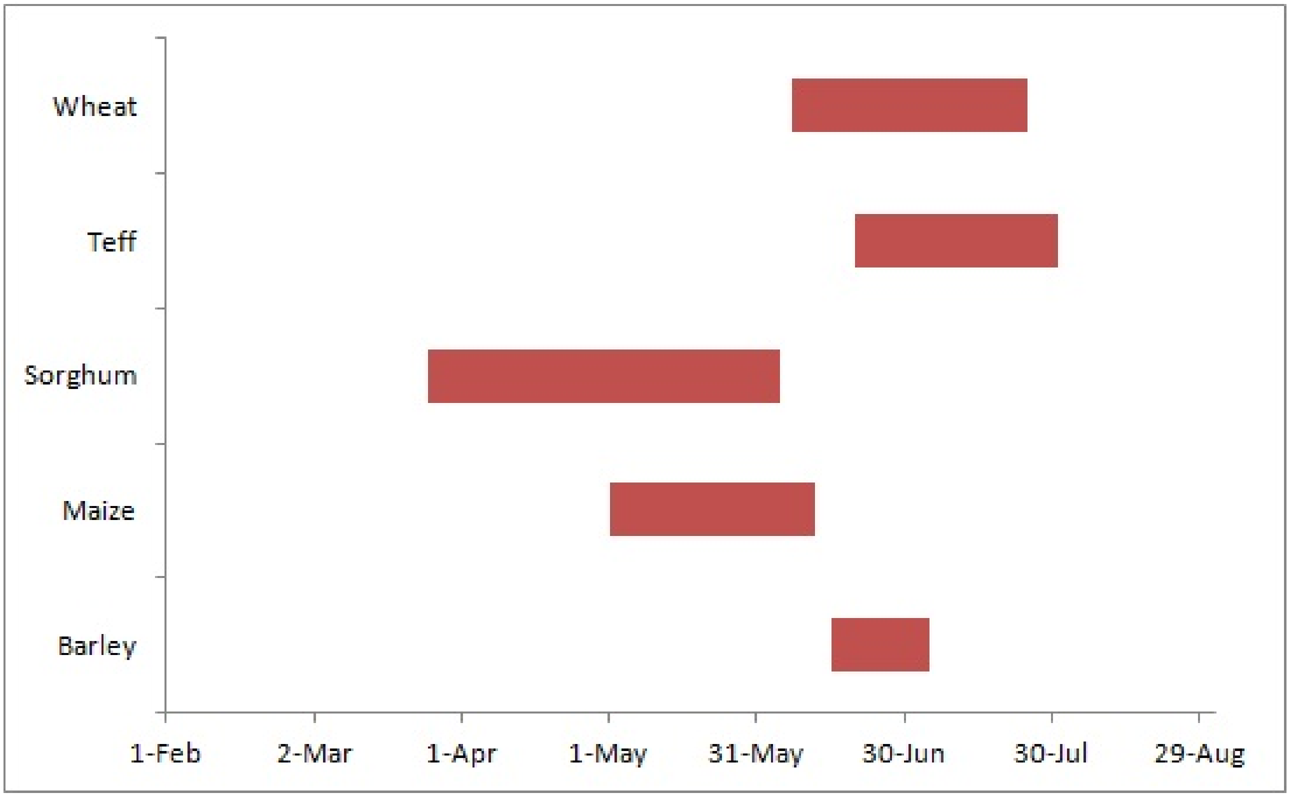


Figure 2.1: Sowing Periods for the Main Rainy Season for the Sub-moist Agro-ecological Zone in Ethiopia

belg season but *belg* rains do not simultaneously affect teff production because sowing for teff begins at the end of July, making the instrument relevant as well as legitimate.

The sowing time for wheat is the end of June and the early days of July while sowing for barley should take place soon after the main rainy season begins in June (Seifu, 2004; FAO, 2012). Thus, the performance of the rain at the beginning of the main rainy season (late May and early June) is important both for wheat and barley (as well as sorghum and maize which are in their growing stage at this time) but is not directly related with teff, which is sown after two weeks into July (i.e, the middle of the main rainy season). The ERHS data set is helpful in this regard because farmers were asked if the first rains of the main rainy season came on time and if there was enough rain on the farmer's plot at the beginning of the rainy season. These two variables, along with their interactions with other exogenous variables, are used to instrument for wheat and barley because they are related to the endogenous variables but not directly related to the left-hand-side variable, making them pass the legitimacy and relevance criteria for good instruments.

2.4 Results

The model is estimated using heteroscedasticity and autocorrelation consistent iterated GMM with the instruments mentioned above and it fits the data well with an overall R^2 of 0.598. Using the Sargen-Hansen or J-test of overidentification (Baum, Schaffer, and Stillman, 2003; Wooldridge, 2002), we fail to reject the validity of the over-identifying restrictions. The J-test resulted in a GMM criterion function value of 41.74 which has a χ^2 distribution of 40 degrees of freedom, which gives a p-value of 0.395. A rejection of this test would have cast a doubt on the validity of our instruments.

Other than the validity of instruments, the other condition needed in GMM estimation is that the instruments be sufficiently related to the endogenous variables. When instruments are weak, the orthogonality conditions hold even at non-optimal values of the estimated parameters when in fact they should hold or get close to zero only at the optimal values. Our instruments do not exhibit the pathologies that GMM estimators demonstrate in the presence of weak identification as suggested by Stock, Wright, and Yogo (2002). For instance, two-step GMM estimators and iterated GMM point estimators can vary significantly and produce very different confidence sets in the presence of weak identification. As shown in Table 2.6 and Table 2.7, the two step GMM and the iterated GMM estimators are almost identical in our case, which differ only after two digits for almost all of the coefficients. Thus, we believe the estimates are based on a suitable set of instruments and are credible.

2.4.1 Inefficiency Effects

We have presented the variables that explain farmers' inefficiency in Table 2.3 even though they were estimated simultaneously in one step with the full set of the distance function variables presented in Table 2.6. As explained in the empirical model, these variables

Table 2.3: Determinants of Technical Inefficiency

Inefficiency Effects	Estimate	Std. Error	t-stat
Age of household head	0.064	0.103	0.627
Male household head	-0.153	0.079	-1.929
Labor Sharing	-0.103	0.057	-1.789
Poor quality soil	0.068	0.041	1.663
Irrigation	-0.088	0.091	-0.970
Conservation	-0.025	0.067	-0.375
Extension	-0.213	0.089	-2.387
Head completed primary school	0.016	0.137	0.119
Household members' highest education	-0.042	0.043	-0.993
Steep plots	0.002	0.060	0.039
Steeper plots	0.236	0.105	2.240
Off-farm income	-0.115	0.049	-2.337
Idir membership	0.003	0.094	0.029
Single	-0.035	0.142	-0.246
Divorced	-0.004	0.125	-0.036
Widowed	-0.094	0.075	-1.242
Separated	0.065	0.169	0.382
$>$ 1 spouse	-0.110	0.194	-0.569

are explaining farmers' inefficiency and hence negative signs show that technical efficiency increases as the explanatory variable increases and positive signs are associated with efficiency reducing effects.

We find that the efficiency of farmers in Ethiopia is highly responsive to having access to the public extension system. Farmers with access to extension are found to be about 35% more efficient than those that do not have access to extension (Tables 2.3 and 2.4). The importance of extension in improving farmers' efficiency gives support to the government of Ethiopia's effort to increase the number of public extension staff almost three-fold in the five years preceding 2008 and to the claim that agricultural extension services are what tie improved seed, chemical fertilizers, and credit together for the Ethiopian smallholder (Spielman, Kelemework, and Alemu, 2011). It is also consistent with the findings of Dercon et al. (2009) who, using five rounds of the same ERHS data set between 1994 and 2004, find that receiving at least one extension visit reduces headcount poverty by 9.8 percentage points and increases consumption growth by 7.1 percentage points.

Farmers engaged in labor sharing arrangements are found to be 16 to 17% more efficient than those who work alone (Tables 2.3 and 2.4). This is due to what Mekonnen and Dorfman (2013) called the synergy effect of labor sharing arrangements, which refers to productivity gains that come from working together such as speed gains and being less bored by tedious agricultural activities or working harder while observed by the labor sharing partners. The synergy effect of labor sharing arrangements is recognized by the farmers as more than two-thirds of the farmers call for labor sharing parties for quick completion of tasks or because a group is the best way of completing the task. In addition, labor sharing schemes appear to be an indigenous response by the farming community to labor and credit market constraints in rural Ethiopia because about a fourth of the farmers participate in labor sharing arrangements either because it is the only way to get large amount of labor, they can not afford paid labor, or no paid labor is available.

