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A Stochastic Metafrontier Approach

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Abstract

This study adopts the stochastic metafrontier approach to investigate the role of soil conservation in small-scale highland agriculture in Ethiopia. Plot-level stochastic frontiers and metafrontier technology-gap ratios were estimated for three soil-conservation technology groups and a group of plots without soil conservation. Plots with soil conservation were found to be more technically efficient than plots without. The metafrontier estimates showed that soil conservation enhances the technological position of naturally disadvantaged plots.

Key Words: Soil conservation, technical efficiency, metafrontier, technology adoption, Ethiopia

JEL Classification: Q12, Q16, L25

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Haileselassie A. Medhin and Gunnar Köhlin*

Introduction

Agriculture is the fundamental economic activity in Ethiopia. It provides livelihoods for more than three-fourths of the country's population and accounts for half of the gross domestic product. The bulk of the agricultural output comes from mainly subsistent small-holders concentrated in the highlands, which are home to more than 80 percent of Ethiopia's population (World Bank 2004). Ethiopian highland agriculture is characterized by high dependency on rainfall, traditional technology, high population pressure, and severe land degradation—compounded by one of the lowest productivity levels in the world.

According to World Bank (2005) estimates, in the period 2002–2004, the average yield was 1318 kg/hectare, which is less than 60 percent of other low-income countries and less than 40 percent of the world average. There were only three tractors per arable area of 100 square km. (The average was 66 tractors for low-income countries generally.) Moreover, the agricultural value-added per Ethiopian worker during this period was US$ 123 (in 2000 US dollars), while it was $375 for low-income countries and $776 for the whole world (World Bank 2005). As a result, Ethiopia has been one of the top food-aid recipients for decades.

In the period 1998–2000, the inflow of food aid was more than triple that of total commercial imports (WRI 2005). The Ethiopian highlands have some of the most degraded lands in the world (Hurni 1988). According to Swinton et al. (2003), over 10 million hectares will not

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be able to support cultivation by 2010. Given such complex environmental and technological constraints, it is a daunting challenge for development agents to design efficient policies and strategies to boost agricultural productivity in order to keep up with the ever-growing population.

Soil and water conservation (SWC) is one of the most important farm technologies for improving agricultural productivity in areas with high land degradation and limited access to modern inputs.[1] As with any other farm technology, SWC is subject to the complexities of farmers' choices. That is, its successful adoption depends on the nature of the maximization problem each farmer faces. Much of the scarce economic literature on SWC is concentrated on this issue of adoption. Most of the studies stress the point that expected yield increase is not the only factor farmers take into consideration in their decision on which technology to adopt. Additional factors include risk behavior and time preference (Yesuf 2004; Shively 2001; Shiferaw and Holden 1999), land tenure issues (Swinton et al 2003; Alemu 1999), off-farm activities and resource endowment (Grepperud 1995; Shively 2001), yield variability effect (Shively 1999), and public policies and market structure (Diagna 2003; Yesuf et al. 2005; Holden et al. 2001).

The economics literature investigating the impact of soil and water conservation shows mixed results. Using nationwide Ugandan plot-level data, Byiringaro and Reardon (1996) found that farms with greater investment in soil conservation had much better land productivity than the average. Nyangena (2006), after controlling for plot-quality characteristics that affect the probability of soil conservation investment, concluded that soil and water conservation increased the yield of degraded plots in three districts in Kenya.

On the other side, Kassie (2005) used plot-level data from a high rainfall area in north-western Ethiopia with a long history of soil conservation, which indicated that returns from non-conserved plots were higher than from conserved plots—even for plots with similar endowments. He also pointed out the inappropriateness of the technology for the local area as the main reason for the negative effect. But, he also stressed that, although the soil conservation structures affected yield negatively by becoming breeding stations for pests and weeds, their advantage as sources of natural grass for fodder could offset their adverse effect. Holden et al.

[1] Nyangena (2006) also notes that inorganic fertilizers could have negative environmental externalities if not properly used.

(2001), too, used data from an Ethiopian highland village and found that conservation technologies had no significant positive short-run effect on land productivity. Shively (1999) assessed the effect of hedgerow contours relative to conventional tillage practices for low-income farms in the Philippines. These results indicated that, although hedgerows can increase yield over time, they also increased yield variability. Given the risk-aversion behavior of poor farmers, the study indicated that establishing hedgerows was not necessarily a better production strategy than conventional practices.

Two points are worth mentioning about the existing literature on the role of SWC in small-scale highland agriculture. First, the results are very case specific, both in the type of SWC and in the agro-ecological characteristics of the study areas. Therefore, one cannot generalize about the impact of SWC on agricultural productivity generally. Second, the divergence of empirical results is partly related to methodological differences, which in turn emanates from the desire to establish theoretically sound and empirically efficient methodological approaches

Based on a concept of productivity decomposition, this study aims to contribute to the assessment of the role of SWC in small-scale farming. Economic theory indicates that productivity change can be decomposed in to two sources: change in technology and change in efficiency (Coelli et al. 1998). In this terminology, "technological change" means pushing the production possibility frontier (PPF) outward, and "improving efficiency" means producing as close as possible to the available PPF. A vital relationship between the two is that a change in technology can also bring a change in efficiency. Most importantly, the effect of technological change on efficiency can be positive or negative. Hence, it can be said that the effect of a SWC technology, as observed in yield change, is the net effect of the two sources: the direct technology effect and the indirect efficiency effect. The existing literature on the yield effect of soil conservation does not distinguish between these two sources of productivity change.

Decomposing the yield change into technology and efficiency effects could have important policy relevance. It has been mentioned above that the application of SWC has shown mixed results with respect to yield. Interventions could be better targeted if it were possible to disentangle these results and show in which circumstances the proposed technology is simply inappropriate as opposed to inefficiently utilized.

2. Conceptual Framework

The main goal of this study was to apply such a decomposition as just mentioned. This task included two steps. First, plot-level stochastic production functions and technical efficiencies were estimated. This gave us a chance to examine the determinants of technical efficiency (TE) in relation to SWC. Second, efficiency gaps were estimated by testing for any technology gaps between plots cultivated under different SWC technologies. A careful look into the role of SWC in the nature of the technology gaps, accounting for plot characteristics, was the core goal of the study.

2.1 Efficiency and Its Measurements

Farrell (1957) proposed that the efficiency of a firm consists of two components: technical efficiency (TE) and allocative efficiency (AE). TE is the ability of a firm to obtain maximum output from a given set of inputs. Thus, technical inefficiency occurs when a given set of inputs produce less output than what is possible given the available production technology. Allocative efficiency is the ability of a firm to use the inputs in optimal proportions, given their prices and the production technology (see Coelli et al. 1998).

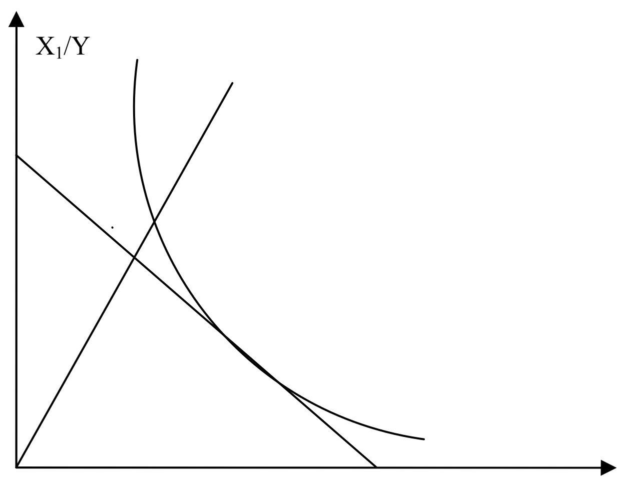
A technically inefficient producer could produce the same outputs with less of at least one input, or could use the same inputs to produce more of at least one output. In short, if there is technical inefficiency, there is a room to increase output without increasing input amounts at the present level of technology.

Farrell (1957) illustrated efficiency measures with the help of diagrams using two types of measures, namely, input-oriented measures and output-oriented measures. Input-oriented measures tell us the amount of input quantity that can be proportionally reduced without changing the output quantities. Output-oriented measures tell us the amount of output quantities that can be proportionally expanded without altering the input amounts used. The choice is a matter of convenience as both approaches are expected to give similar measures, at least theoretically. The input-oriented approach is adopted in this study.

