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The Role of Soil Conservation on Mean Crop Yield and Variance of Yield - Evidence from the Ethiopian Highlands

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Abstract

Land degradation has been one of the major areas of concern in Ethiopia. Governments and development agencies have invested substantial resources to promote land management technologies and reduce land degradation. However, there is little understanding of the impacts that land management technologies have on yield and yield variability. This paper investigates the impact of stone bunds on mean yield and variance of yield, using multiple plot observations per household in low- and high-rainfall areas of the Ethiopian highlands. Our analysis incorporated the propensity score matching method, stochastic dominance analysis, and exogenous and endogenous switching regression methods. We found statistically significant and positive impact of stone bunds on yield in low-rainfall areas. This did not hold in high-rainfall areas. We did not find a statistically significant stone-bund impact on production risk in either high- or low-rainfall areas. The results were robust to both parametric and non-parametric analysis. The overall conclusion from the analysis is that the performance of stone bunds varies by agro-ecology type. This implies the need for designing and implementing appropriate technologies that enhance productivity and are better adapted to local conditions.

Key Words: Switching regression, stochastic dominance, propensity score matching, stone bunds, yield, yield risk, Ethiopia

JEL Classification Numbers: C35, O33, Q15, Q24

Contents

The Role of Soil Conservation on Mean Crop Yield and Variance of Yield: Evidence from the Ethiopian Highlands

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Introduction

The economic development of Ethiopia is dependent on the performance of the agriculture sector, and the contribution of this sector depends on how the natural resources are managed. Unfortunately in Ethiopia, the quality and the quantity of natural resources are degrading due to a multitude of factors.

Land degradation—in the form of soil erosion, depletion of nutrients, deforestation, and overgrazing—is one of the basic problems facing farmers in the Ethiopian highlands, and it limits their ability to increase agricultural production and reduce poverty and food insecurity. To sustain food production in Ethiopia, a number of land management technologies, such as soil and water conservation, have been developed and implemented over the last three decades by governmental and non-governmental institutions. Despite their promotion, the adoption of anti-land degradation measures by farmers has been limited, and land degradation remains a major threat to agricultural production in the country. Small-scale subsistence farmers have been reluctant to accept these measures, most likely due to low profitability or risks associated with the promoted land management technologies (LMTs).

The main emphasis of soil conservation in Ethiopia is on physical measures to reduce soil loss and run-off. It is not clearly known, however, if it is economically justifiable in different

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contexts to invest in soil conservation measures. To reverse the problem of land degradation, it is important to understand the actual impact of LMTs on resource-poor farmers and identify constraints that inhibit adoption of these measures. LMTs can improve agricultural productivity (e.g., Shively 1998a, 1998b; Pender and Gebremedhin 2006, Roumasset et al. 1989), and also help decrease production risk (e.g., Shively 1998; Roumasset et al. 1989). Empirical studies assessing the productivity and production risk impacts of LMTs used in the Ethiopian highlands are quite limited. The purpose of this paper is to analyze the effects of stone bunds on mean yield and variance of yield in low- and high-rainfall areas of the Ethiopian highlands.

The main contributions of this paper to the literature are threefold. First, unlike previous studies (e.g., Shively 1998a; Bekele 2005; Kassie and Holden 2006), we simultaneously controlled for possible selection bias to the regression estimates induced by observed and unobserved individual characteristics. Often in the literature, researchers only controlled for selection bias due to unobserved effects. Second, our regression and stochastic dominance analysis estimates were based on matched observations, unlike previous studies where all observations were used. This means that previous studies on conservation effects using regression and stochastic dominance analysis were not concerned with how similar treated groups (plots with conservation measures) and control groups (plots without conservation measures) are in the distribution of covariates. They might have compared incomparable observations, which would lead to incorrect conclusions on conservation effects. Third, we compared the performance of stone bunds on yield and production risk (as measured by the square of residuals from yield regression) in high-rainfall (Amhara region) and low-rainfall (Tigray region) areas of the Ethiopian highlands, using multiple plot-level data per household. This helped us understand the performances of soil conservation by agro-ecology types.

The overall conclusion from the analysis was that the impact of stone bunds varies by agro-ecology type. Stone bunds are more productive in semi-arid areas than in high-rainfall areas. The results were robust with regard to different methods. In effect, this means that in high-rainfall areas conserving moisture via physical structures may not be important, but choosing appropriate conservation measures and properly placing them (e.g., diversion ditches) could help protect soil during extreme rainfall. Furthermore, the results indicated that the hypothesis—that stone bunds reduce yield variance—was rejected in both regions. We also did not find a statistically significant impact of stone bunds on production risk.

The rest of the paper is organized as follows. Following a brief review of earlier empirical research in section 2, section 3 provides the theoretical framework. In section 4, we discuss the econometric methodology. Section 5 describes the data set, followed by empirical results and discussion in section 6. Finally, section 7 summarizes the main findings and conclusions.

2. Earlier Empirical Work

Few empirical studies have directly examined the impact of soil conservation on mean yield using econometric and cross-sectional data (e.g., Shively 1998a, 1998b, 1999; Byiringrio and Reardon 1996; Bekele 2003; Kaliba and Rabele 2004). Byiringiro and Reardon (1996) used farm-level data in Rwanda and found that farms with greater investment in soil conservation had much greater land productivity than did farms without such investment. However, the authors did not specify the type of conservation in their article. In the Philippines, using data collected at the farm level, Shively (1998a; 1998b; 1999) found a positive and statistically significant impact on yield from contour hedgerows used for conservation. In Lesotho, Kaliba and Rabele (2004) found a statistically significant, positive association between wheat yield and short- and long-term soil conservation measures. Kassie and Holden (2005) found that physical conservation measures (specifically *fanya juu*[1]) resulted in lower yield in a high-rainfall area of Ethiopian highlands, compared to plots without conservation measures. However, this study was not able to compare yield effects of conservation measures in low- versus high-rainfall areas and did not address impacts on production risk.