Male-headed households are found to be more efficient than female headed households which implies that the design of extension systems in Ethiopia should have a gender component that addresses efficiency-reducing challenges that women household heads in particular face. As shown in Table 2.4, male headed households are on average about 16% and 18% more efficient than female headed households in 1999 and 2004.

We also find that farmers exposed to external information through off-farm activities are 8 to 15% more efficient than those that do not have such exposures (Tables 2.3 and 2.4). The most important kind of off-farm activities among the sampled households is food-for-work, which accounts for 39% and 54.4% of all off-farm activities in 1999 and 2004. The food-for-work program in Ethiopia is a welfare safety net for food insecure areas and instead of distributing food aid to those in need, the program involves able-bodied people performing public work in exchange for a food wage. The food-for-work program focuses on rehabilitation of forest, grazing, and agricultural lands as well as construction of wells, ponds, dams, terraces, and roads. The efficiency-enhancing effects of off-farm activities suggests that farmers involved in the food-for-work program have taken home productivity-improving methods from the public works to their individual plots.

Table 2.4: Technical Efficiency Scores by Determinants of Inefficiency

		TE in 1999	TE in 2004
Gender of the household head	Male	0.60	0.60
	Female	0.51	0.52
	% difference	-0.18	-0.16
Labor Sharing Participation	Yes	0.61	0.63
	No	0.53	0.54
	% difference	-0.16	-0.17
Acess to extension services	Yes	0.76	0.74
	No	0.56	0.55
	% difference	-0.35	-0.35
Off-farm income	Yes	0.62	0.64
	No	0.57	0.55
	% difference	-0.08	-0.15
Average slope of the plots	Flat plots	0.59	0.59
	Steeper plots	0.42	0.43
	% difference	0.30	0.26

Even more troubling is the efficiency differentials between farmers who claimed their plots to be flat and those who are forced to harvest on steeper plots. On the ERHS survey, farmers were asked to classify their plots to be flat, sloped, or steep. We find no statistically significant efficiency differential between those whose plots are flat and those whose plots are sloped. However, farmers with steep plots are found to be 30% and 26% less efficient in 1999 and 2004 as compared to those whose plots are on average flat (Tables 2.3 and 2.4).

In addition, the average fertility of the farmers' plot plays a role in determining the technical efficiency of farmers. The soil fertility variable was measured in such a way that higher values refer to less fertility and hence the positive coefficient in Table 2.3 shows that farmers with plots of inferior quality are less efficient than farmers whose plots are more fertile.

Table 2.5 presents the marginal productivity and elasticity of agricultural inputs evaluated at the mean of their 2004 values. The marginal productivity of land is both statistically

Table 2.5: Partial Effects and Elasticities Evaluated at 2004 Values

	Marginal Productivity	Std. Error	Elasticity
Land	0.844	0.493	1.033
Oxen	0.115	0.305	0.139
Urea	-0.014	0.214	-0.016
DAP	0.037	0.294	0.049
Other Purchased Inputs	0.008	0.201	0.064
Labor	0.133	0.384	0.191
Wheat	-0.548	0.266	-0.649
Barley	-0.231	0.202	-0.414
Maize	-0.295	0.232	-0.340
Sorghum	0.073	0.249	0.080

and economically significant, a reflection of how production is constrained by the small land size of the farmers.

Among the sampled households in 2004, the average land size used for teff, wheat, barley, sorghum, and maize was 0.4 hectares in Tigray region, 1.5 hectares in the SNNPR region, 1.8 hectares in Amhara region, and 4 hectares in Oromiya region. Given the small landholding of small scale farmers in Ethiopia, agricultural output is expected to be responsive to acreage expansion. The result from this study also confirms that a percentage increase in land size increases teff production by a little more than one percent, implying slightly increasing returns to scale.

Land is owned by the government and farmers can not sell or mortgage agricultural farm lands. Although renting agricultural land is allowed, all regions except Amhara, where land can be rented for up to 25 years, have legal provisions limiting the amount of land to be rented out to 50% of holding size with a maximum duration for rental contracts of 3 years (Deininger et al., 2008). Population pressure and lack of alternative non-agricultural jobs in villages have forced household heads to further redistribute part of their farming land to their adult kids when the kids form their own family. The (near) absence of land markets and land fragmentation have forced farmers to harvest on small plots of lands, making land the most valuable input of all and production to be highly constrained by small land size.

The trade-off between teff production versus wheat production is significant (Table 2.5) while the relationships with the other crops are statistically insignificant.

2.4.2 Farmer Technical Efficiency Scores

The average technical efficiency of the 815 farmers included in the final estimation was found to be about 58.4% both in 1999 and 2004. These figures imply that at the current levels of inputs, farmers are producing, on average, less than 60% of the output of the most efficient farmer in the sample. Thus, there is room to increase farmers' production by over two thirds through better management of the existing resources. The evidence in Table 2.3 suggests the government needs to intensify efficiency-enhancing investments such as extension, irrigation, and off-farm activities, as well as facilitating venues for farmers to work together.

For the years between 1999 and 2004, the annual efficiency change is close to zero while the average technical change is close to one percent per year. As a result, the productivity change, which is the sum of efficiency change and technical change, is also about one percent per year.

As shown in Figure 2.4.2, there is significant variation in the efficiency scores of farmers in different peasant associations (PAs) in 2004, from 46.4% in Geblen PA of Tigray Regional State to about 69.2% in Doma PA of the Southern Nations, Nationalities, and Peoples Regional (SNNPR) State. In terms of average efficiency scores, the two lowest performing PAs (Geblen and Haresaw) are found in Tigray, whereas Korodegaga PA of Oromiya Regional State closely follows the best performing Doma PA with 69.1% efficiency score.

However, such direct comparisons of the efficiency scores of peasant associations can not be conclusive because they do not take into account the variance of efficiency scores within each PA. From the econometric results, the three PAs whose efficiency scores are statistically significantly different from our base PA of Debre-Berhan Bokafia are Yetmen, Sirbana Godeti, and Trirufe Ketchema. These three PAs are known in the country for their high quality teff production and have long experience with improved teff production technologies. Yetmen is