Figure 1 is a simple representation of the measurement of efficiency using conventional isoquant and isocost diagrams. Assume a firm which produces output Y, using two inputs X_1 and X_2. SS' is a set of fully efficient combinations of X_1 and X_2 which produce a specific amount of output Y*—an isoquant. Similarly, AA' is a minimum cost input-price ratio or simply an isocost. Now assume that the actual input combination point to produce Y* is P. Clearly the firm is experiencing both technical and allocative inefficiencies. The measures can be estimated as follows:

$$TE = \frac{OQ}{OP} = 1 - \frac{QP}{OP} \tag{1}$$

Figure 1 Input-Oriented Technical and Allocative Efficiencies



Source: Coelli et al. (1998)

It is easy to see from equation (1) that TE is always between zero and 1. If the firm is fully technically efficient, or if it produces on the isoquant, OP equals OQ—which makes the value of TE unity. As technical inefficiency increases, the distance OP increases, which pushes the value of TE towards zero.

Similarly, allocative efficiency (AE) is defined as:

$$AE = \frac{OR}{OQ} \tag{2}$$

Equation (2) suggests the possible reduction in costs that can be achieved by using correct input proportions or by producing at the point where the isocost line is tangential to the isoquant line. Note that it is possible for a technically efficient point to be allocatively inefficient. More specifically, the extent of TE does not affect the level of allocative efficiency. On the other hand, an allocatively efficient point is also technically efficient, as Q' is the only allocatively efficient input mix to produce Y'.

The total economic efficiency (EE) is defined as the product of the two measures, TE and AE. That is,

$$EE = \left(\frac{OQ}{OP}\right) \bullet \left(\frac{OR}{OQ}\right) = \frac{OR}{OP} \quad . \tag{3}$$

The above efficiency measures assume that the underlining production function is known. Therefore, the estimation of the production is mandatory for the estimation of efficiency measures. Throughout the years, various methods of estimating production frontiers have been developed for the purpose of predicting reliable efficiency measures. These methods vary from deterministic and non-deterministic (stochastic) econometric models to non-econometric models. While the stochastic frontier analysis is the most commonly used among the first group, data envelopment analysis is the competent representative of the latter group. Battese (1992) indicated that stochastic frontier models better fit agricultural efficiency analysis, given the higher noise usually experienced in agricultural data. The stochastic metafrontier model is a stochastic frontier model designed to incorporate regional and technological differences among firms in an industry. In this study, we are mainly interested with the measurement of TE.

2.2 The Stochastic Metafrontier Model

As the prefix "meta" indicates, the stochastic metafrontier[2] is an umbrella of stochastic production frontiers estimated for groups of firms operating under different technologies. Hence, it is more instructive if we start with the definition of stochastic production frontier.

The stochastic frontier, first introduced by Aigner et al. (1977), was developed to remedy the constraints of deterministic models, mainly the assumption that the production frontier is common to all firms and that inter-firm variation in performance is therefore attributable only to differences in efficiency. Førsund et al. (1980) also stated that such an assumption ignores the very real possibility that a firm's performance may be affected by factors entirely beyond its control, as well as by factors under its control (inefficiency). In general terms, a stochastic production frontier can be written as:

$$Y_i = f\left(X_i ; \beta\right) e^{\left(V_i - U_i\right)} \quad i = 1,2,\ldots, n_j \ , \tag{4}$$

where Y_i = output of the i^{th} firm, X_i = vector of inputs, β = vector of parameters, V_i = random error term, and U_i = inefficiency term.

In agricultural analysis, the term V_i captures random factors, such as measurement errors, weather condition, drought, strikes, luck, etc. (Battese 1992).[3] V_i is assumed to be independently

[2] The stochastic metafrontier applied here is mainly adopted from Battese and Rao (2002), Rao et al. (2003), and Battese et al. (2004).

and identically distributed normal random variables with constant variance, independent of U_i, which is assumed to be non-negative exponential or half-normal or truncated (at zero) variables of $N(\mu_i, \sigma^2)$, where μ_i is defined by some inefficiency model (Coelli et al.1998; Battese and Rao 2002). This arises from the nature of production and/or cost functions. The fact that these functions involve the concepts of minimality or maximality puts bound to the dependent variable. To allow this, most econometric frontiers assume one-sided inefficiency disturbances (Førsund et al. 1980).

Another important point here is the choice of the functional form of $f(\cdot)$. Battese (1992) noted that the translog or Cobb-Douglas production functions are the most commonly used functional forms for efficiency analysis. The Cobb-Douglas specification was adopted for this study. It is worth noting that each functional form has its own limitations, most of which are related to the technical convenience of the functions, and is not the result of deliberate empirical hypotheses. In this case, the robustness and the parametric linearity of the Cobb-Douglas function make it superior over other functional forms (Coelli 1995; Afriat 1972). The use of translog functions may also lead to excessive multicollinearity (Andre and Abbi 1996; Nyangena 2006).

For this application, assume that there are j groups of firms in an industry, classified according to their regional or organizational differences (or simply based on their "technology"). Suppose that for the stochastic frontier for a sample data of n_j firms, the j^{th} group is defined by:

$$Y_{ij} = f\left(X_{ij};\beta\right)e^{\left(V_{ij}-U_{ij}\right)}, \quad i = 1,2,\ldots, n_j \quad . \tag{5}$$

Assuming the production function is a Cobb-Douglas or translog form, this can be re-written as:

$$Y_{ij} = f\left(X_{ij};\beta\right)e^{\left(V_{ij}-U_{ij}\right)} = e^{X_{ij}\beta+V_{ij}-U_{ij}} \quad i = 1,2,\ldots, n_j \quad . \tag{6}$$

[3] One would argue that attributing rainfall and moisture differentials as error elements in a region known for its high dependence on rainfall and severe droughts excludes relevant variables. It is a reasonable argument. Unfortunately, the data used in this study are not endowed with such variables. However, we firmly believe that, as far as efficiency and productivity differentials are concerned, this will have a limited impact on the results for two reasons. First, the data deal with areas of similar geo-climatic characteristics. Second, the study uses cross-sectional data. Therefore, it is more likely that rainfall and drought variations would affect efficiency and productivity evenly.

We can soon see the advantage of such a representation. Think now about the "overall" stochastic frontier of the firms in the industry without stratifying them into groups. Such a frontier can be written as:

$$Y_i = f\left(X_i; \beta^*\right) e^{\left(V_i^* - U_i^*\right)} = e^{X_i \beta^* + V_i^* - U_i^*} \quad i = 1,2,..., n \; ; \; n = \sum n_j \; . \; (7)$$

Equation (7) is nothing but the stochastic metafrontier function. The super-scripts * differentiate the parameters and error terms of the metafrontier function from the group-level stochastic functions. Note that Y_i and X_i remain the same: the only difference here is that separate samples of output and inputs of different groups are pooled into a single sample. The metafrontier equation is considered to be an envelope function of the stochastic frontiers of the different groups. This indicates that we can have two estimates of the TE of a firm, with respect to the frontier of its group and with respect to the metafrontier.

Mathematically, $TE_i = e^{-U_i}$ and $TE_i^* = e^{-U_i^*}$, respectively.

The parameters of both the group frontiers and the metafrontier can be estimated using the method of maximum likelihood estimation. After estimating β and β*, it is expected that the deterministic values $X_{ij}\beta$ and $X_i\beta^*$ should satisfy the inequality $X_{ij}\beta \leq X_i\beta^*$ because $X_i\beta^*$ is from the metafrontier. According to Battese and Rao (2002), this relationship can be written as:

$$1 = \frac{e^{\mathrm{Xij}\beta}}{e^{\mathrm{Xi}\beta^*}} \cdot \frac{e^{Vi}}{e^{Vi^*}} \cdot \frac{e^{-Ui}}{e^{-Ui^*}} \; . \qquad (8)$$

Equation (8) simply indicates that, if there is a difference between the estimated parameters of a given group and the metafrontier, it should arise from a difference in at least one of the three ratios, namely the technology gap ratio (TGR), the random error ratio (RER), and the technical efficiency ratio (TER). That is,

$$TGR_i = \frac{e^{\mathrm{Xij}\beta}}{e^{\mathrm{Xi}\beta^*}} \equiv e^{-Xi(\beta^* - \beta)}, \;\; RER_i = \frac{e^{Vi}}{e^{Vi^*}} \equiv e^{Vi - Vi^*} and \;\; TER_i = \frac{e^{-Ui}}{e^{-Ui^*}} \equiv \frac{TE_i}{TE_i^*} \; . \; (9)$$

The technology gap ratio indicates the technology gap for the given group according to currently available technology for firms in that group, relative to the technology available in the who industry. Note that this assumes all groups have potential access to the best available technology in the industry. The TGR and the TER can be estimated for each individual firm.