With a few exceptions (e.g., Shively 1998a; Kassie and Holden 2005), previous studies suffered from serious methodological and inadequate data problems. First, these other studies—except Kassie and Holden (2005)—used a single equation model that assumed that technology only had intercept effects and that the same set of variables equally affected farmers who adopted technology and those who did not. The study did not show empirically if this specification represented the reality. Second, with exception of Shively (1998) and Kassie and Holden (2005), these other studies did not take into account the endogeneity of the technology and self-selection problems. Third, again except for Kassie and Holden (2005), none of the studies accounted for unobserved household and plot heterogeneity that might affect their findings. The Kaliba and Rabele (2004) study was limited by its small sample size (50

[1] "*Fanya juu* terraces are made by digging a trench along the contour of the land and throwing the soil uphill to form an embankment. The embankments are stabilized with fodder grasses. The space between the embankments is cultivated. Over time, the *fanya juu* develop into bench terraces." (IIRR n.d.)

households) and did not control for plot characteristics. If there was a correlation between soil conservation and the quality of the plot in this study, the return to conservation might be biased.

Empirical evidence of the contribution of soil conservation to reducing yield variability across production seasons and in securing stable returns to farmers has received little attention in the agricultural economics literature.[2] As discussed by Shively (1999), when yield improvements occurred with some delay and returns were often negative in the short run, the potential impact of conservation on yield variability could be a key factor influencing the value of conservation investment to low-income farmers. Conservation measures can reduce yield variability in at least two ways. First, conservation can improve moisture retention during low-rainfall periods and thereby reduce moisture stress and enhance plant growth (Hengsdijk et al. 2005). Second, conservation technology can mitigate the consequences of flooding and thus can reduce associated crop damage and topsoil run-off during high-rainfall periods (Shively 1999; 2001).

The available empirical econometric works on the impact of soil conservation on variance of yield, using parametric regression and cross-sectional data and non-parametric analysis (stochastic dominance analysis), include Shively (1998; 1999) in the Philippines and Bekele (2003) in Ethiopia. Shively found that, controlling for the sample selection process, the impact of contour hedgerows on variance of yield turned out to be insignificant. Bekele also rejected the hypothesis that physical soil conservation results in lower yield variability.

3. Theoretical Framework

Following Shively (1997) and Just and Pope (1978), this section describes the theoretical framework we used to explain farm households' investment and production decisions. Since farm households in developing countries engaged in husbandry face production uncertainty and multifaceted market imperfection, we used an expected utility maximization framework to represent investment and production decisions made under uncertainty. Conservation effort (C) is assumed to be an essential input in the production process. The farm household's problem is defined as:

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[2] A recent agronomic study using crop and soil modelling by Hengsdijk et al. (2005) found that farmers' use of stone bunds in eastern Tigray could increase farm yields (although the optimal planting date is not known) by conserving soil moisture and allowing planting in sub-optimal conditions.

$$1)\ \max_{C,X} E[U(\pi)] = \int_0^T [E[U(\pi)]] e^{-\rho t} dt \tag{1}$$

$$s.t\ \pi_t = \{[f(C,X) + \theta h(C,X)] - q(C,X)\}\ , \tag{2}$$

where E is the expectation operator, ρ is a per-period discount factor, π is the per-period return from farming, f is the deterministic (non-stochastic) part of the output, and the function h describes how inputs and other factors influences yield variance. X is all other inputs, and θ is a random variable with mean zero. Output and input prices are normalized to 1 for ease of exposition, and $U(\ )$ is assumed to be a concave function. The additive specification in equation (2) permits increasing, decreasing, or constant marginal yield risk (Just and Hope 1978). This functional form is also important since it permits the inputs to have different effects on the mean yield and variance of yield.

The Hamiltonian for the problem, after inserting the definition of π into (1), is:

$$H = EU\{[f(C,X) + \theta h(C,X)] - q(C,X)\}\ . \tag{3}$$

The maximization of the objective function above, with respect to C, results in the following optimality condition:

$$\frac{\partial H}{\partial C} = E\left[U'\left(\left\{\frac{\partial f}{\partial C} + \theta\frac{\partial h}{\partial C}\right\} - \frac{\partial q}{\partial C}\right)\right] = 0. \tag{4}$$

A similar procedure can be followed to derive the first order conditions of other inputs.

Considering a first order Taylor series approximation of U' about expected income, $\bar{\pi}$ [3]

$$U'(\pi) = \bar{U}' + \bar{U}''(\pi - \bar{\pi})\ , \tag{5}$$

where $\bar{U}'$ and $\bar{U}''$ are U' and U'' evaluated at mean income, respectively. Further, let the Arrow-Pratt measure of absolute risk aversion be denoted by $p(\pi) = -U''(\pi)/U'(\pi)$, so that at mean income $\bar{p} = -\bar{U}''/\bar{U}'$. Then, using (4) in (3) and after some manipulation, the FOC is approximated by:

$$\frac{\partial f}{\partial C} - \frac{\partial q}{\partial C} - \left[\bar{p}\sigma^2 h(C,X)\frac{\partial h}{\partial C}\right] = 0\ . \tag{6}$$

[3] The full derivation of Taylor series approximation is available from the authors upon request.