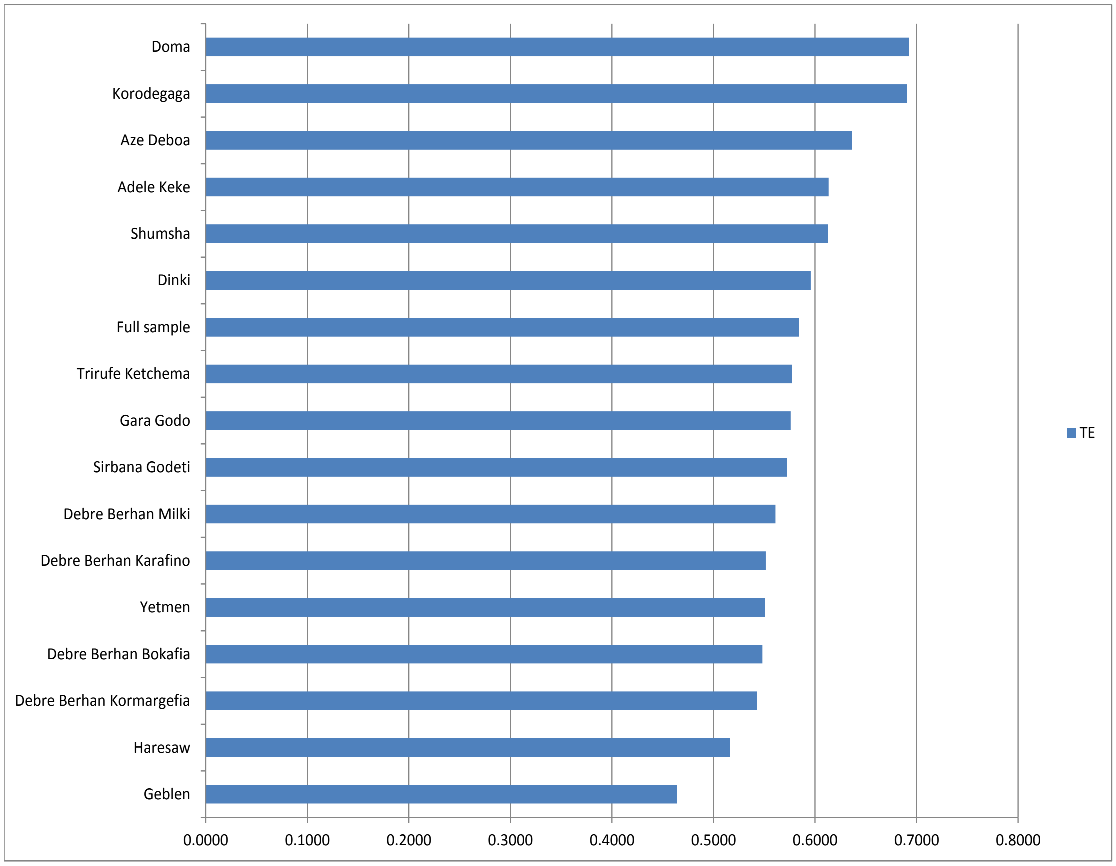


Figure 2.2: Mean Technical Efficiency in 2004 by Peasant Association

located about 248 km north west of Addis Ababa between the towns of Dejen and Bichena. An improved variety of teff was introduced in Yetmen three decades ago by development agents and was tried first by the producers' cooperatives, and soon adopted by all the peasants following its success (ERHS, 2011). Sirba na Godeti PA, located about halfway between Debre Zeit and Mojo towns and with generally fertile soil (ERHS, 2011), is known for its teff production and supply to the capital Addis Ababa. Turufe Kecheme is a PA located about 12.5 km north east of the town of Shashemene in the area of the Great Lakes of Zwai, Langano, Abiyata and Shalla, a plain area with fertile soil suitable for agriculture (ERHS, 2011).

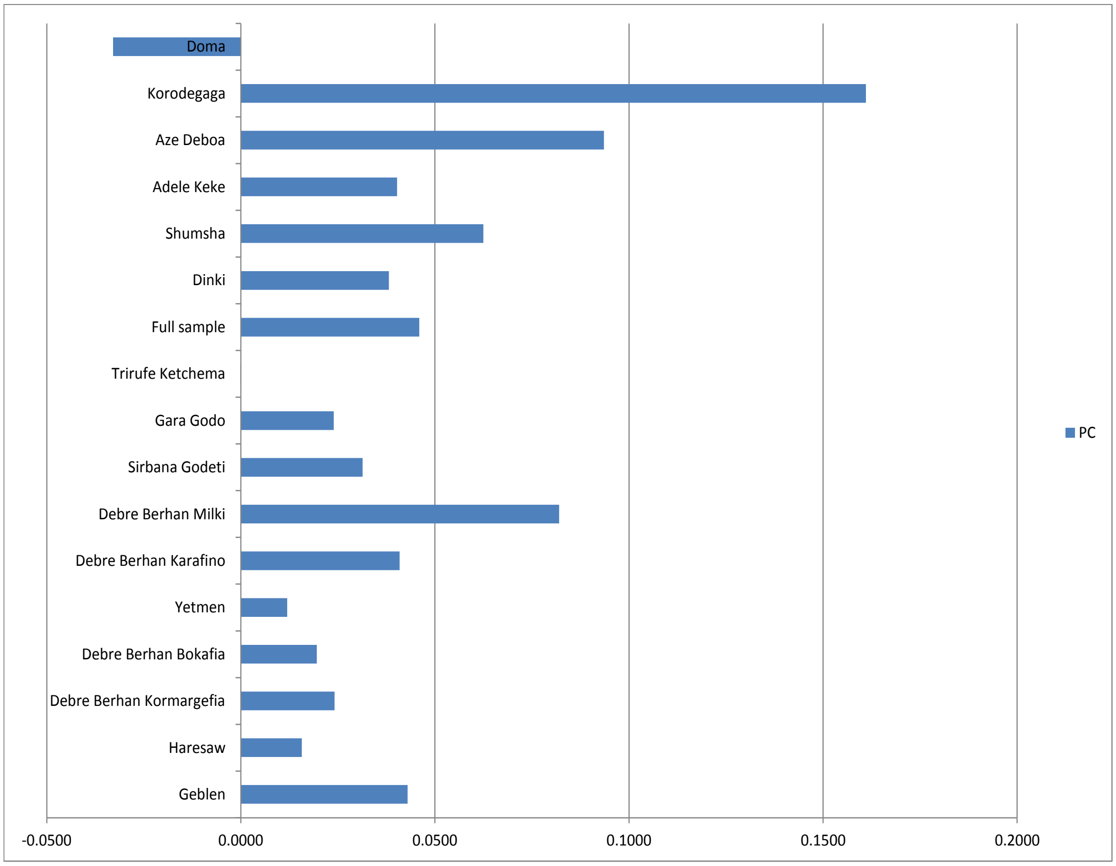


Figure 2.3: Mean Productivity Change between 1999 and 2004 by Peasant Association

Except for the Doma PA, all the other PAs exhibit positive productivity changes between 1999 and 2004 as shown in Figure 2.3. The positive values for productivity change reflect the outward shift of the frontier. Though farmers display no efficiency improvement, it is not as dismal as it first seems since farmers are able to maintain their efficiency score while the production frontier is being pushed outward at one percent per year by the best performing farmers.

As shown in Figure 2.4, the lowest efficiency score among the sampled farmers in 2004 is about 35% while about a fifth of the farmers have efficiency scores below 50%. The efficiency scores of almost half of the farmers concentrate between 50% and 63%. Only 25% of the farmers have efficiency scores above 64% and less than 5% of the farmers have efficiency scores above 80%. Figure 2.4 also show that even though the average efficiency scores of farmers remain more or less the same between 1999 and 2004, the dispersion has slightly increased in 2004.

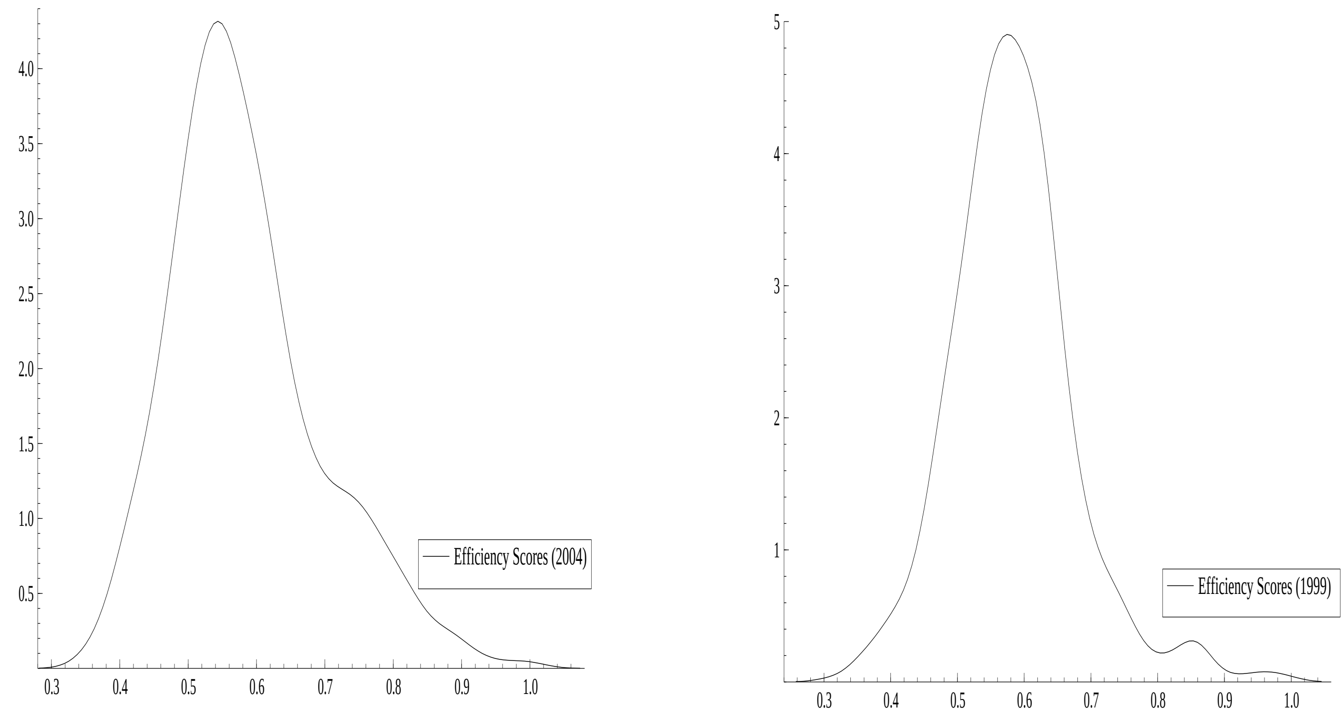


Figure 2.4: Distribution of Technical Efficiency Scores among Sampled Farmers in 1999 and 2004