Note from our previous graphical presentation that $0 < TE_i \leq 1$ and $0 < TE_i^* \leq 1$. It also should be the case that $TE_i^* \leq TE_i$. That is, given that the frontier function of the group containing firm *i* is enveloped by the metafrontier function, the TE of firm *i* relative to the metafrontier is at least lower than that of relative to the group frontier. Hence, the TER is expected to be greater than or equal to unity.

The random error ratio is not observable because it is based on the non-observable disturbance term V_i. Therefore, as far as estimation is concerned, equation (8) can be rewritten as:

$$1 = \frac{e^{\mathrm{Xij}\beta}}{e^{\mathrm{Xi}\beta^*}} \cdot \frac{e^{-Ui}}{e^{-Ui^*}} = TGR_i \times TER_i \ . \tag{10}$$

Combining (9) and (10) gives:

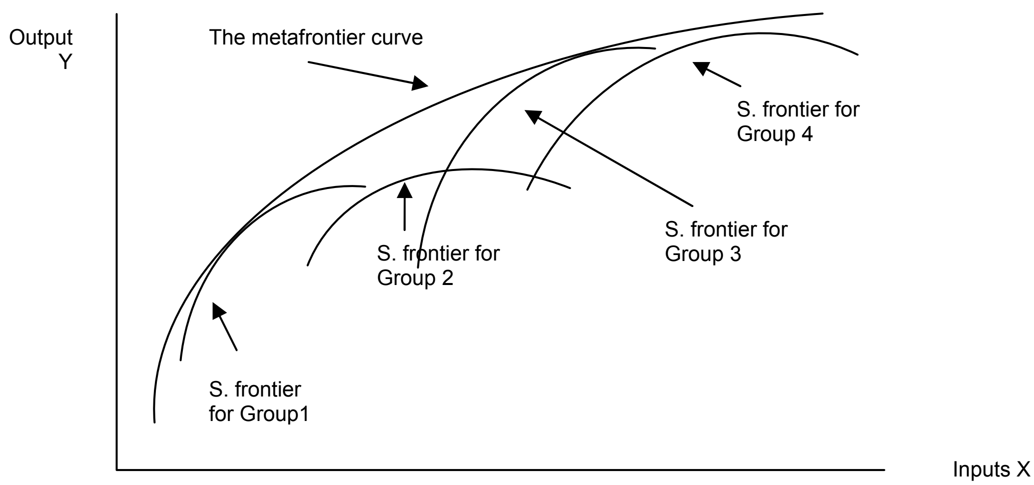
$$TE_i^* = TE_i \times TGR_i \ . \tag{11}$$

Thus, from equation (11), the TE relative to the metafrontier function is the product of the TE relative to the group frontier and the TGR of the technology group. This is a very important identity in the sense that it enables us to estimate to what extent the efficiency (hence productivity) of a given firm or group of firms could be increased if it adopted the best available technology in the industry. In our case, we used this approach to estimate the technology gap between plots with and without soil conservation and investigate the role of different soil conservation practices in defining the technology of farm plots.

2.3 Estimation of the Stochastic Metafrontier Curve

The metafrontier curve is an envelope of the stochastic frontier curves of the technology groups under discussion. If each technology group has at least one firm which uses the best technology in the industry (i.e., if the TGR for the firm is 1), the metafrontier would be the curve connecting these best-practice firms from all groups. In cases where no single firm of a given group qualifies for the best technology requirement, the stochastic frontier of the group would lie below the metafrontier curve. Stochastic frontiers for groups 2 and 4 in figure 2 are examples of this case.

Figure 2 The Stochastic Metafrontier Curve



In reality, all production points of the group stochastic frontiers may not lie on or below the metafrontier. That is, there could be outlier points to group stochastic frontiers (that is why they are stochastic!), which could be also outliers to the metafrontier. This indicates that estimating the metafrontier demands the very definition of the metafrontier as an assumption. That is, it assumes that all production points of all groups are enveloped by the metafrontier curve. Therefore, given the coefficients of group production functions, output values, and input values, estimating the metafrontier is simply the search for the meta coefficients that result in a curve which best fits to the tangent points of the frontier group production functions with best technology firms.

According to Battese et al. (2004), for a Cobb-Douglas production function (or any function log-linear in parameters) β, the metafrontier can be estimated using a simple optimization problem, expressed as:

$$\text{Minimize } \mathbf{X'}\beta$$

$$\text{Subject to } X_i\beta \leq X_i\beta^* \qquad (12)$$

In equation 12, $\mathbf{X'}$ is the row vector of means of all inputs for each technology group; β is the vector group coefficients and β^* is the vector of meta coefficients we are looking for. This is simply a linear programming problem. Each plot's production point will be an equation line in a sequence of simultaneous equation with an unknown right hand side variable. Note that βs are the maximum likelihood coefficients of the group stochastic frontier from our FRONTIER 4.1[4] estimations. The constraint inequality is nothing but the envelope assumption we pointed out above.

Once we obtain the solutions to out linear programming problem (β*s), it is easy to calculate the TGRs and metafrontier technical efficiencies. From equation (9), we know that $TGR_i = \frac{e^{\mathrm{Xij}\beta}}{e^{\mathrm{Xi}\beta*}}$; and from equation (11), we have $TE_i^* = TE_i \times TGR_i$. Note that the TE_i is already estimated in our group stochastic frontiers.

2.4 A Brief Empirical Review

A number of studies have investigated the TE of agriculture in various countries. Helfand and Levine (2004) assessed the relationship between farm size and efficiency for Brazilian farmers using the data envelopment analysis and found that the relationship is more quadratic than the usual inverse linear relationship. It also indicated that type of tenure, access to institutions, and modern input use have a significant relationship with efficiency differences. Coelli and Battese (1996) used a stochastic frontier analysis for three villages in India. Their results indicated that farm size, age of household head, and education are positively related with TE. Battese at al. (1996) found the same results for four agricultural districts of Pakistan. On the other hand, Bravo-Utreta and Evenson (1994), although they found significant levels of inefficiency for peasant farmers in Paraguay, found no clear relationship of the high inefficiency with the determinants.

Very few studies have assessed the relationship of soil conservation and efficiency. In their TE analysis of potato farmers in Quebec, Amara et al. (1998) found that efficient farmers were most likely to invest in soil conservation. Yoa and Liu (1998) assessed the TE of 30 Chinese provinces. Their results showed that efficiency differentials were significantly related to the "disaster index," which included physical characteristics such as soil, water, and infrastructure. Irrigation was also found to have positive effect on TE.

In the Ethiopian case, Admassie and Heindhues (1996) found a positive relationship between TE and fertilizer use. Seyum et al. (1998) compared farmers within and outside the Sasakowa-Global 2000 project, which primarily provided extension and technical assistance for

[4] FRONTIER 4.1 is a software commonly used to estimate production frontiers and efficiency.

farmers. Their results showed that farmers participating in the project performed better. Abrar (1998) pointed out that farm size, age, household size, and off-farm income are the major determinants of TE in highland Ethiopia.

To our knowledge, no study has used the metafrontier approach to investigate agricultural efficiency in Ethiopia. More importantly, we have not found any other study that has used the metafrontier approach to assess the role soil conservation technologies in improving agricultural productivity.

3. Data and Empirical Specification

The study is based on the Ethiopian Environmental Household Survey data collected by the departments of economics at Addis Ababa University and University of Gothenburg, and managed by the Environmental Economics Policy Forum for Ethiopia (EEPFE). The survey covers six *weredas*[5] of two important highland zones in the Amhara Region in north Ethiopia. Given the similarity of the socio-economic characteristics of the survey areas with other highland regions, we believe that the results of the study can be used to comment on policies that aim to increase the productivity of highland small scale agriculture in Ethiopia.