Equation (6) is the marginal (marginal-benefit and marginal-cost) condition for adoption. For risk-neutral farmers, the term in the square bracket of (6) will disappear and adoption of technology will depend on the classical marginal conditions. For risk-averse farmers, this term is different from zero. In this case, whether farmers adopt technology will be governed by production risk and their attitude toward risk, in addition to adoption costs and other factors. Farm-specific attributes, such as plot quality and slope, may influence adoption decisions by influencing technology performance or adoption costs.

A vector of household socioeconomic characteristics can parameterize risk and risk-aversion behavior of the households (Holden et al. 1998). When market imperfections are important, inclusion of household characteristics and resource endowments in explaining investment and production decision is important (Pender and Kerr 1998; Holden et al. 2001), in addition to other determinants of investment and production decisions. For instance, imperfection in labor markets forces households to equate labor demands with family labor supply. Thus, families with a greater labor supply are more likely to adopt labor-intensive technologies. The same can be said about credit or capital market imperfections. Households with greater savings or productive assets will be able to invest if the technologies are capital-intensive. Pender and Kerr (1998) found that imperfections in labor markets led to differences in soil and water conservation investments among farmers in India (Aurepalle village), where investment was greater among households that had more adult males, had fewer adult females, and farmed less land.

Following the theoretical dynamic household model illustrated above and the empirical work of Pender and Gebremedhin (2006), we derived the following reduced form of equations for the empirical investigation of decisions to adopt stone bund and the resulting productivity and risk impacts of stone bund adoption:

$$C_{hp} = c(NC_{hp}, PC_h, HC_h, FC_h, X_v, \upsilon_{hp}) \ , \tag{7}$$

$$y_{hp} = y(NC_{hp}, PC_h, HC_h, FC_h, X_v, \varepsilon_{hp}) \ \text{, and} \tag{8}$$

$$\sigma^2_{hp} = \sigma(NC_{hp}, PC_h, HC_h, FC_h, X_v, \varepsilon_{hp}) \ , \tag{9}$$

where C_{hp} is a binary treatment variable for adoption $(C_{hp} = 1)$ if adoption takes place by household h on plot p , and $C_{hp} = 0$ otherwise); y_{hp} is the value of crop production by household h on plot p , and σ^2_{hp} is the square of residuals from mean yield regressions that approximate production risk; NC_{hp} is the “natural capital” of the plot (biophysical characteristics); PC_h is the household’s endowments of physical capital (land, livestock, radio); HC_h is human capital (education, age, and gender of household head, size of household); SC_h is financial capital (accumulation of savings); X_v are village-level factors that determine local comparative advantages (agro-ecological conditions, access to markets and infrastructure, and population density); and random factors are (e_{hp}).

Some of the conditioning variables not included in the above equations—such as conventional inputs, land tenure (land rental contract), and household specific variables (credit access and extension contact, participation in the off-farm activities and local association)—will be used to estimate the propensity score. We discuss this issue further in section 4.2.3.

4. Methodology: Econometric Estimation Challenges, Techniques and Procedures

This section will thoroughly discuss the econometric estimation challenges, techniques and procedures.

4.1 Econometric Estimation Challenges

Directly measuring the impact of soil conservation on agricultural yield using farm level data is not an easy task, given that it is fraught with methodological problems. First, we did not observe the outcome of plots with conservation if they did not have physical conservation structures (or the reverse).

Second, ex-post assessment of the gains with conservation versus without conservation was also difficult with observational data because the unobserved household and plot attributes were likely to influence soil-conservation (technology) adoption, input-application choices, and observed output. Farmers might not be randomly assigned to the two groups (adopters and non-adopters): they might make the adoption choice themselves or they might be systematically selected by development agencies based on their attributes to participate in the use of technologies.[4] Therefore, farmers who adopt technology and farmers who do not might be systematically different. These differences might manifest themselves in farm performance and could be confounded with differences due purely to adoption. This is a self-selection problem where failure to account for this would lead to inconsistent estimates of the impact of technology adoption.

[4] Farmers may also have selected plots on which to place the technology based on the attributes (observed and unobserved) of the plots. Failure to account for this might also lead to biased estimates of technology impact.

Third, even if we could account for the self-selection process and/or there was no selection problem, using a pooled sample of adopters and non-adopters (a dummy regression model where a binary indicator is used to pick up the effect of soil conservation on yield) might be inappropriate. This is because pooled model estimation assumes that the estimated parameter has the same effect across individuals and over plots regardless of their adoption status. That is to say, the same sets of covariates have the same impacts on adopters as non-adopters (with common slope coefficients for both regimes). This implies that soil conservation has only an intercept effect that is always the same, irrespective of the values taken by other covariates that determine yield (common effect). However, a Chow test of equality of coefficients for adopters and non-adopters of stone terraces [chi2 (54) = 83.21 (p-level = 0.008) and chi2 (61) = 153.29 (p = 0.000)] for Amhara and Tigray regions, respectively) rejected the equality of the non-intercept coefficients between adopters and non-adopters. This required a separate estimation of revenue functions of adopter and non-adopters.

4.2 Econometric Estimation Techniques

The following two sub-sections discuss the econometric models and methods that allowed us to control for the econometrics problems mentioned above. Two estimation techniques were considered in this paper: 1) parametric (switching regression models) and 2) non-parametric (stochastic dominance analysis and matching methods).