2.5 Conclusion

We have estimated a distance function of grain production that explicitly takes into account the interdependence among the different crops farmers produce. We have used Box-Cox transformations, instead of logarithmic transformations, of variables to be able to include variables with zero values in the distance function. The generalized method of moments estimation that we follow allows us to control for the endogeneity among the different outputs in the distance function.

The average technical efficiency of the sampled farmers is 58.4%, implying the potential to increase agricultural production by over two thirds by investing in efficiency-enhancing factors. The results indicate that the most important factors determining farmers' efficiency in Ethiopia are having access to the public extension system, participation in off-farm activities, participation in labor sharing parties, gender of the household head, and the extent to which farmers are forced to produce on marginal and steeply sloped plots.

Technical change in Ethiopia's agriculture is found to be less than one percent per year between 1999 and 2004, while efficiency change is insignificant between the two periods. This calls for a double sword agricultural development policy: measures that can bring about an outward shift of the production technology such as intensification of input use and measures that improve farmers' efficiency given their current level of input use. Efficiency enhancing policies in Ethiopia should emphasize an even greater expansion of the public extension system, an extension system that has a gender component that addresses efficiency-reducing challenges that women household heads in particular face, that understands the traditional wisdom of farmers to work together in the face of labor and credit market constraints, as well as one that gives due consideration to the availability and generation of off-farm opportunities in rural Ethiopia.

Table 2.6: Full Set of Coefficients for Production and Inefficiency Effects (Iterated GMM)

Dep. Var. = teff; Overid. test = 41.74, p-value = 0.395, degrees of freedom= 40; $R^2 = 0.598$

	est.	s.e.		est.	s.e.		est.	s.e.		est.	s.e.
λ	0.65	0.08	c	1.89	0.49	pa1	-0.19	0.30	Age	0.06	0.10
b_lab	0.11	0.07	land	-0.75	0.16	pa2	-0.02	0.33	Male	-0.15	0.08
m_lab	0.02	0.05	oxen	-0.14	0.07	pa3	-0.06	0.53	Labor Sharing	-0.10	0.06
s_lab	-0.05	0.05	input	0.02	0.07	pa4	-2.75	0.51	Soil	0.07	0.04
b_d	-0.06	0.05	urea	0.00	0.08	pa5	-0.56	0.43	Irrigation	-0.09	0.09
m_d	0.13	0.08	dap	-0.03	0.08	pa6	-2.01	0.46	Conserv.	-0.03	0.07
s_d	-0.12	0.07	labor	-0.29	0.12	pa7	0.50	0.49	Extension	-0.21	0.09
b_u	0.01	0.04	l_o	-0.18	0.11	pa8	-0.27	0.45	Education	0.02	0.14
m__u	-0.03	0.05	l_i	-0.08	0.11	pa9	-1.06	0.50	Mem Educ	-0.04	0.04
s_u	0.07	0.06	l_u	-0.15	0.12	pa10	-0.34	0.38	Steep	0.00	0.06
b_i	-0.01	0.03	l_d	-0.02	0.09	pa11	-0.21	0.37	Steeper	0.24	0.11
m_i	-0.03	0.03	l_lab	-0.03	0.11	pa12	0.52	0.41	Off-farm	-0.11	0.05
s_i	0.08	0.04	l_sq	0.22	0.06	pa13	-0.10	0.22	*Idir*	0.00	0.09
b_o	0.15	0.08	o_i	-0.05	0.06	pa14	0.24	0.27	Single	-0.03	0.14
m_o	0.06	0.05	o_u	0.16	0.11	pa15	0.11	0.24	Divorced	0.00	0.12
s_o	0.00	0.07	o_d	-0.04	0.11	t_d	-0.06	0.08	Widowed	-0.09	0.08
b_l	-0.06	0.09	o_lab	0.07	0.15	w_sq	-0.07	0.07	Separated	0.06	0.17
m_land	-0.14	0.08	o_sq	-0.09	0.14	b_sq	-0.02	0.05	> 1 Spouse	-0.11	0.19
s_l	0.20	0.08	i_u	-0.02	0.05	m_sq	-0.07	0.05			
w_s	-0.03	0.07	i_d	0.13	0.06	s_sq	0.02	0.01			
b_s	0.01	0.05	i_lab	0.00	0.08	w_l	0.00	0.10			
m_s	0.00	0.04	i_sq	-0.02	0.03	w_o	-0.20	0.09			
b_m	-0.01	0.05	u_d	0.05	0.04	w_i	-0.04	0.04			
w_m	0.08	0.04	u_lab	-0.13	0.08	w_u	-0.05	0.05			
w_b	0.02	0.05	u_sq	-0.02	0.05	w_d	0.05	0.07			
b	0.29	0.15	d_lab	-0.04	0.10	w_lab	-0.08	0.08			
m	0.29	0.13	d_sq	-0.03	0.11	lab_sq	-0.01	0.12			
s	0.01	0.10	wheat	0.40	0.15						

s ≡ sorghum; m ≡ maize; b ≡ barley; w ≡ wheat; o ≡ oxen; i ≡ purchased inputs;
u ≡ urea; d ≡ dap; lab ≡ labor; l≡ land; _ ≡ interacting with; sq ≡ squared; pa ≡ village
λ ≡ Box-Cox transformation parameter; c ≡ constant; Conserv. ≡ conservation;
Mem Educ ≡ highest years of schooling in the household; steep ≡ average slope of the plots;
soil ≡ average soil fertility (lower values more fertile).

Table 2.7: Full Set of Coefficients for Production and Inefficiency Effects (Two-step GMM)

Dep. Var. = teff; Overid. test = 47.87, p-value = 0.184, degrees of freedom= 40; $R^2 = 0.637$