Due to the huge coverage of the data set in terms of crop type and land management activity, the study focused on two major crop types (teff[6] and wheat) and three main soil conservation activities, namely, stone bund terracing, soil bund terracing and bench terracing. It should be noted that, even though this data was dropped in the analysis part, plots with other soil conservation types were also included in estimating the metafrontier efficiency estimates for the sake of methodological accuracy.

The core motive for the need of the metafrontier approach to estimating efficiency is the expectation that plots under different soil conservation practices operate under different technologies. If that is the case, the traditional way of estimating efficiency by pooling all plots into the same data set may give biased estimates, as plots with better technology will appear more efficient. This indicates that one needs to test for the feasibility of the traditional approach before adopting the metafrontier. That is, we should test whether, indeed, plots under different

[5] *Wereda* is the name for the second lowest administrative level in Ethiopia. The lowest is *kebele*.

[6] Teff is a tiny grain used to make Ethiopia's most common food item, *injera*. The grain has many variants based on its color.

soil conservation practices have regularities in technical efficiency that make it useful to analyze them as different technologies. In the meantime, we will call them technology groups.

As in former studies that applied the metafrontier approach, this study uses the likelihood ratio test (LRT). To perform the LRT, separate estimations should be performed for each technology group, followed by an estimation of the pooled data.[7]

Teff and wheat crops were grouped according to the type of soil conservation applied in the 2002 main harvest season. As can be seen from table 1, there are seven SWC technology groups. The first four groups are the emphasis of this paper. The stochastic frontier will have two major parts estimated simultaneously: the production function and the technical effects. While the first part estimates the coefficients of the farm inputs and the attached inefficiency, the second part assesses the relationship between the estimated inefficiency and any expected determinants.

This indicates that we have two sets of variables, inputs and (efficiency) determinants. Except for seed, the inputs are described in table 1 for each group and for the pooled data. The determinants include plot characteristics, household characteristics, market characteristics, and social capital that are expected to affect the extent of TE. Table 2 holds the details.

Some input variables like fertilizer and manure have zero values for some plots. As the model requires input and output values to be converted into logarithms, dummy variables which detect such values were included in the production function. This means the production function part of the model has two additional variables, fertilizer dummy and manure dummy. Hence 8 input and 23 determinant coefficients were estimated for each technology group. While we identified the input coefficients as β_i, we identified the determinant coefficients as δ_i.

[7] The test compares the values of the likelihood functions of the sum of the separate group estimations and the pooled data. In a simple expression, the value of the likelihood-ratio test statistic (λ) equals $-2\{ln[L(H_0)] - ln[L(H_1)]\}$; where $ln[L(H_0)]$ is the value of the log-likelihood function for the stochastic frontier estimated by pooling the data for all groups, and $ln[L(H_1)]$ is the sum of the values of the log likelihood functions of the separate groups (Greene 2003).

Table 1 SWC technology Groups

Technology Group	Variable	Min.	Max.	Mean	Std. dev.	Var.
None *(667 plots)*	Yield(kg/ha)	6.88	10972.93	1035.87	981.43	963211.66
	Labor(days)	1.90	284.00	38.61	30.10	906.20
	Traction(days*)	.25	60.00	5.74	5.77	33.37
	Fertilizer(ETB)	.00	549.00	24.99	77.26	5970.56
	Manure(kg)	.00	6200.00	41.79	305.40	93272.22
Stone bunds *(357 plots)*	Yield(kg/ha)	60.18	8091.60	955.76	922.67	851327.08
	Labor(days)	3.50	317.00	48.97	41.86	1752.93
	Traction(days*)	.25	26.00	4.79	4.09	16.76
	Fertilizer(ETB)	.00	488.50	20.66	63.82	4073.89
	Manure(kg)	.00	930.00	58.03	152.55	23272.20
Soil bunds *(98 plots)*	Yield(kg/ha)	60.18	4744.22	815.32	667.99	446213.1
	Labor(days)	7.50	259.00	39.80	37.42	1400.54
	Traction(days*)	.50	36.00	5.23	4.61	21.27
	Fertilizer(ETB)	.00	251.00	14.16	48.85	2386.94
	Manure(kg)	.00	689.34	37.26	124.40	15477.51
Bench terraces *(106 plots)*	Yield(kg/ha)	9.94	3974.72	943.79	635.97	404464.14
	Labor(days)	7.00	210.00	47.96	35.01	1225.85
	Traction(days*)	.50	57.00	6.99	6.95	48.32
	Fertilizer(ETB)	.00	280.00	28.74	69.63	4848.94
	Manure(kg)	.00	2433.35	64.96	273.13	74605.20
Contour furrowing *(473 plots)*	Yield(kg/ha)	13.24	17263.84	1251.40	1201.68	1444035
	Labor(days)	6.00	208.00	45.16	27.07	733.1
	Traction(days*)	1.00	36.00	7.56	4.33	18.80
	Fertilizer(ETB)	.00	922.00	43.19	120.55	14533.
	Manure(kg)	.00	8050.05	43.37	412.47	170132.
Contour plowing *(97 plots)*	Yield(kg/ha)	204.15	5277.98	1432.05	917.21	841267.
	Labor(days)	13.00	109.00	44.21	21.72	471.7
	Traction(days*)	1.00	45.00	8.11	4.62	21.31
	Fertilizer(ETB)	.00	501.00	65.44	142.32	20255.
	Manure(kg)	.00	2146.68	51.86	269.64	72703.
Others *(85 plots)*	Yield(kg/ha)	38.33	2991.54	979.34	631.59	398906.
	Labor(days)	8.50	249.00	45.63	40.86	1669.1
	Traction(days*)	1.00	19.00	4.84	3.43	11.76
	Fertilizer(ETB)	.00	501.00	27.16	85.30	7276.6
	Manure(kg)	.00	17600.10	281.89	1911.80	3654970
Pooled *(1883 plots)*	Yield(kg/ha)	6.88	17263.84	1076.02	996.43	992862.
	Labor(days)	1.90	317.00	43.42	33.03	1092.1
	Traction(days*)	.25	60.00	6.15	5.14	26.37
	Fertilizer(ETB)	.00	922.00	30.57	91.80	8427.0
	Manure(kg)	.00	17600.10	57.70	504.30	254318.

Notes: Std. dev. = standard deviation; ha = hectare; ETB = Ethiopian birr; US$ 1 = ETB 8.5.
* Oxen days

Notes: Std. dev. = standard deviation; ha = hectare; ETB = Ethiopian birr; US$
= ETB 8.5
* Oxen days

Table 2 Definition of Variables

Part 1 Production function	**Part 2 Technical effects function**		
Plot output and inputs	***Plot characteristics***	***Household characteristics***	***Social capital***
***Ln*Output**: natural logarithm of kg output	**plotage**: plot age (years that the household cultivated the plot)	**Malehh:** dummy for sex of household head (1 if male, 0 if female)	**deboD**: dummy for Debo participation (1 if yes, 0 if no)
***Ln*Land**: natural logarithm of hectare plot area	**plotdishome**: distance from home (minutes of walking)	**Agehh:** age of household head in years	**trust**: number of people the household trusts
***Ln*Labor**: natural logarithm of labor (person days)	**hireD**: hired labor use dummy (1 if used, 0 otherwise)	**Educhh:** years of schooling attended by household head	**assi-inD**: dummy for any assistance received from neighbors (1 if yes, 0 if no)
***Ln*Traction**: natural logarithm of animal traction (oxen days)	***Plot Slope, meda as a base case:***	**Hhsize:** total family size of the household	**assi-outD**: dummy for any assistance forwarded to neighbors (1 if yes, 0 if no)
***Ln*Seed**: natural logarithm kg seed	**dagetD**: dummy for daget (1 if daget, 0 otherwise)	**mainacthh:** dummy for main activity of the household head (1 if farming, 0 otherwise)	
***Ln*Fert**: natural logarithm of fertilizer applied (ETB)	**hillyD**: dummy for hilly (1 if hilly, 0 otherwise)	**Offarm:** total income earned off farm throughout the year	
***Ln*Man**: natural logarithm of manure (kg)	**gedelD**: dummy for gedel (1 if gedel, 0 otherwise)	**Liv-value:** total value of livestock owned by the household	
fertD: dummy for fertilizer use (1 if used, 0 otherwise)	**LemD**: dummy for soil quality (1 if lem, 0 otherwise)	**Farmsize:** total farm size cultivated by the household in hectares	
ManD: dummy for manure use (1 if used, 0 otherwise)	***Cultivation arrangement, own cultivation as a base case:***	**Distownm:** distance to the nearest town in walking minutes	
	sharecD: dummy for share cropping (1 if share cropped, 0 otherwise)		
	rentD: dummy for rented plot (1 if rented, 0 otherwise)		
	irrigD: irrigation dummy (1 if irrigated, 0 otherwise)		