4.2.1 Switching yield regression model

A two-stage econometric model using a sub-sample of adopters and non-adopters was specified to investigate the impact of adopting stone bunds on mean yield. The first stage of the switching regression model was to determine those factors influencing a farm household's decision to invest in soil conservation. The adoption model (switching or selection criterion equation) can be described as follows (for ease of notation, subscripts were dropped):

$$\begin{cases} C_i = 1 \; if \;\; \omega' z_i + \upsilon_i > 0 \\ C_i = 0 \; if \;\; \omega' z_i + \upsilon_i \leq 0 \end{cases} \quad u \sim N(0,1) \;, \tag{10}$$

where $z_i \; (i = 0,1)$ is a matrix of characteristics that predicts conservation adoption, ω is an unknown parameter, υ_i is the disturbance term, and other variables are as defined above. The first subscript distinguishes the individual household h and the second distinguishes the plot p.

The second stage in the switching regression model was to estimate the separate revenue function for the two groups of plots (adopters and non-adopters), as defined below.

$$y_1 = f_1(X_{1i}, C_i) + h_1(X_{1i}, C_i)\varepsilon_{1i} \text{ if } C_i = 1 \tag{11}$$

$$y_0 = f_0(X_{0i}, C_i) + h_0(X_{0i}, C_i)\varepsilon_{0i} \text{ if } C_i = 0 \ , \tag{12}$$

where y_i denotes the value of crop production per hectare, X_i is a matrix of explanatory variables believed to influence yield, ε_{1i} and ε_{0i} are the disturbance terms, and other variables are as defined above. The non-stochastic part of the production function for adopters and non-adopters is represented by f_i. The function h_i is the stochastic part, which relates explanatory variables to the variance of yield.

Under the selection rule described above, and denoting $f(X, C)$ by $x\beta$, we have (for ease of notation, subscripts were dropped):

$$E(y_1 / C = 1) = x\beta_1 + E(\varepsilon_1 / u > -\gamma' z) \tag{13}$$

$$E(Y_0 / C = 0) = x\beta_0 + E(\varepsilon_0 / u \leq -\gamma' z) \tag{14}$$

If the expected value of the error terms in equations (13) and (14) are non-zero, regressing $y_i (i = 0,1)$ on x will yield an inconsistent estimator of β_i (Maddala 1983). The error terms $\varepsilon_0, \varepsilon_1$, and u have trivariate normal distribution, with zero mean and non-singular covariance matrix of the following structure (Ibid.).[5]

$$\begin{bmatrix} \sigma_1^2 & \sigma_{10} & \sigma_{1\mathrm{u}} \\ & \sigma_0^2 & \sigma_{0\mathrm{u}} \\ & & 1 \end{bmatrix} \tag{15}$$

To obtain unbiased estimators, equations (13) and (14) should be estimated simultaneously, using a maximum likelihood method. To simplify this estimation, however, Lee (1978) suggested a two-step procedure where the self selectivity is treated as a missing variable problem. A zero conditional mean in equations (13) and (14) can be restored by including an estimate of the selection bias terms, $E(\varepsilon_1 | u > -\gamma' z)$ and $E(\varepsilon_0 | u \leq -\gamma' z)$. These terms are proportional to the inverse mills ratios (we used λ to denote the inverse mills ratio), and depend only on the unknown parameters of equation (10) estimated by bivariate probit model. Substituting the inverse mills ratio into equations (13) and (14) yields:

$$y_1 = x\beta_1 + \sigma_{1u}\lambda_1 + \varepsilon_1 \text{ if } C = 1 \tag{16}$$

[5] The normality assumption made here is conventional but not of trivial significance (Shively 1998).

$$y_0 = x\beta_0 + \sigma_{0u}\lambda_0 + \varepsilon_0 \text{ if } C = 0 \ . \tag{17}$$

The term $\sigma\lambda$ is the truncated mean and λ defined as follows:

$$\lambda_1 = \frac{\phi(\omega' z)}{\Phi(\omega' z)} \text{ (for positive observations, } C = 1) \tag{16a}$$

$$\lambda_0 = -\frac{\phi(\omega' z)}{1 - \Phi(\omega' z)} \text{ (for the zero observations,} C = 0) \ , \tag{17a}$$

where ϕ and Φ are, respectively, the probability density and cumulative distribution function, and other variables are as defined above.

Consequently, estimation of the augmented yield regression (16) and (17), which includes the additional term (inverse mills ratio), will produce a consistent estimator of β. These additional terms were labeled control functions (Heckman and Robb 1985) and eliminated the bias induced by the endogeneity of conservation adoption. The inverse mills ratio (λ) was estimated from the probit model of equation 10. The yield equations (16) and (17) required an exclusion restriction (identification condition) that at least one variable included in the switching equation (10) was excluded from the yield equations. In this paper, we assumed that the models would be formally identified by the non-linearity of the adoption equation.

Equations (16) and (17) were referred to as a switching regression with endogenous switching, when $\sigma_{1u} = \sigma_{ou} \neq 0$, and when $\sigma_{1u} = \sigma_{ou} = 0$, these equations were defined as a switching regression with exogenous switching.

The mean yield difference between adoption and non-adoption of stone bunds is estimated as:

$$E(y_1 | C = 1) - E(y_0 | C = 0) = x(\beta_1 - \beta_0) + \sigma_{1u}\lambda_1 - \sigma_{0u}\lambda_0 . \tag{18}$$

The above approach to restore the zero conditional mean of the error terms (controlled for selection bias) was the control function approach (Heckman and Robb 1985), assuming selection was on unobservables' heterogeneity. Although this approach appeared to offer an elegant means of obtaining an estimate of the effect of conservation on the treated in the presence of selection, it had two main drawbacks. First—although in the literature it is assumed that the non-linearity of adoption equation (inverse mills ratio) serves as an identification condition—credible implementations of this approach included an instrument; that is, a variable was included in the estimation of the adoption equation that was excluded from the outcome (yields) equation (Bryson et al. 2006). However, the identification of a suitable instrument is often a significant practical obstacle to successful implementation. Second, the resulting estimates were entirely contingent on the underlying distributional assumption relating to the unobserved variables (a trivariate normal distribution). Research has shown that estimates can be surprisingly sensitive to these assumptions not being met (Puhani 2000).