	est.	s.e.		est.	s.e.		est.	s.e.		est.	s.e.
λ	0.66	0.08	c	1.74	0.51	pa1	-0.14	0.31	Age	0.04	0.11
b_lab	0.15	0.08	land	-0.69	0.17	pa2	0.06	0.33	Male	-0.18	0.08
m_lab	0.03	0.05	oxen	-0.14	0.08	pa3	0.00	0.56	Labor Sharing	-0.11	0.06
s_lab	-0.07	0.05	input	-0.02	0.07	pa4	-2.49	0.54	Soil	0.07	0.04
b_d	-0.07	0.05	urea	0.01	0.08	pa5	-0.42	0.44	Irrigation	-0.13	0.09
m_d	0.11	0.08	dap	-0.08	0.08	pa6	-1.61	0.47	Conserv.	-0.05	0.07
s_d	-0.12	0.07	labor	-0.31	0.13	pa7	0.53	0.50	Extension	-0.21	0.09
b_u	0.01	0.04	l_o	-0.11	0.11	pa8	-0.17	0.46	Education	-0.02	0.14
m__u	-0.01	0.05	l_i	-0.14	0.11	pa9	-0.88	0.51	Mem Educ	-0.04	0.04
s_u	0.06	0.06	l_u	-0.10	0.12	pa10	-0.23	0.39	Steep	0.01	0.06
b_i	-0.01	0.03	l_d	0.04	0.08	pa11	-0.08	0.38	Steeper	0.24	0.11
m_i	-0.03	0.03	l_lab	0.04	0.11	pa12	0.76	0.41	Off-farm	-0.10	0.05
s_i	0.05	0.04	l_sq	0.14	0.04	pa13	0.00	0.24	*Idir*	-0.02	0.10
b_o	0.14	0.08	o_i	0.00	0.06	pa14	0.41	0.28	Single	-0.08	0.14
m_o	0.05	0.05	o_u	0.16	0.11	pa15	0.28	0.26	Divorced	-0.07	0.12
s_o	-0.01	0.07	o_d	-0.06	0.12	t_d	-0.11	0.08	Widowed	-0.11	0.08
b_l	-0.07	0.09	o_lab	0.00	0.15	w_sq	-0.10	0.08	Separated	-0.04	0.16
m_land	-0.03	0.08	o_sq	-0.12	0.15	b_sq	-0.03	0.05	> 1 Spouse	-0.10	0.20
s_l	0.16	0.08	i_u	-0.01	0.05	m_sq	-0.09	0.05			
w_s	-0.06	0.07	i_d	0.11	0.06	s_sq	0.01	0.01			
b_s	0.02	0.06	i_lab	0.01	0.09	w_l	-0.05	0.09			
m_s	0.03	0.04	i_sq	-0.02	0.03	w_o	-0.18	0.09			
b_m	-0.05	0.05	u_d	0.02	0.04	w_i	-0.02	0.04			
w_m	0.11	0.04	u_lab	-0.14	0.09	w_u	-0.06	0.05			
w_b	0.05	0.05	u_sq	-0.01	0.05	w_d	0.08	0.08			
b	0.29	0.16	d_lab	-0.05	0.11	w_lab	-0.11	0.09			
m	0.35	0.13	d_sq	-0.02	0.12	lab_sq	0.02	0.13			
s	-0.02	0.10	wheat	0.39	0.15						

s ≡ sorghum; m ≡ maize; b ≡ barley; w ≡ wheat; o ≡ oxen; i ≡ purchased inputs;
u ≡ urea; d ≡ dap; lab ≡ labor; l≡ land; _ ≡ interacting with; sq ≡ squared; pa ≡ village
λ ≡ Box-Cox transformation parameter; c ≡ constant; Conserv. ≡ conservation;
Mem Educ ≡ highest years of schooling in the household; steep ≡ average slope of the plots;
soil ≡ average soil fertility (lower values more fertile).

Chapter 3

Innovation Systems and Technical Efficiency in Developing-Country Agriculture

3.1 Introduction

Developing-country agriculture is frequently characterized by low productivity, small-scale subsistence farming, acute susceptibility to weather shocks, and low levels of market integration and value addition (World Bank, 2006). However, there is significant variation across countries. This suggests a need for a better understanding of the factors that influence productivity and variations in productivity.

While many studies have estimated the transformation of agricultural inputs into outputs through a standard production function approach, few have ventured into opening the "black box" of this approach, or understanding the many and complex factors that influence total factor productivity (TFP) in agriculture, whether in terms of efficiency changes that measure a country's progress in "catching up" to the production frontier in agriculture, or technical changes that measure a country's progress in "pushing out" the production frontier in agriculture.

This chapter addresses this issue by grounding a production function analysis within a comprehensive innovations systems approach to agricultural production. The innovation systems approach examines sets of heterogeneous actors who interact in the generation, exchange, and use of agriculture-related knowledge in processes of social or economic relevance, as well as the institutional factors that condition their actions and interactions (Spielman and Birner, 2008). In effect, the approach moves our inquiry away from a more linear, input-output model of innovation through research, development, and dissemination, to a model of innovation that mirrors a web of related individuals and organizations that learn, change and innovate through iterative and complex processes.

Using variables that characterize a given country's agricultural innovation system (AIS), we utilize a stochastic frontier production function analysis to estimate the production possibility frontier under a given innovation system and a given level of input use to determine where each country stands in relation to this frontier. Conditional on this distance, we estimate the technical efficiency of agriculture for each country.

This chapter is organized as follows. Section 2 briefly reviews the literature on cross-country analysis of variations in agricultural productivity and the recent contributions of the innovation systems approach to this literature. Section 3 discusses the empirical model and the data used in the econometric estimation while section 4 focuses on results and discussion. Section 5 concludes the chapter.

3.2 Agricultural Innovations System Framework

The literature on how total factor productivity changes over time in agriculture is largely tied to the study of investment in agricultural research and development (R&D). Griliches (1964, 1963) provides some of the earliest empirical guidance on the contributions of R&D to the estimation of an agricultural production function. Seminal work by Hayami and Ruttan (1971) enhances the theoretical structure of this relationship with their induced innovation model in which sustained agricultural growth results from technological changes that are induced by agents' responses to changes in relative factor endowments and prices. Evenson and Kislev (1973) and Evenson (1974) provided further empirical evidence that the transfer and dissemination of technology and knowledge across geographic and national boundaries is an essential determinant of agricultural productivity growth, and is accelerated by a given country's imitative capacity but impeded by agro-ecological differences between regions and countries.

This work gave rise to an extensive literature in the field of economics on the rates of returns to agricultural research, including research produced during Asia's Green Revolution that was associated with the introduction of semi-dwarf rice and wheat varieties, as well as many other productivity-enhancing interventions that followed in subsequent decades. In essence, these studies evaluate how investments in agricultural R&D change the ratios in which agricultural inputs are transformed into outputs, how the net benefits of the investment are distributed between consumers and producers, and how the returns on alternative investment opportunities compare. Subsequent studies extended the conceptual, methodological, and empirical frontiers of these seminal works.

One important vein of this literature relates to the collection and analysis of data. Pardey (1989) and Pardey (1991) provide an early treatment of this topic by designing and collecting indicators on public investments in agricultural R&D. Evenson (2003) contributes with an effort to measure innovative performance with indicators that capture country stocks of "innovation capital" and "imitation capital." Other studies attempt to compile and analyze hard-to-get innovation-related indicators such as agricultural research organization performance (Peterson and Perrault, 1998); biotechnology research capacity in developing country's national agricultural research systems (NARS) (Byerlee and Fischer, 2002); private investment in agricultural research in Asia (Pray, 2001); and changes in agricultural TFP (Coelli and Rao, 2005).

The main difference between these approaches and the innovation systems approach is the degree to which R&D-related indicators are perceived as the key drivers of changes in productivity. Arguably, a narrow reliance on R&D indicators omits the contributions of other factors to changes in productivity.

To give more structure to this idea of "other factors," we consider an agricultural innovation system as a theoretical construct that contributes to productivity growth through four main components: knowledge and education, business and enterprise, bridging institutions, and the enabling environment, based broadly on a construct developed by Arnold (2001) and extended to the realm of agriculture and agricultural development by Spielman and Birner (2008).

In this construct, the key domains of an innovation system are described as follows. The knowledge and education domain captures the contribution of agricultural research and education to technological change, and is essentially the component most frequently measured and examined in the economics literature cited above. The business and enterprise domain captures the set of value chain actors and activities that leverage outputs from research and education for commercial purposes, and is typically far less measured in the economics literature on agricultural development. Bridging institutions represent the domain in which individuals and organizations facilitate the transfer of knowledge and information between the knowledge and business domains, and tend to capture the role of non- or quasi-market actors in the innovation process. This includes, for example, public extension services, farmer organizations, or political processes and platforms that are inclusive of rural communities. Circumscribing these domains are the enabling or frame conditions that foster or impede innovation, including: public policies on innovation and agriculture; informal institutions that establish the rules, norms, and cultural attributes of a society; and the behaviors, practices, and attitudes that condition the ways in which individuals and organizations within each domain act and interact. See Spielman and Birner (2008) for a more complete description of this construct of an agricultural innovation system.

To date, the literature on innovation systems in agriculture has avoided the use of formal models like the one explored in this chapter. Rather, the innovation systems literature has focused on descriptive and context-specific analysis of how technological and institutional changes occur around a given market or commodity, and how diverse actors influenced this process of change (see, e.g., World Bank (2006)). However, the growing popularity of this approach among scientists and policymakers alike necessitates more rigorous testing of questions such as whether the approach - with its nuanced recognition of the complexity within developing-country agriculture - translates into a better understanding of the drivers behind productivity growth. If so, then a better understanding can assist public policymakers, private entrepreneurs, and civil society interests in allocating resources to agricultural development more effectively.