The mathematical expressions of the two parts of the stochastic frontier to be estimated are:

(the production function)

$$\ln Output_{ij} = \beta_{oj} \ln land_{ij} + \beta_{oj} \ln labor_{ij} + \beta_{oj} \ln traction_{ij} + \beta_{oj} \ln seed_{ij} + \beta_{oj} \ln fert_{ij} + \beta_{oj} \ln man_{ij} + \beta_{oj} FertD_{ij} + \beta_{oj} manD_{ij} + \exp(V_{ij} - U_{ij}) \tag{13}$$

and the technical effects function (where μ_i is the mean level of technical inefficiency[8] for plot i in technology group j, calculated from (13):

$$\mu_{ij} = \delta_{oj} + \delta_{1j} malehh_{ij} + \delta_{2j} agehh_{ij} + \delta_{3j} educhh_{ij} + \delta_{4j} hhsize_{ij} + \delta_{5j} mainactD_{ij} + \delta_{6j} offarm_{ij} + \delta_{7j} liv-value_{ij} + \delta_{8j} farmsize_{ij} + \delta_{9j} distown_{ij} + \delta_{10j} deboD_{ij} + \delta_{11j} trust_{ij} + \delta_{12j} assi-outD_{ij} + \delta_{13j} assi-inD_{ij} + \delta_{14j} plotage_{ij} + \delta_{15j} sharecD_{ij} + \delta_{16j} rentD_{ij} + \delta_{17j} irrigD_{ij} + \delta_{18j} lemD_{ij} + \delta_{19j} dagetD_{ij} + \delta_{20j} gedelD_{ij} + \delta_{21j} hillyD_{ij} + \delta_{22j} hiredD_{ij} + \delta_{23j} plotsid\,\mathrm{hom}\,e_{ij} + \omega_{ij} \tag{14}$$

(w_{ij} is a random error term.)

For each technology group, equations (13) and (14) are (simultaneously) estimated using FRONTIER 4.1. In addition to the β and δ coefficients, the TE of each plot and the log-likelihood functions are also estimated. The pooled data are also estimated in the same manner. The pooled estimation is critical to the formation of the metafrontier, as one should perform the log likelihood test described above.

If the LRT gives a green light for use the metafrontier; the next step is estimating the stochastic metafrontier function. This is done in accordance with the approach discussed in the second chapter. Note that in our model, we have 8 inputs, 7 groups, and 1883 plots.

The Mathematica 5.1 software was used to solve the linear programming problem and estimate the meta coefficients. Once we estimated the meta coefficients, it was easy to calculate the TGR and metafrontier efficiency of each plot in each technology group. Besides getting more precise estimates of TE, a major emphasis of this study was to assess the extent of the technology-based productivity differential especially between the first four soil conservation groups in table 3, if any. It should be noted that the fact that the LRT signals for the use the

[8] μ_i is discussed in appendix 1, together with the maximum likelihood estimation of TE.

metafrontier approach does not guarantee that some groups have better technology than others. That is, even if the test indicates plots with different soil conservation technologies cannot be pooled into the same frontier model, it does not necessarily guarantee that some conservation technologies have better productivity than others. Neither does it guarantee that technology gaps, if any, are only because of soil conservation, as plot technology also constitutes many other factors, some related to soil conservation adoption.

4. Discussion of Results

Productivity change is caused by efficiency and/or technology change. If the production process of farm plots involves technical inefficiency, this means that there is room for improving productivity at the presently available technology, at least in the short run. But an important point in the technology-efficiency paradigm of productivity change is that technology change may affect the level of efficiency, either positively or negatively. Therefore, a careful analysis of any effect of technology on efficiency is important as it may give a clue to why some technologies that are efficient in controlled environments fail, and why others happen to be surprisingly effective when they are applied in the real world. The hypothesis is that the hidden change in efficiency because of the technological change may be the reason. In this section, our main emphasis is looking into the relationship of SWC and the determinants of TE.

4.1 Technical Efficiency and Soil Conservation: Group Stochastic Frontiers

Table 3 summarizes the maximum likelihood coefficient estimates of the stochastic production for the different technology groups, including the pooled data. Most of the estimates are positive and significantly different from zero. Note that the parameter estimates of the pooled data are still relevant for the production function, even if the LRT rejects the pooled representation. That is, technological variability within the pooled representation will only bias the TE estimates, not the production function coefficient estimates.

Plots cultivated under all SWC technologies experience a considerable level of technical inefficiency. An important point is that plots without any SWC technology are the least efficient ones, with a TE of 0.654. At this stage, we cannot conclude that plots with SWC have higher productivity than plots without SWC because they have higher TE. Such comparison is valid only if we are sure that the two groups operate at similar technology or if the pooled

Table 3 Coefficients of the Production Function (βs)

Variable	Coefficient (t-ratio)				
	None	*Soil bunds*	*Stone bunds*	*Bench terraces*	*Pooled*
β_0	4.2487** (20.4663)	4.3130** (4.7752)	4.5430** (14.7057)	5.8685** (6.3162)	4.3618** (35.4124)
Land	0.3496** (8.0103)	0.3436* (1.6600)	0.2377** (4.3778)	0.7310** (3.8998)	0.3149** (12.0299)
Labor	0.2794** (5.9290)	0.2992 (1.6263)	0.1408** (2.5056)	0.0082 (0.04735)	0.2290** (8.4113)
Traction	0.2081** (5.3726)	-0.1521 (-1.1041)	0.3395** (6.0643)	0.3116** (2.4046)	0.2071** (8.2998)
Seed	0.2502** (10.3058)	0.2678** (2.8847)	0.1193** (3.1099)	0.0866 (1.2983)	0.2337** (15.5857)
Fertilizer	-0.0878 (-1.5757)	-0.1332 (-0.6145)	-0.0248 (-0.1993)	0.0381 (0.3887)	-0.0038 (0.1303)
Manure	0.0613 (1.1711)	0.1215 (0.6437)	0.1541** (2.3833)	-0.1461 (-1.0644)	0.0235 (0.8208)
Fertilizer use dummy	0.4230 (1.6245)	0.5533 (0.5705)	0.0575 (0.0973)	-0.0605 (-0.1352)	0.0410 (0.2832)
Manure use dummy	-0.2959 (-1.1053)	-0.3893 (-0.3986)	-0.6386* (-1.8279)	1.1504 (1.4711)	0.0116 (0.0758)

Note: ** significant at α=0.05; * significant at α=0.10

representation is valid. The value of the LRT statistic (λ) was calculated to be 371.24. The Chi-square test at 8 degrees of freedom[9] shows that this is significant at $\alpha = 0.005$.[10] That is, the null hypothesis that says the pooled stochastic estimation is a correct representation of the data is

[9] The number of restrictions is 8.

[10] $\chi^2_8(0.005) = 21.9550 < 371.24$; the null hypothesis is rejected.

rejected. Most importantly, it means that there is a significant technology differential among the four groups in tables 3 and 4.