A possible alternative approach—which made no functional form, identification condition, and distributional assumptions to tackle selection issues (restore zero conditional expectation) when the dataset is particularly rich, as in our case—was matching method. The basic idea was to match two observations (observations of conserved and non-conserved[6] plots), which had approximately the same plot and household characteristics x_{hp} , and which might affect both selection equation and outcome equations (yield regression) simultaneously. This helped estimate the effect of conservation by comparing one plot, which had the propensity to be conserved and did actually conserve, with another plot or plots that had the same (or very similar) propensity to be conserved, but did not actually conserved. We will return to this issue in section 4.2.3.

Finally, the panel nature of our data may also help to control for selection bias by providing the means for controlling the effects of omitted or unobserved variables.

4.2.2 Variance regression

In addition to impacts on productivity, agricultural technologies have also have an impact on production risk (e.g., Antle and Crissman 1990; Traxler et al. 1995; Kim and Chavas 2003; Shively 1998). Thus, consideration of risk plays a vital role in the choice and use of production inputs and adoption of technologies.

The square of residuals (measure of variance of yield) from the mean yield regressions is used as a dependent variable(s) in the variance regressions. Examples of previous studies used to estimate yield variability measured as the square of the residuals of yield include (Just and Pope 1979; Antle 1983; Antle and Goodger 1984; Traxler et al. 1995; Shively 1998a, 1999; Kim and Chavas 2003; Koundouri et al. 2004). Shively (1998a; 1999) and Koundouri et al. (2004) used cross-sectional data and others used time series data.

4.2.3 Propensity score matching method

[6] "Conserved" and "non-conserved" are shorthand for "with conservation measures" and "without conservation measures," respectively. Hence, a conserved plot is a plot of land on which conservation technology is being used.

The propensity score matching method is one of the non-parametric estimation techniques that do not depend on functional form and distributional assumptions. In this paper, the propensity score matching method was used for two reasons. First, we needed to produce comparable observations of conserved and non-conserved plots with the same distribution of observed characteristics that serves as an input for parametric regression and stochastic dominance analysis. This was important because conventional regression and stochastic dominance analysis estimates typically are obtained without ensuring that there comparable treated (conserved plots) and non-treated (non-conserved plots) observations actually exist for every x_i . That is, parametric regression and stochastic dominance analyses are not concerned with how similar treated groups and control groups are in the distribution of covariates. In the literature of evaluation, this refers to lack of common support. Using propensity score matching estimates the impact of conservation on yield based on common support.

Second, we used the propensity score matching method to cross-check the results obtained from parametric regression, since the conventional regression estimators achieve comparability by imposing functional form assumptions (usually linear) and extrapolating over regions of no support where there are no similar treated and non-treated observations. The evidence in Heckman et al. (1998a), Dehejia and Wahba (1999; 2002), and Smith and Todd (2005) suggested that avoiding functional form assumptions and imposing a common support condition can be important for reducing selection bias. The other advantage of using the propensity score matching method was that it was non-parametric where it avoided restrictions involved in models that require the relationship between regressors and outcomes to be specified.

Following the literature of program evaluation, let Y_1 be the value of yield when plot p is subject to treatment $(C = 1)$, and Y_0 is the same variable when a plot is exposed to the control $(C = 0)$. Let x_i denote a set of observed variables affecting both conservation decision and yields.[7]

Our main goal was to identify the average effect of treatment (*ATT*—here the conservation investment) on the treated plots (those plots that received soil conservation investment), which can be defined as:

$$ATT = E(Y_1 - Y_0 \mid C_i = 1) = E(Y_1 \mid C_i = 1) - E(Y_0 \mid C_i = 1) . \tag{19}$$

[7] For a more detailed and technical presentation of matching methods, we referred to Heckman et al. (1998b), Smith and Todd (2005), Rosenbaum and Ruben (1983), and Becker and Ichino (2000).

The evaluation problem was that we only observed Y_1 o r Y_0, but never both. $E(Y_1 \mid C_i = 1)$ could be constructed from the data. Missing was the information required to identify $E(Y_0 | C_i = 1)$, referred to as the counterfactual outcome (what would have been the yield of plots with conservation had they not had conservation, or the converse). If conservation adoption was non-random and we substituted the unobservable $E(Y_0 | C_i = 1)$ for the observable $E(Y_1 \mid C_i = 1)$ when estimating *ATT*, we ended up with selection bias equal to $E(Y_0 \mid C_i = 1)$ - $E(Y_0 | C_i = 0)$ (Wooldridge 2002).

The method of matching solved the evaluation problem by assuming that, conditional on x_i, Y_1 and Y_0 are independent of C:

$$Y_1, Y_0 \perp \mathrm{C_i} | x_i . \tag{20}$$

This was referred to as the conditional independence assumption (CIA).[8] The intuition behind this crucial assumption was that it made random treatment assignment conditional on x_{hp}, which, in a sense, ex post reproduced the essential feature of a randomized experiment. The CIA required that all sets of x_i affecting both the outcome (yield) and treatment be included in the matching. In the parametric regression, this was equivalent to saying that the error term in the probability model (probit model) used to estimate stone-bund adoption was uncorrelated with the outcomes of interest. When CIA held, we could therefore use the yields of non-conserved plots as an approximation of the counterfactual outcome. Formally expressed, we had $E(Y_0 | C_i = 1) = E(Y_0 | C_i = 0)$, which allowed for an unbiased estimation of *ATT*.