3.3 A stochastic frontier production function

We use a translog stochastic production frontier that accounts for technological change and unobserved country level fixed effects

$$lny_{it} = \alpha + \sum_{k=1}^{K} \beta_k lnx_{kit} + 0.5 \sum_{k=1}^{K} \sum_{j=1}^{J} \beta_{kj} lnx_{kit} lnx_{jit} + \phi_1 t + \phi_2 t^2 + \sum_{i=1}^{n-1} \delta_i D_i + V_{it} - U_{it} \quad (3.1)$$

where y_{it} is the value of net agricultural production for country i at time t; x_{kit} is an (l x k) vector of the values of inputs of production for country i at time t; β is a (k x 1) vector of parameters to be estimated; t is a time trend that accounts for technological change and it enters the production function in a quadratic form to allow technological change to potentially affect both average output as well as marginal rates of technical substitution; the D_i's are n-1 country dummy variables that control for unobserved country fixed effects where i indexes countries; ϕ_1, ϕ_2, and δ_i are parameters to be estimated; V_{it} is iid $N(0, {\sigma_v}^2)$ random error, independently distributed of the U_{it}; U_{it} is a non-negative random variable associated with the technical inefficiency of production which is assumed to be independently distributed, such that U_{it} is obtained by truncation of the normal distribution with mean $z_{it}\phi$ and variance σ_u^2; and z_{it} is an (l x m) vector of inefficiency explaining variables with the corresponding unknown (m x 1) vector of coefficients, ϕ.

Factors that affect the technical inefficiency, U_{it}, of a country's agriculture are specified as

$$U_{it} = \theta + z_{it}\phi + \varepsilon_{it} \quad (3.2)$$

where z_{it} refers to a vector of inefficiency explaining variables coming from the different domains of the agricultural innovation system discussed in the preceding section, representing the environment under which agricultural production takes place in the countries under consideration. θ and ϕ are parameters to be estimated. The ε_{it} term refers to normally distributed error terms.

Our empirical strategy is to use the innovation system variables to directly influence the stochastic component of the production frontier by estimating equation 3.1 and equation 3.2 simultaneously in one step. Maximum likelihood estimation of the translog stochastic frontier model is conducted using panel data for 45 developing countries between 2008 and 2010. Our hypothesis in this study is that the different components of the agricultural innovation system will significantly affect the technical efficiency of agricultural production.

As implied by microeconomic theory, the regularity conditions of homogeneity and symmetry restrictions are imposed on the translog specification as follows (Coelli et al., 2005).

Symmetry:

$$\beta_{kj} = \beta_{jk} \ \forall \ k, j; \tag{3.3}$$

Linear homogeneity of output in inputs:

$$\begin{gathered} \sum_k \beta_k = 1; \ and \\ \sum_k \beta_{kj} = \sum_j \beta_{kj} = 0 \ \forall \ k, j; \end{gathered} \tag{3.4}$$

The technical efficiency of country i at time t is given as

$$TE_{it} = exp(-U_{it}). \tag{3.5}$$

3.4 Data

Data for this study cover 45 low-income and lower-middle-income countries between 2008 and 2010. According to the classification by the World Bank, these are countries with a per-capita gross national income (GNI) of $4,036 or less and the classification is done based on the countries' GNI per capita in the middle year, 2009. We restrict the countries to low-income and lower-middle-income countries to make the productivity and efficiency analysis among comparable countries.

The dependent variable, output, is defined as the value of net agricultural production in 1,000 international dollars. These international prices are derived using a Geary-Khamis formula for the agricultural sector and are used to avoid the use of nominal exchange rates and facilitate more accurate cross-country comparisons (FAOSTAT, 2013). The method assigns a single price to each commodity regardless of the country where it was produced (FAOSTAT, 2013).

Inputs to agricultural production, measured as follows, are obtained from FAOSTAT (2013). Fertilizer is measured in tones of inorganic plant nutrients consumed in agriculture by a country in a given year. Land is measured in terms of arable land in thousand hectares. Agricultural labor is measured in thousands of total economically active population in agriculture. The livestock variable represents the sheep-equivalent of cattle, buffaloes, pigs, sheep, and goats. The conversion factors are 8.0 for buffalo and cattle, 1.0 for sheep, goat, and pigs (Hayami and Ruttan, 1970). Total area equipped for irrigation is measured in thousands of hectares.

We use gross capital formation as a share of GDP from the (World Bank, 2013) as proxy for capital. This variable consists of outlays on additions to the fixed assets of the economy plus net changes in the level of inventories but it includes non-agricultural sectors as well.

Average annual precipitation data is obtained from the Climate Research Unit of the University of East Anglia (Climate Research Unit, 2013) through direct communication with the researchers.

The variables that are used to explain the character and performance of a given country's agricultural innovation system are obtained from the World Economic Forum (Various years) and the (World Bank, 2013) as follows. The knowledge and education component is measured by: the quality of the educational system (World Economic Forum, Various years); the quality of scientific research institutions (World Economic Forum, Various years); number of scientific and technical journal articles (World Bank, 2013); and gross enrollment ratio of primary school (World Bank, 2013). We expect all the variables in the knowledge and education domain to be efficiency enhancing as they facilitate the generation, distribution and acquisition of better ways of production.

One of the limitations of this study is that most of the innovation system variables do not pertain directly to agricultural production due to a general absence of sector-specific data for all countries during the period under consideration. Hence, a cautious interpretation of the coefficients that recognizes the proxy nature of the variables to their agriculture specific counterparts is called for because the proxies may not perform well to the extent that there is a systematic difference in these variables between agriculture and the general economy.

The business and enterprise indicators were assumed to affect agricultural productivity and efficiency through their influence on the nature and performance of business and business innovation in the agricultural sector as well as through the quality of institutions and infrastructure that enable business innovation in agriculture. Variables in this domain include the number of business start-up procedures that include interactions to obtain necessary permits and licenses and to complete all inscriptions, verifications, and notifications to start operations (World Bank, 2013); time required to start a business measured in the number of days needed to complete the procedures to legally operate a business (World Bank, 2013); total tax rate as a percent of commercial profits (World Bank, 2013); and ease of access to loan with only a good business plan and no collateral (World Economic Forum, Various years) ranging from 1 (impossible) to 7 (very easy).

Bridging institutions that facilitate the transfer of knowledge and information between the knowledge and business domains are represented by the degree of university-industry research collaborations (World Economic Forum, Various years) that measures the collaboration between the business community and local universities in the area of R&D ranging from 1 (minimal or non-existent) to 7 (intensive and ongoing); mobile cellular subscriptions per 100 people (World Bank, 2013); and number of internet users per 100 people (World Bank, 2013).

To capture the enabling environment, we use indicators that measure the underlying quality of governance and related institutions that directly or indirectly influence the performance of the agricultural sector. Specifically, we use the World Bank's strength of legal rights index that measures the degree to which collateral and bankruptcy laws protect the rights of borrowers and lenders and thus facilitate lending. The index ranges from 0 to 10, with higher scores indicating that these laws are better designed to expand access to credit. In addition, we use net official development assistance (ODA) received per capita measured in US dollars (World Bank, 2013). The direction of relationship between ODA and the level of inefficiency is arguably either positive or negative depending on whether development assistance is reinforcing public sector commitment in agriculture or crowding it out and/or creating a sense of complacency by aid-receiving countries. Other variables in the enabling environment domain include health expenditure per capita (World Bank, 2013) and agricultural policy costs that measure the level of support to agriculture vis-à-vis other sectors of the economy (World Economic Forum, Various years). The agricultural policy costs variable ranges from 1 (excessively burdensome for the economy) to 7 (balances the interests of taxpayers, consumers, and producers).

3.5 Results and Discussion

The results in Tables 3.1 and 3.2 are from maximum likelihood estimations of three different specifications of the stochastic frontier translog production function. The production frontier and the inefficiency effects model are estimated simultaneously in one step, even though we present the coefficients separately in Table 3.1 and Table 3.2 below for easy exposition. In model I, the regularity conditions of homogeneity is not imposed on the model and no country-level fixed effects are included to control for country level unobserved heterogeneity. The average technical efficiency score for this model is 0.84 and most of the production inputs as well as inefficiency explaining variables are statistically insignificant. In model II, we have imposed the homogeneity conditions consistent with microeconomic theory, but still country level unobserved heterogeneity is not controlled for. The average technical efficiency score in this model is 0.71 and the coefficients appear to be estimated with better precision as most of the production inputs and inefficiency effects become statistically significant.