Table 4 Mean TE and the Coefficients of the Technical Effects Function

Variable	None	Soil bunds	Stone bunds	Bench	Pooled
Mean TE	***0.65498***	***0.77971***	***0.67615***	***0.68731***	***0.67825***
δ_0	-6.8962** (-2.6735)	.10558 (0.1076)	-2.6569** (-2.0452)	-.43708 (-0.4472)	-9.6613** (-4.3111)
Sex (dummy)	1.2182* (1.7476)	-.68500 (-0.8454)	3.7077** (2.7549)	.12617 (0.1090)	1.9818** (3.7108)
Age	.04960** (2.9383)	-.00433 (-0.3123)	.02702** (2.3600)	.04447** (2.2635)	.06415** (4.8117)
Education	-.01404 (-0.4175)	-.03246 (-0.4170)	-.01417 (-0.3791)	-.11810 (-1.0822)	-.03474* (-1.8520)
Household size	02045 (0.5005)	-.00578 (-0.0520)	-.01968 (-0.3112)	.25167* (1.6728)	.07351** (2.7342)
Main activity	-1.0623* (-1.7635)	.21261 (0.2891)	-1.9442** (-2.5224)	-1.07105 (-1.0941	-.94019** (-2.9118)
Off-farm income	-.00079* (-1.8921)	-.00007 (-0.3056)	.00060* (1.8899)	-.00134 (-1.4099)	-.00064** (-3.3254)
Livestock value	-.00059** (-2.9657)	-.00030 (-1.2549)	-.00009 (-0.8834)	-.00034* (-1.8948)	-.00077** (-5.1426)
Total farm size	.21393* (1.8683)	.12783 (0.40663)	-0.2277 (-1.1995)	1.0189** (3.0714)	.2992** (3.6047)
Distance to town	.00788** (2.7139)	.00312 (0.4933)	0.0023 (0.9623)	-.00263 (-0.4255)	.00578** (3.9907)
Debo participation‡	.82177** (2.5904)	.32114 (0.6406)	-1.2368** (-2.0270)	-1.7534* (-1.6866)	.69117** (3.0831)
Trust	.29064** (2.7174)	.30401 (1.2716)	0.1730 (1.4437)	-.64733** (-2.4664)	.37709** (4.5653)
Assistance out	.08798 (0.2607)	.10665 (0.1862)	-0.1818 (-0.2995)	.24201 (0.2505)	.28926 (1.4989)
Assistance in	.54461 (1.6355)	.16024 (0.2104)	-.43070 (-0.8385)	1.24097 (1.5060)	1.4449** (4.6344)
Plot age	.00060 (0.583)	-.00979 (-0.4386)	-0.0145 (-0.71709	-.1211** (-3.7327)	-.02968** (-3.4008)
Sharecropping	.9664** (2.5071)	-.46274 (-0.4832)	-0.6560 (-1.0204)	-2.3074** (-2.3585)	-.32866 (-1.3362)

Variable	None	Soil bunds	Stone bunds	Bench	Pooled
Rented plot	2.7494** (2.3689)	-1.0917 (-1.0949)	-1.57011 (-1.3543)	.00000 (0.0000)	1.17834 (1.2167)
Irrigated plot	-1.77503 (-1.5543)	.00000 (0.000)	.45381 (0.4590)	-.66149 (-0.5901)	-.37566 (-0.3838)
Soil quality (*lem*)	1.1298** (2.9373)	.15768 (0.4681)	.29235 (1.2979)	-1.1431* (-1.8835)	.13511 (1.3065)
Slope 1: *daget*	.30071 (0.8710)	-.24226 (-0.7463)	-.40035 (-1.3371)	-.58438 (-1.0081)	-.3894** (-2.7111)
Slope 2: *gedel*	-6.3602** (-2.2769)	-.99969 (-1.1439)	.41842 (0.4611)	.61680 (0.6356)	-1.0658** (-2.3365)
Slope 3: hilly	-5.8643* (-1.8064)	.11059 (0.1106)	1.4767** (2.5999)	.00000 (0.0000)	3.76805** (4.2053)
Hired labor	-.8983* (-1.7960)	.49991 (0.5541)	-1.4379* (-1.9570)	-.87772 (-1.1541)	-1.5919** (-4.1300)
Plot distance to home	.0066* (1.6809)	.00162 (0.1325)	.00915 (1.1901)	.01137 (0.6470)	.00594** (2.4021)
Sigma 2	2.0749** (3.9425)	.2720** (2.9200)	.8152** (5.3933)	.59377** (3.6084)	2.8803** (5.9753)
Gamma	.8977** (35.8897)	.19297 (0.6559)	.7453** (11.2089)	.77165** (9.0520)	.9260** (89.1217)

Notes: ** significant at α=0.05; * significant at α=0.10
‡ See text footnote 13 for explanation of Debo project.

Before going to the details, it is important to clarify what the TE-determinant estimates in table 4 mean and what they do not mean in the presence of the technology differential. First, the estimates of the pooled specification, in the last column, are not valid any more. Second, any TE-based productivity comparison among the four groups should take into account that they operate at different technologies. That is, the fact that a given group has higher TE does not mean it is more productive: it means plots under this group operate closer to their group technology frontier, which is not necessarily the best technology frontier, compared to frontiers of other groups. Therefore, productivity comparisons are only possible only if we know the position of group frontiers relative to the best technology frontier in all groups, or the metafrontier. Third, the fact that the LRT rejects the pooled representation of the data does not invalidate the group-level TE and inefficiency-determinant coefficient estimates. It only limits their universality across technology groups: group technical inefficiency for plot *i* in technology group *j* is the potential improvement in output, if plot *i* applies the best technology available in group *j*. This will be clear when we look into our results from the stochastic metafrontier estimation.

In addition to technology differentials, it is also appropriate to deal with non-random forces that could affect output. The user cost of SWC is one such variable. Even though our data failed to give a precise estimate, some studies have shown that SWC investment takes away a considerable amount of land and labor from the production process (Shiferaw and Holden 1998; 2001). In our case, the land cost is important because the plot size in our production functions does not account for the land lost to SWC. While the labor input in our production function does not include the amount of labor spent on constructing or maintaining SWC structures,[11] the land lost is included in the plot size as if it was used for crop cultivation. Hence, every unit of output lost for every unit of land occupied by SWC structures is detected as if it resulted from technical inefficiency. This indicates that TE estimates for plots with SWC could be understated by our model, which stresses our point that conserved plots are more efficient that unconserved ones. Such downward effect is more interesting if the land cost varies with plot characteristics, as will soon be shown.

Some plot characteristics in the technical-effects model could be related to SWC adoption. In such cases, the results for each technology group should be interpreted by taking into consideration the adoption effect. If, for example, the probability of a plot being conserved increases with the plot having an attribute *i*; and if—for a given SWC technology—efficiency is positively related with attribute *i*, it is logical to suspect that it is the presence of attribute *i*—not soil conservation—that is the reason for better efficiency. On the other hand, if we have no evidence that the probability of soil conservation is related to the plot having attribute *i*, and if efficiency is positively related to attribute *i* for conserved plots and negatively related (or not related at all) for unconserved plots, we can conclude that SWC positively affects efficiency through attribute *i*. However, it should be noted that our results may not be as simple as these clean cases. This is mainly because efficiency may have various determinants which could have different effects for each conservation technology.[12]

[11] The labor cost of SWC does not affect the TE estimate, even though it could affect allocative efficiency (AE) estimates.

[12] This indicates that SWC could also be related to AE. Although the analysis of AE is far from the scope of this study, we believe that it would have helped in understanding the complex relationship between soil conservation and productivity. Among other things, this requires good price data.

It is assumed that farmers tend to conserve highly degraded plots relative to less degraded plots. In the absence of detailed soil composition data, plot slope and soil quality are the best proxies for soil degradation. That is, if highly degraded plots have a better chance of being conserved, the probability of SWC could also increase with steep slope and poorer soil quality. Table 5 shows the results of the Mann-Whitney test.

Table 5 Mann-Whitney Test for Plot Slope and Soil Quality

Plot characteristics	Hypotheses	Z-value	P-value
Slope	H_0: $Slope^C = Slope^U$ H_1: $Slope^C > Slope^U$	6.6104***	0.000
Soil quality	H_0: Soil Q^C = Soil Q^U H_1: Soil Q^C < Soil Q^U	1.4220*	0.0778

Notes: C= conserved; U = unconserved; *** significant at α = 0.01; * significant at α = 0.1

The null hypothesis that conserved plots and unconserved plots have similar slopes is rejected at a very high level of significance. That is, steeper plots have a higher likelihood of being conserved in the study areas. As for soil quality, the null hypothesis that plots with poorer soil quality get more attention in the conservation decision is not rejected unless we are willing to accept a 7.78-percent room for error. The moderate decrease in soil quality with soil conservation could be because of the negative correlation between slope and soil quality (with partial correlation of 0.158). In other words, conservation decision may be based on expected vulnerability to soil erosion rather on increasing soil quality. More specifically, farmers may choose to conserve better soil-quality plots on steep slopes rather than low quality plots on moderate slopes. This is certainly worth investigating in further research as it could be related to the risk aversion of poor farmers: invest to protect what you already have rather than upgrade what is lost.