The basic idea of matching is to pair treated and non-treated observations on the basis of their observable characteristics. It assumes that selection can be explained purely in terms of observable characteristics.[9] Matching on covariates is difficult to implement when the set of covariates is large. To overcome the curse of dimensionality, Rosenbaum and Rubin (1983) showed that if matching on x_i is valid, so is matching on the propensity score $p(x_i)$. It is more matching on a single index (a scalar variable) than matching on multidimensional x_i variables.

[8] This was also the identifying assumption for the simple regression estimator. Having controlled for observables, the adoption decision was independent of the process determining outcomes (yields). In other words, observables which entered the regression captured selection into the conservation adoption decision.

[9] This was a strong assumption and ignored selection bias due to unobservables. This was more a problem to the cross-sectional matching estimator. The problem of selection bias due to unobserved effects could be solved using panel data, where each unit of analysis was observed more than once (time-series cross-sectional observations or repeated observations per unit, as in our case).

Our propensity score (response probability) was defined as the conditional probability that plot p received conservation treatment given covariates:

$$p(x_i) = pr(C_i = 1)\big| x_i \ . \tag{21}$$

Although the matching method has many desirable features, it was not without problems. The model depends on CIA and ignores selection bias due to unobservables. These problems are a function of data richness, which in our case was not a problem. We had a rich plot, household, and village-level dataset.

The question raised, when applying the propensity score (pscore) matching method, is which estimating models and matching variables to use when estimating the pscore. Smith (1997) suggested that if the choice of method is not crucial, one could use a logit or probit model. Matching methods essentially offer no guidance as to which variables to include or exclude in the conditioning sets, yet the choice of which variables to include can influence results (Heckman et al. 1998b). Selecting covariates requires choosing a set of variables that will plausibly satisfy the conditional independence assumption. However, since the CIA is an untestable assumption, the researcher will never know whether it has been met. Knowledge of the empirical and theoretical literature is thus a prerequisite for analyzing the impact of program participation (or employing soil conservation measures) when using propensity score matching.

In our paper, we depended on the theoretical framework above and the adoption and yield determinants literature to choose a set of conditioning variables which influenced both adoption decision and yields (e.g., Yesuf and Pender 2005; Pender and Gebremedhin 2006). Matching variables for the pscore were the land management practices; the "natural capital" of the plot; the tenure characteristics of the plot; the household's endowments of physical capital, human capital, financial capital, and social capital; the household's participation in off-farm activities; and village-level factors that determine local comparative advantages.

To estimate propensity scores, one has to split the sample into *k* equally spaced intervals of the pscore and, within each interval, test that the average pscore of treated and control units do not differ. If the test in one interval fails, one can split the interval further and/or include interaction and higher orders of covariates. This process is continued until, in all intervals, the average propensity score of treated (conserved plots) and control (non-conserved plots) units do not differ.[10] This is called balancing property in the literature of evaluation. For details on the algorithm of pscore matching, we referred to Dehejia and Wahba (2002).

It is rare to find two observations with exactly the same propensity score since the estimated pscore is a continuous variable. Therefore, the objective is to match a treated unit to a control unit whose propensity score is sufficiently close that they can be regarded as approximately the same. That is, one must allow for the possibility of matching in the neighborhood of the propensity score. There are a number of possible ways of doing this, such as the nearest-neighbor, kernel, and stratification matching methods. We chose the nearest neighbor matching algorithm since it enabled us to identify those observations which were actually used (matched) and save these observations for further use. (Not all controls—non-conserved plots—were necessarily used in the computation of *ATT*.)

The nearest-neighbor matching method involved taking each treated plot in turn and identifying the non-treated plot with the closest propensity score. The resulting set of non-treatment plots constituted the comparison group. It may be that a single non-treatment plot provides the closest match for a number of treatment plots. In our case, the non-treatment plot was featured in the comparison group more than once. The end result was that the comparison group was the same size as the treatment group, although the comparison group might feature fewer plots. That is, each treated plot had one match, but a non-treated plot might be matched to more than one treated plot.

In this paper, propensity score matching and *ATT* were implemented using the pscore and attnd procedures created by Becker and Ichino (2002). (The *ATT* used the nearest-neighbor matching option and a probit model to compute propensity scores.)

4.2.4 Stochastic dominance analysis

Like propensity score matching, stochastic dominance analysis (SDA) does not depend on functional form and distributional assumptions. Unlike matching and linear regression models, the entire density of yields is examined in SDA instead of focusing on the single value of mean and variance of yields. Like the propensity score matching method, SDA makes no

[10] Within each interval, the means of each characteristic are tested for differences between treated and control units. This is a necessary condition for the balancing hypothesis (see Becker and Ichino 2002).

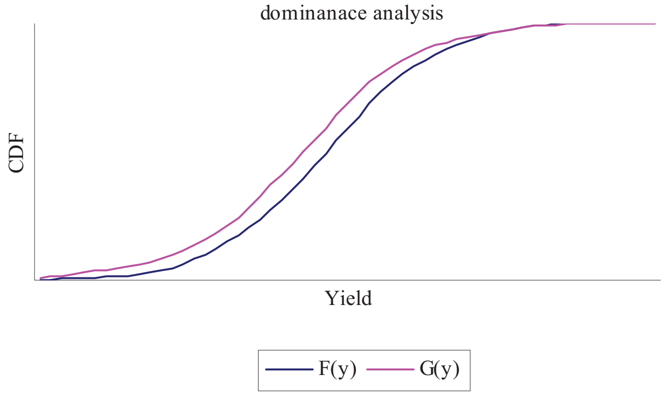
assumptions on relationship between the regressors and outcome variables, nor does it make distributional assumptions.