The results from model II shows that number of scientific journal articles published, primary school enrollment rate, quality of research institutions, and high number of internet users improve the technical efficiency of agriculture in these countries while higher tax rates and aid per capita are detrimental to improvements in efficiency. However, model II exhibits the unexpected negative impact of higher university-industry collaboration and quality of education on agricultural efficiency. The results in model II, are likely to be biased and inconsistent because the model does not take into account unobserved country-level heterogeneity.

Our preferred specification, Model III, is theoretically consistent in terms of having the proper regularity conditions imposed on the model and in addressing country-level unobserved heterogeneity through country dummy variables. In addition, the country-level dummy variables allow the production function to have different intercepts for each country, which, along with having comparable lower income and lower middle income countries in the sample, helps issues related with estimating a single production frontier for the countries. Model III shows that the mean technical efficiency score among these countries is about 0.97, showing limited potential (approximately 3.1 percent) to increase production through efficiency gains at the current level of inputs. Two inefficiency effects that stand out to be statistically and economically significant in our preferred model in terms of affecting technical efficiency of agriculture are the investments the countries make in improving education and health. Table 3.2 shows that quality of education from the knowledge and education domain, and health expenditure per capita from the enabling environments domain improve technical efficiency, implying that strengthening quality of education and health have productivity improving effects in other sectors such as agriculture. However, most of the remaining inefficiency explaining variables become statistically insignificant in this preferred model, possibly because the level of inefficiency to be explained is small.

Model III shows evidence that the impact of precipitation in affecting agricultural production is more pronounced when accompanied by a good amount of agricultural labor and land under irrigation (Table 3.1). Output is highly responsive to agricultural labor, and the impact of labor increases in countries with bigger land size under irrigation.

The inefficiency scores are estimated against the components of the innovation systems approach. The variables from the innovations systems framework are allowed to directly influence the stochastic component of the production function which is achieved by estimating the production function and the inefficiency effects (equations 3.1 and 3.2) simultaneously. In doing this, we avoid the problem that failure to include environmental variables in the first stage causes such as biased estimators of the deterministic part of the production frontier and biased predictors of technical efficiency (Coelli et al., 2005).

The mean level of technical efficiency in 2008, 2009, and 2010 is about 97 percent (Table 3.3). After accounting for country fixed effects, agriculture in most of these countries appears to be efficient with the implication that policies to improve agricultural production should better focus on investments that push the production frontier outward. However, it is to be noted that technical efficiency is a relative measure, so the frontier is only for the sample of countries included in the estimation. Thus, the result means that the technical efficiency among the sampled low-income and lower-middle-income countries is equal, not high. If developed countries are included in the sample and are more efficient, then agriculture in the low income countries could reveal to be low, with the implication that there could still be more room for efficiency gains.

The technical efficiency of Morocco's agriculture has shown a 21 percentage point increase between 2008 and 2010. Mongolia, Zambia, Cameroon, Kenya, Cambodia, Guyana, and Tanzania have also registered improved efficiency between 2008 and 2010 with changes in efficiency scores in the range of 4 to 9 percentage points (Figure 3.1). As shown in Figure 3.1, Armenia is the country whose agricultural efficiency dropped significantly from about 99% to 82% in the three years under consideration. Tajikistan, Honduras, Egypt, Guatemala,

Table 3.1: Maximum Likelihood Estimates of the Translog Production Frontier

	Model I			Model II			Model III		
Regularity restrictions	No			Yes			Yes		
Country Fixed Effects	No			No			Yes		
Mean Efficiency Score	0.84			0.71			0.97		
Parameter	Estimate	s.e.		Estimate	s.e.		Estimate	s.e.	
Intercept	-24.271	28.136		23.471	9.016	**	21.919	9.524	**
Land	1.782	2.467		7.348	1.096	**	0.920	1.636	
Livestock	4.099	3.786		-2.427	1.447	*	-3.784	1.808	**
Fertilizer	-0.828	1.180		-2.378	0.483	**	0.150	0.263	
Irrigation	-0.183	1.523		0.422	0.354		1.070	1.082	
Labor	-1.750	1.221		-0.142	0.643		3.144	1.133	**
Precipitation	0.862	1.567		-2.530	0.750	**	0.238	0.506	
Capital	-1.193	3.601		0.707	0.994		-0.737	0.608	
Land-precipitation	-0.030	0.118		0.037	0.040		-0.068	0.053	
Livestock-precipitation	-0.064	0.125		0.165	0.054	**	-0.008	0.049	
Capital-precipitation	-0.351	0.219		-0.203	0.042	**	-0.008	0.051	
Fertilizer-precipitation	-0.120	0.084		0.035	0.038		-0.045	0.019	**
Irrigation-precipitation	0.016	0.103		-0.166	0.046	**	0.062	0.025	**
Labor-precipitation	0.173	0.112		-0.029	0.039		0.091	0.041	**
Land-labor	0.026	0.090		-0.027	0.036		0.125	0.154	
Livestock-labor	-0.031	0.069		-0.001	0.061		-0.159	0.112	
Capital-labor	0.111	0.204		-0.134	0.052	**	0.024	0.037	
Fertilizer-labor	0.028	0.046		-0.059	0.038		-0.005	0.017	
Irrigation-labor	-0.193	0.057	**	-0.022	0.038		0.268	0.089	**
Land-irrigation	0.029	0.082		0.223	0.040	**	0.056	0.081	
Livestock-irrigation	0.072	0.069		-0.041	0.029		-0.195	0.096	**
Capital-irrigation	0.087	0.099		0.020	0.043		-0.001	0.027	
Fertilizer-irrigation	-0.057	0.041		-0.014	0.031		-0.001	0.015	
Land-fertilizer	-0.112	0.080		-0.205	0.059	**	-0.030	0.030	
Livestock-fertilizer	0.067	0.063		0.240	0.046	**	0.014	0.023	
Capital-fertilizer	0.127	0.118		-0.020	0.049		0.066	0.029	**
Land-capital	-0.397	0.300		0.117	0.051	**	-0.095	0.038	**
Livestock-capital	-0.115	0.189		0.014	0.067		0.041	0.052	
Land-livestock	0.021	0.195		-0.565	0.101	**	-0.078	0.159	
Land square	0.079	0.182		0.420	0.078	**	0.090	0.270	
Livestock square	-0.240	0.264		0.188	0.121		0.384	0.177	**
Capital square	1.885	0.608	**	0.205	0.061	**	-0.027	0.062	
Fertilizer square	0.120	0.027	**	0.023	0.043		0.000	0.011	
Irrigation square	0.102	0.051	**	-0.001	0.035		-0.189	0.076	**
Labor square	0.175	0.136		0.272	0.069	**	-0.345	0.161	**
Precipitation square	0.289	0.130	**	0.162	0.035	**	-0.025	0.051	
γ	0.741	0.262	**	0.970	0.017	**	1.000	0.000	**
σ^2	0.071	0.074		0.081	0.023	**	0.004	0.002	**

Note: 44 country dummies are suppressed. ** and * denote significant at 5 and 10% levels

Table 3.2: Efficiency Effects from the AIS Framework

	Model I		Model II			Model III		
Regularity restrictions	No		Yes			Yes		
Country Fixed Effects	No		No			Yes		
Inefficiency Effects	Est.	S.E.	Est.	S.E.		Est.	S.E.	
Intercept	0.283	1.990	1.000	1.235		-0.038	0.358	
Time trend	0.205	0.194	0.218	0.084	**	-0.006	0.029	
Time trend square	-0.050	0.044	-0.048	0.020	**	0.010	0.007	
Knowledge and Education Domain								
Quality of education	-0.029	0.309	0.286	0.165	*	-0.195	0.109	*
Journals	0.000	0.000	-0.013	0.004	**	0.000	0.000	
Primary school enrollment	-0.004	0.011	-0.011	0.005	**	0.000	0.002	
Quality of research institutions	-0.023	0.295	-0.691	0.255	**	0.010	0.103	
Business and Enterprise Domain								
Business start-up procedures	0.002	0.037	-0.042	0.029		0.004	0.010	
Total tax rate	0.000	0.002	0.004	0.001	**	-0.001	0.001	
Time required to start business	0.004	0.010	-0.001	0.005		-0.003	0.002	
Access to loan	-0.108	0.344	-0.043	0.214		0.120	0.076	
Bridging Institutions Domain								
University-industry collaboration	-0.248	0.464	1.152	0.240	**	-0.055	0.097	
Internet users	-0.004	0.020	-0.062	0.017	**	0.004	0.004	
Mobile subscriptions	-0.002	0.007	-0.003	0.004		0.002	0.001	
Enabling Environment Domain								
Ag policy cost	0.357	0.586	-0.223	0.152		0.117	0.073	
Official development assistance	-0.001	0.002	0.006	0.002	**	0.000	0.001	
Health expenditure per capita	0.000	0.003	0.001	0.002		-0.002	0.001	*
legal rights index	0.000	0.045	0.031	0.034		0.006	0.014	

Note: 44 country dummies are suppressed for brevity.
** and * denote significant at 5 and 10% levels.
These inefficiency effects are estimated with the production function simultaneously in one step.