We now have evidence that plot slope is related to the conservation decision. This indicates that any relationship between slope and efficiency should be assessed critically, taking into consideration that conserved plots have steeper slopes. From table 4, steep slope is negatively related to technical inefficiency for plots without SWC. On the other hand, steep slope is positively related to technical inefficiency for plots with stone bunds, while there is no significant relationship for the other SWC technologies. That is, unconserved steep plots have better TE than conserved steep plots. An explanation for this could be the relationship between the per-hectare land cost of SWC with plot slope. Shiferaw and Holden (2001) estimated that, for a 45-percent increase in slope, the per-hectare land lost for SWC increases by 900 percent. The fact that the negative impact of such high land costs on output is now absorbed as technical inefficiency justifies the result that the positive relationship of high slope and TE disappears with the introduction of SWC.

High soil quality and TE are negatively related for unconserved plots and positively related for plots with bench terraces. Furthermore, there is no significant relationship for plots with stone bunds and soil bunds. That is, soil conservation erases or alters the negative relationship of high soil quality and TE. This means, even though high soil-quality plots have a slightly lower likelihood of being conserved, they have higher TE than unconserved high soil-quality plots, other things held constant.

The relationship between the gender of household heads and TE is surprising. The fact that a household is headed by a male is negatively related to TE for unconserved plots and for plots with stone bunds, the relationship being stronger in the latter group. This is contrary to many studies which showed female-headed households are less efficient than male-headed households. Age of household head is also negatively related to efficiency, except for plots with soil bunds, where there is no significant relationship. Education has a non-significant positive relationship with TE for all technology groups. Unconserved and stone bund plots cultivated by household heads with farming as a main activity have higher TE. The positive relationship is more pronounced in the case of stone bunds. Off-farm income has a weak positive relationship with efficiency for plots without soil conservation and a rather weaker negative relationship for stone bund plots. Increasing livestock wealth has a small but positive effect on efficiency, although it is insignificant for stone and soil bunds. Larger total farm size has a negative relationship with efficiency, at least for unconserved plots and plots with bench terraces.

Plot distance from home has a negative effect on TE for plots without conservation, while it has no significant effect for plots with SWC. The same is true for distance to the nearest town. Sharecropping is negatively related to efficiency for unconserved plots, while it has a strong positive relationship for plots with bench terraces. Land rental is also negatively related to efficiency for plots without conservation, while it has a non-significant relationship for conserved plots. Plots which employed hired labor have better efficiency, especially if they have stone bund structures.

Unconserved plots cultivated by households who participate in Debo[13] have lower efficiency, while Debo participation is positively related to efficiency for plots with stone bunds and bench terraces. It has no significant relationship for plots with soil bunds. Unconserved plots cultivated by peasants who trust more people in their neighborhood are also less efficient than conserved plots. That is, soil conservation alters the negative relationship of higher social capital and efficiency.

The above paragraphs indicate that, in most cases, negative relationships between various plot and household attributes and TE disappear or are reversed in the presence of one of the soil conservation technologies. That is, for some reason, soil conservation positively affects the role of the determinants of efficiency. Studying the explicit aspect in which soil conservation affects the role of plot, household, market characteristics, and social capital in determining the level of TE could shed new lights on the economics of soil conservation adoption and productivity analysis. This is certainly an attractive area of further research.

It is important to note that the fact that conserved plots have higher TE does not necessarily mean they also have higher yield than plots without soil conservation. It simply means that the chosen amounts of inputs were used more effectively in the case of conserved plots. Table 6 below compares the yield and input values of plots with and without soil conservation. The average yield for plots with conservation is significantly lower than that of plots without conservation, even though the difference is not significant. Conserved plots use a significantly higher amount of labor than unconserved plots, while the latter use a higher amount of seed. The differences in manure, fertilizer, and traction are insignificant.

As can be seen in table 6, even though conserved plots have higher TE than unconserved plots, they still have lower mean yield. One reason for this is the fact that conservation decision is partly based on plot characteristics, such as plot slope and soil quality, that have a significant impact on yield in their own right. Therefore, direct yield and input comparisons can only be used to comment on the effect of productivity technologies if plots are homogenous or if the

[13] Debo is a non-profit organization focused on helping alleviate extreme poverty in rural Ethiopia. It offers a wide range of projects (education, agriculture, health, water development, and reforestation, plus microcredit and job skills training), implemented with a local, non-profit partner, Debo Yeerdata Mahiber. The agricultural projects work with rural communities "to boost food production, promote sustainable environment, and overcome poverty," primarily through reforestation to reclaim soil erosion and creation of local nurseries to supply trees. See http://deboethiopia.org/source/Programs/DeboPrograms.html.

conservation decision is independent of plot characteristics that affect output. One point that should be kept in mind is that SWC could be productivity enhancing, even if it does not lead to the highest yield, simply because it is not the only determinant of yield. The discussion of the metafrontier results in the next section elaborates this point.

Table 6 Yield and Input Use Comparison

Variable	With soil conservation		Without soil conservation		Difference	
	Mean	*Std. dev.*	*Mean*	*Std. dev.*	*With-without*	*P-value*
Yield (kg/h)	928.97	834.91	1035.87	981.43	**-106.90**	**0. 0421**
Labor (days)	47.18	39.98	38.62	30.10	**8.56**	**0.0002**
Manure (kg)	55.71	177.61	41.80	305.40	**13.91**	0.3309
Fertilizer (ETB)	21.05	62.71	24.99	77.27	**-3.94**	0.3594
Traction (oxen days)	5.28	4.91	5.74	5.78	**-0.46**	0.1391
Seed (kg)	18.05	40.74	26.19	40.18	**-8.14**	**0.0000**

Std. dev. = standard deviation; ETB = Ethiopian birr; US$ 1 = ETB 8.5.

4.2 Technical Efficiency and Technology Gaps: Metafrontier Estimation

Table 7 illustrates the results of the metafrontier estimation, in combination with the group TE results from table 4. Note that while group technical inefficiency (1 - group TE) for plot *i* in technology group *j* is the potential improvement in output if plot i applies the best technology available in group *j*. On the other hand, metafrontier technical inefficiency for plo*t i* in technology group *j* is the potential increase in output if plot *i* applies the best technology available in all groups. The mean TGR for a given group quantifies the average gap between group technology and overall technology. The maximum value, 1.000, indicates that at least one plot in the group uses the best technology available for all groups. In other words, group frontiers with maximum TGR of 1.000 are tangential to the metafrontier curve. All group frontiers are tangential to the metafrontier except for bench terraces.

Plots with soil bunds have the lowest mean TGR, 0.7806. This simply indicates that, even if all soil bund plots attain the maximum technology available for the group, they will still be about 21.9 percent away from the output that they could produce if they used the maximum

Table 7 Technology Gaps and Metafrontier TE

Technology group	Variable	Minimum	Maximum	Mean	Std. dev.
None	***TGR*** [a]	0.6134	1.0000	***0.9494***	0.09972
	Meta TE	0.1133	0.98682	***0.62061***	0.17301
	Group TE	0.1133	0.98687	***0.65497***	0.16892
Stone bunds	***TGR***	0.6558	1.0000	***0.9539***	0.08123
	Meta TE	0.12449	0.93073	***0.64607***	0.18027
	Group TE	0.14898	0.93080	***0.67614***	0.17716
Soil bunds	***TGR***	0.5264	1.0000	***0.7806***	0.08881
	Meta TE	0.15034	0.92095	***0.60600***	0.15727
	Group TE	0.17841	0.97442	***0.77970***	0.19122
Bench terraces	***TGR***	0.5499	0.9999	***0.9629***	0.08881
	Meta TE	0.13687	0.94353	***0.65748***	0.20040
	Group TE	0.13688	0.94464	***0.68733***	0.20766

* TGR= technology gap ratio; Std. dev. = standard deviation.

technology available in the whole sample. The significantly lower value of the meta TE, relative to the all higher group TE, says exactly the same. Although the potential improvement in output relative to the best technology available for soil bund plots is only 22.03 percent, it is 39.4-percent relative to the best technology available for all groups. Note that meta TE is not a real efficiency measure, per se. It only quantifies by how much output could be increased if a given group had the best technology. We can say a plot is technically inefficient only if it fails to produce the maximum attainable output using the technology it applies.

Now it is time to face the big question: is SWC a good technology?