Two outcome distributions can be compared based on their level of return (yield) and dispersion of return. SDA is used to compare and rank distribution of alternative risky outcomes, according to their level of return (yield) and according to the dispersion (riskiness) of yield (Mas-Colell et al.1995). The comparison and ranking is based on cumulative density functions (CDF). The two dominance measures discussed below are first order stochastic dominance (FOSD) analysis and mean-normalized second order stochastic dominance (SOSD) analysis. The FOSD was used to compare the level of yields with and without conservation. The SOSD was used to compare the variability of yields with and without conservation (Mas-Colell et al.1995; Formby et al. 1999). First order stochastic dominance analysis assumes that households maximize expected utility and only prefer more yields to fewer yields. A sufficient condition for conservation with CDF $F(y)$ to first order stochastically dominates without conservation, with CDF $G(y)$ if:

$$F(y) \le G(y) \forall y \quad . \tag{22}$$

Equation (15) is graphically represented in figure 1. As can be seen from the graph, for a given level of yield y, the probability of yield greater than y is higher for F than G.

Fig 1. Graphical represenation of first-order stochastic dominanace analysis



Assuming that the decision maker (in the farm household) prefers more yield to less, the farm household will choose to take the action associated with F , as the cumulative density function always lies to the right of G .

The SOSD assumes that the farm household (i) prefers more to less and (ii) is risk averse. Given the cumulative distribution of $F(\bar{y})$ and $G(\bar{y})$ with mean-normalized yield (the distribution of yield is divided by its mean), $F(\bar{y})$ is less risky than (or second-order stochastically dominates) $G(\bar{y})$ if:

$$F(\bar{y}) \leq G(\bar{y}) \forall \bar{y}, \text{ where } \bar{y} \text{ is mean normalized yield.} \tag{23}$$

The SOSD assumes that the two distributions have the same mean. However, it is less likely to get two yield distributions with the same mean. This is the reason mean-normalized SOSD analysis is suggested to rank distributions with different means (Foster and Sen 1997).

The idea of SOSD analysis is correspondence to mean-preserving spread. If the cumulative distribution of $G(y)$ is a mean preserving spread of $F(y)$, then $F(y)$ second-order stochastically dominates $G(y)$ (Mas-Colell et al.1995). Formby et al (1999) also showed that the coefficient of variation is closely related to the mean-normalized stochastic dominance.

We assumed the most widely used Gaussian kernel-density estimate (KDE) to obtain estimates of the CDF. The challenge to compute the KDE is to select the appropriate smoothing parameter (bandwidth). There is no firm theory for choosing the bandwidth. Common applications typically use a bandwidth equal to some multiple of $n^{-1/5}$ (Green 2003). In our case, we used a bandwidth of $0.5\,n^{-1/5}$ following Bekele (2005).[11]

The SDA assumes that the difference in the yield distribution between the two states (e.g., with conservation measures and without conservation measures) is due only to technology effects. It rules out the contribution of other inputs on yield differences. For instance, differences in yield distributions that arise from differences in plot and household specific characteristics remain embedded in the distributions being compared. To minimize this problem, the SDA was based on matched observations obtained from propensity-score nearest-neighbor matching method. This helped obtain comparable non-conserved plots with the same distribution of observed characteristics as conserved plots.

Previous studies on stochastic dominance analysis using non-experimental farm-level data include Shively (1999). He compared observed yields obtained from farmers' fields with and without contour hedgerows in the Philippines. He found that the hedgerow technology did not constitute an unambiguously dominant production strategy, compared to plots without hedgerows. Bekele (2003) used a time-series Soil Conservation Research Project database from a low-rainfall area of eastern Ethiopian and found that physical conservation (level bunds) had an

[11] Using different bandwidths did not result in significant changes in the shape of the CDFs.

unambiguous dominance over the non-conservation condition. Kassie and Holden (2006) used cross-sectional farm-level data from a high-rainfall area in northwestern Ethiopia and found that yield distributions without conservation unambiguously dominated yield distributions with conservation (*fanya juu* bunds) for all yield levels.

4.3 Econometric Estimation Procedures

For the reasons mentioned above, matched observations obtained from the propensity-score nearest-neighbor matching method were used to estimate stone-bund adoption and the impacts of stone bunds on the mean yield and the variance of yield. The panel nature of our data (repeated plot observations per household or cluster-level data) allowed us to apply panel data models. The equations outlined above were modified by including individual heterogeneity effects or decomposing the error terms in equations (9) and (10) into two $(\varepsilon_{hp} = e_{hp} + u_h)$.

$$y_{hp} = x_{hp}\beta + u_h + e_{hp}, \qquad (24)$$

where y_{hp} is value of crop production per hectare obtained by household h on plot p, depending on the conservation status of the plot; u_h is the unobserved household heterogeneity that captures unreported household characteristics (such as farm management ability, average land fertility, households' risk preferences, time preferences, etc.) that affect productivity; e_{hp} is the random variable which summarizes the plot specific component other than the ones reported in the survey (such as unobserved variation in plot quality and plot specific production shocks—for example, plot level variation in rainfall, hail, frost, floods, and pest and weed infestation; x_{hp} includes both plot-invariant and variant observed explanatory variables; and β is a vector of parameters to be estimated.