Table 3.3: Mean Technical Efficiency Scores

Mean Efficiency (2008-2010)				0.97			
	2008	2009	2010		2008	2009	2010
Mean Efficiency	0.97	0.97	0.96		0.97	0.97	0.96
Albania	0.98	0.99	1.00	Kenya	0.96	0.98	1.00
Angola		0.99	1.00	Kyrgyzstan	1.00	0.97	0.97
Armenia	1.00	0.97	0.82	Madagascar	1.00	0.97	0.95
Benin	1.00	0.98	1.00	Malawi	0.89	1.00	0.91
Bolivia	0.98	1.00	0.99	Mongolia	0.85	0.98	0.94
Burundi	0.99	1.00	0.97	Morocco	0.79	0.94	1.00
Cambodia	0.96	0.99	1.00	Mozambique	1.00	0.99	0.98
Cameroon	0.95	0.99	1.00	Nicaragua	0.99	0.95	1.00
China	1.00	0.98		Pakistan	0.95	1.00	0.92
Cte dIvoire	1.00	0.93	1.00	Paraguay	0.99	0.77	0.98
Ecuador	0.98	1.00	1.00	Philippines	1.00	0.97	0.90
Egypt	0.89	0.91	0.80	Rwanda		0.98	0.98
El Salvador	1.00	0.95	0.99	Senegal	1.00	0.99	1.00
Ethiopia	0.98	1.00	0.99	Sri Lanka	0.99	1.00	1.00
Gambia	1.00	0.97	1.00	Syria	0.98	0.99	0.96
Georgia	0.99	1.00	0.97	Tajikistan	0.99	0.96	0.90
Ghana	0.98	1.00	0.98	Tanzania	0.93	0.92	1.00
Guatemala	0.97	0.93	0.91	Thailand	0.98	0.99	
Guyana	0.94	0.95	1.00	Uganda	0.99	0.98	0.95
Honduras	0.98	0.87	0.89	Ukraine	0.99	1.00	0.95
India	1.00	0.97	0.99	Viet Nam	0.97	0.99	0.94
Indonesia	1.00	1.00	0.97	Zambia	0.92	0.99	1.00
Jordan	1.00	1.00					

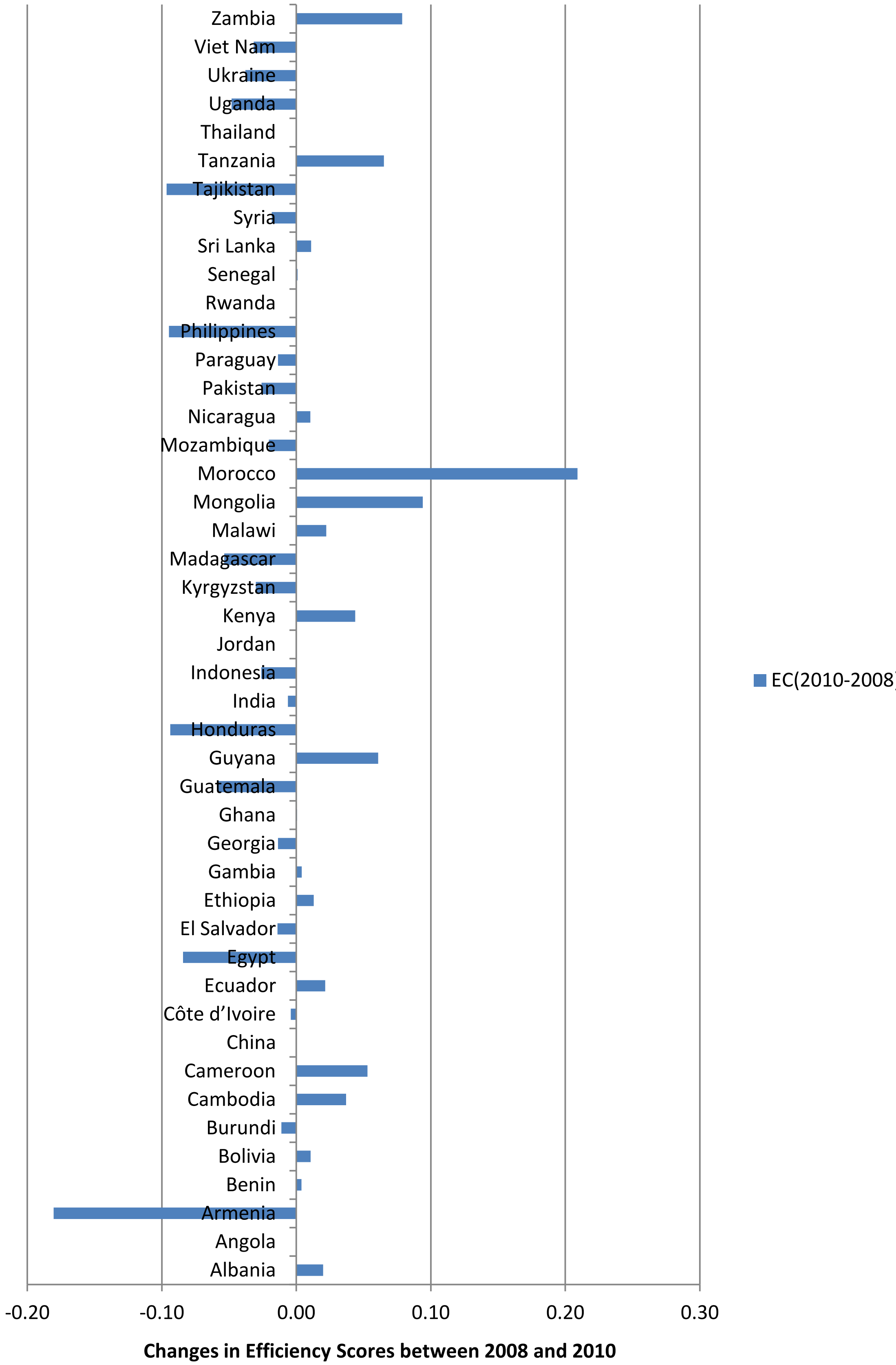
and the Philippines are the other countries whose agriculture exhibit big losses in technical efficiency scores between 2008 and 2010.

3.6 Conclusion

The chapter uses a stochastic production frontier to estimate the levels of technical efficiency of agriculture for 45 developing countries between 2008 and 2010. A translog stochastic production frontier is modeled in such a way that agricultural innovation systems framework and indicators of its different domains (the knowledge and education domain, the business and enterprise domain, the bridging institutions domain, and the enabling environment domain) serve as an environment that determine the level of technical inefficiency. The production function and the inefficiency effects were estimated simultaneously.

The results show that the mean level of technical efficiency among the sampled countries is about 97 percent, showing limited potential (approximately 3.1 percent) to increase production through efficiency gains at the current level of inputs. This calls for a focus on investments that push the technology frontier outward in these countries. Agricultural production in Morocco, Mongolia, Zambia, Cameroon, Kenya, Cambodia, Guyana, and Tanzania has shown efficiency improvements between 2008 and 2010 while efficiency dropped in countries such as Armenia, Tajikistan, Honduras, Egypt, Guatemala, and the Philippines.

Figure 3.1: Technical Efficiency Changes between 2008 and 2010



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