From table 7, we see that plots without SWC have no significant technology gap, relative to plots with three SWC technologies. Moreover, it is plots with soil bunds which have the highest technology gap (lowest TGR). From these results, it seems logical to conclude that plots with SWC do not use higher technology than plots without soil conservation. This may seem a short answer to the big question, but it is not. Actually, it is not an answer to the question at all! Our question is not whether plots with SWC have better technology; it is whether SWC is a good technology. Given that a given plot's technology constitutes other factors,[14] in addition to soil conservation, it could be the case that plots without SWC have a better composite technology than plots with soil conservation—so, soil conservation could still be a good technology.

Note that this point is strictly related to our earlier finding that soil conservation adoption is dependent on plot characteristics.[15] This means adoption of a given type of SWC technology is related to a plot's prior composite technology. More specifically, SWC technology has been shown to be adopted in plots with poor conditions. In such cases, it is possible that SWC improved the composite technology of conserved plots and that, still, unconserved plots have a higher composite technology. Accordingly, we can say that a given type of SWC is a better technology if, among others, one of the following is satisfied. First, a given SWC technology is good if conserved plots could have performed worse had they not been conserved. Second, soil conservation is a good technology if unconserved plots could have performed better had they been conserved.

One way to assess these requirements is to start by answering the question of which plots have the best technology. These are the plots with a TGR very close to the value 1.000 from our metafrontier estimation. Studying the technology characteristics of these frontier plots in some detail could shed some light on the role of soil conservation. Table 8 is a summary of descriptive values and frequencies of plot characteristics that define the metafrontier technology. We have now identified the 147 plots that define the best practice in the 1228 plots that were cultivated under the four technology groups, including plots without conservation (which are 54.3 percent of the sample). Our goal was to look for the role of plot characteristics[16] in making the frontier in all conservation types. That is, we were looking for the remaining variables that defined the composite technology, besides soil conservation.[17]

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14 Plot characteristics, farming equipment, and farmer ability are also primary components of the composite technology. If plots and their farmers were homogenous, we could argue that the difference in technology is only because of soil conservation.

15 Plot characteristics could include plot slope and soil quality. For simplicity, we can identify them as natural technologies.

16 Usage of modern inputs, such as fertilizer, also affects the composite technology. But in table 6, we found that there is no significant difference in the use of such inputs between conserved and unconserved plots.

17 If we had plot-level moisture data, table 8 could have been more informative as moisture level would certainly affect the technology position of plots.

Table 8 Characteristics of Best Technology Plots

Plot characteristics		Soil conservation technology (% share)					% share in whole sample
		None	***Stone bunds***	***Soil bunds***	***Bench terraces***	***All best***	
Plot slope	*Meda*	77.3	67.9	25.0	83.3	*72.8*	*70.0*
	Dagetma	22.7	25.0	50.0	8.3	*23.1*	*26.7*
	Gedel	0	7.1	25.0	8.3	***4.1***	***2.4***
	Hilly	0	0	0	0	*0*	*0.7*
Soil quality	*Lem*	41.3	48.2	25.0	25.0	*42.2*	*40.1*
	Lem-tef	30.7	37.5	50.0	75.0	*37.4*	*41.6*
	Tef	28.0	14.3	25.0	0.0	***20.4***	***18.0***
	Other	0.0	0.0	0.0	0.0	*0.0*	*0.1*
	Chora	0.0	0.0	0.0	0.0	*0.0*	*0.1*
Soil type	*Black*	24.0	46.4	0	83.3	*36.7*	*42.0*
	Red	69.3	50.0	100.0	16.7	*58.5*	*51.1*
	Brown	1.3	0.0	0.0	0.0	*.7*	*.2*
	Gray	1.3	1.8	0.0	0.0	*1.4*	*1.9*
	Black/ red	2.7	1.8	0.0	0.0	*2.0*	*2.9*
Crop type	*White teff*	14.7	19.6	50.0	50.0	*20.4*	*29.8*
	Mixed teff	14.7	1.8	0.0	8.3	*8.8*	*12.1*
	Black/red teff	18.7	14.3	25.0	16.7	*17.0*	*24.3*
	Wheat	52.0	64.3	25.0	25.0	*53.7*	*33.8*
Number of frontier plots		75	56	4	12	147	
Total number of plots		667	357	98	106	1228	
Percentage of frontier plots		11.2	**15.6**	4.0	11.3	11.9	

The roles of plot slope, soil quality, soil type, and crop type were examined. Of the plots which define the best practice, 72.8 percent have a plain slope (*meda*), and 39.4 percent have no soil conservation technology. It is worth noting that the share of steep plots in the best-practice group increases with SWC technology. This could be again related to the fact that steep plots have a higher likelihood of being conserved. This finding asserts our earlier proposition that the positive relationship between plot slope and technical inefficiency emanates from the increase of land costs of SWC with slope. In all conservation types, good soil-quality plots also have a better share in the best technology group.

Corrected to its sample share, the stone bunds group has the highest number of plots that qualify as best practice (15.6 percent). Bench terraces, none, and soil bunds follow with shares of

11.3 percent, 11.2 percent, and 4.0 percent, respectively. This indicates that, even though the "no SWC" group has the highest share of plots in the sample space, soil conservation groups outrank it in the best plots scenario, except for soil bunds. In general, the shares of different plot-characteristics categories in the best-practice group are closely related to their shares in the sample space. An important lesson from table 8 is that plots with a better soil and topographic condition (advantaged plots), with or without SWC, still define the best technology in the survey areas. SWC helps by giving this chance to disadvantaged plots. Therefore, soil conservation is a good technology.

The metafrontier approach also gives new insights into the group-level TE estimates. The best example in our case is the soil bunds group. Although plots cultivated with soil bunds have a relatively lower technology, their high mean group TE indicates their lower technology is used more efficiently than plots cultivated with other soil conservation practices. If, in some way, their high efficiency is related to their soil bund terraces, we cannot conclude that soil bund terracing is a bad technology, as there could be a net productivity improvement. Output of plots with soil bunds could be increased by 4 percent if they were conserved with stone bunds because of better technology. On the other hand, the output of plots with stone bunds could be increased by 10.4 percent if they were conserved by soil bunds because of higher efficiency. Therefore, the output of plots with stone bunds could be increased by 6.4 percent if they were conserved by soil bunds because what matters is the net effect of technology and efficiency. Soil bund terracing is an even better technology.

5. Concluding Remarks

This study used the newly developed metafrontier approach to assess the TE of small-scale food production in the Ethiopian highlands at plot level, with the main goal of investigating the role of soil conservation technology in enhancing agricultural productivity. To this end, stochastic frontiers were estimated for four technology groups, including a group of plots without soil conservation technology. After testing for technological difference among groups, a metafrontier production curve was estimated and technology gaps of each plot in each technology group were calculated.

The group stochastic frontier estimations showed that plots with SWC technologies are relatively more efficient than plots without soil conservation. For all soil-conservation technology groups, mean technical inefficiency was regressed against various plot, household, market, and social capital variables. The results indicated that the likelihood of negative technical effects decreased with SWC. Most importantly, these results showed that that the decomposition of the yield productivity effect of farm technologies into technology and efficiency effects has, indeed, relevant policy values. Studying the aspects in which a given SWC affects efficiency could shed some light on why laboratory-effective SWC technologies underperform in the real world.

The stochastic metafrontier estimation showed that plots cultivated under different SWC practices operated under different technologies. This indicated that efficiency estimations that fail to take into account such technology differential could lead to biased results. An in-depth look at the characteristics of best-practice plots showed that SWC is a major part the definition of a plot's composite technology, but not all of it. While advantaged plots dominated the frontier regardless of their conservation status, disadvantaged plots made it to the frontier with the help of SWC. Hence, SWC proved to be good technology.

The stochastic metafrontier proved to be promising in the quest for a methodology that enables us to assess the productivity effect of new technologies or policy interventions, in industries with heterogeneous firms and production strategies. In small-scale agriculture, the prevalence of such heterogeneities is usually the biggest challenge in the design of policies and strategies to boost productivity. For example, a critical issue in the economics of SWC in small-scale agriculture is the matching problem: which SWC practice fits which agro-economic environment? One can approach this problem by performing a metafrontier estimation on plots under different agro-economic environments and identifying which SWC works better with which plot/household attributes.

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