Linear fixed and random effects regression models are common to apply on equation (25). In our case, we did not use a fixed effects model as we had many households with only a single plot observation, which could not play a role in a fixed effects analysis. The plot demeaning for such observation yielded all zero, which was not used in the estimation. The random effects models were consistent only under the assumption that unobserved heterogeneity was uncorrelated with the explanatory variables. The estimates are biased (heterogeneity bias) if this condition does not hold. To overcome this assumption, we used a Mundlak's (1978) approach. He approximated the unobserved effects (u_h) by a linear function and included the mean value of plot varying explanatory variables as specified below:

$$u_h = \bar{x}_h\gamma + \eta_h,\ \eta_h \sim \mathrm{iid}(0, \sigma_\eta^2)\ , \qquad (25)$$

where $\bar{x}_h$ is the mean of plot-varying explanatory variables (cluster mean), γ is the corresponding vector coefficients, and η_h are random terms and unrelated to the $\bar{x}'s$.

This approach is particularly important for a non-linear model (e.g., probit model), where differencing or the within transformation are not options for removing the individual specific effect in non-linear models due to the incidental parameter problem. The Mundlak approach relies on the assumption that the individual (unobserved) effects are correlated with the explanatory variables linearly. In our case, this approach was most important to capture average plot characteristics, such as average plot fertility, soil depth, slope, and conventional inputs use, which we assumed had more impact on production and the technology adoption decision. We had rich plot-level variables that varied over plot.

Equation (25) could be readily incorporated in the main regression equation (24) of adopters and non-adopters and yielded the following model:

$$y_{hp} = x_{hp}\beta + \bar{x}_h\gamma + \psi_{hp}\text{, where } \psi_{hp} = e_{hp} + \eta_h \ . \qquad (26)$$

The test γ=0 showed whether the regressors are correlated with the household fixed effects, and, if so, the estimation of the model redefined above allowed us to take this correlation into account.

We used the panel-data sample-selection estimation approach of Wooldridge (1995) to estimate the endogenous SR model. The basic idea is to parameterize u_h as an explicit function of the explanatory variables, in the fashion proposed by Mundlak (1978), and to add these expressions as additional regressors to the main equation. To estimate the inverse mills ratio, pooled probit regression was estimated in the first step.[12] In the second step, the main equation was estimated by pooled ordinary least squares (OLS) regression. Wooldridge showed that estimates obtained using this approach are consistent and asymptotically normal. For comparison purposes, we also estimated the pooled probit and OLS regression without unobserved effects. (We called this the traditional approach.)

We tried to address the selection bias problem by using different econometrics approaches, as mentioned in section 6. In parametric regression, we simultaneously modeled both the process of adoption decision and the process of generating yields, using matched

[12] In the selection equation, the individual effect u_h is replaced by a linear combination of the means of plot-varying explanatory variables. Including inverse mills ratio as additional regressor in equation (19) becomes an endogenous switching regression model.

observations and inverse mills ratio to control for selection due to observed and unobserved characteristics, respectively. In addition, we also used a propensity score matching method that included in the log-yield equation factors that affected both the adoption decision and yield. We assumed that individuals/plots that are the same in the observable dimension of x_{hp} or $p(x_{hp})$, but chose a different level of conservation (adopting and not adopting) which did not differ on average in the unobserved dimension. As a result, estimating the effects of conservation using matched plots might yield unbiased estimates.

The selectivity issue could also be captured using the panel nature of our data, as outlined above, if selection bias was due to plot invariant unobserved factors (household heterogeneity). The unobserved factor could be captured using Mundlak's (1978) approach in the context of our data. The selection problem based on idiosyncratic errors (plot heterogeneity) was addressed as much as possible, using observed plot quality characteristics and inputs. We had a rich dataset from which to capture plot quality. However, there still could be unobserved variations in plot quality that affect productivity and that are correlated with input use or other explanatory variables.

5. Data Sources and Types

The dataset used in this study was from a farm survey conducted in 1998 and 2000 in the Ethiopian highlands (>1500 meters above sea level) in the Tigray and Amhara regions by researchers from Mekelle University (Tigray), Bureau of Agriculture (Amhara), the International Food Policy Research Institute, and the International Livestock Research Institute. The data included household-, village-, and plot-level data. The Amhara region dataset included 435 farm households, 98 villages, 49 *kebeles*,[13] and about 1365 plots after deleting missing observations for some variables. The Tigray region dataset included 500 farm households, 100 villages, 50 kebeles, and 1178 plots. However, using a propensity-score nearest-neighbor matching estimator (see section 4) left us with a sample of 387 (232 conserved and 155 non-conserved plots) in Amhara and 618 (416 conserved and 202 non-conserved plots) plots in Tigray. (We could not compare the pscore and probit models because pscore used all sample observations, but probit used matched observations.).

[13] A kebele, or neighborhood association, is a small administrative unit of local government.

Tables A.1A and A.1T in the appendix present the descriptive statistics by region for all samples before and after matching and the sub-samples of conserved and non-conserved plots. In Amhara, 17 percent of the sampled plots had stone bunds, versus 37 percent in Tigray. Soil bunds were also used in some of the plots, but there were not enough observations to run parametric regressions on them. (Also, we believed that these were less permanent structures than stone bunds.) The average annual rainfall is 1981 mm in Amhara (we rechecked this figure, but saw no difference, given a minimum of 934 mm and maximum of 3389 mm) and 649 mm in Tigray. The mean plot altitude, which is associated closely with temperature and micro-climates, is 2178 and 2350 meters above sea level for the Tigray and Amhara regions, respectively. [For a detailed study of these areas, sampling techniques, and criteria used to select sample areas, please see Pender and Gebremedhin (2006) and Benin and Pender (2001).]

6. Results and Discussion

This section presents and discuses results obtained from the different estimation techniques and procedure discussed above.

6.1 Propensity-Score Nearest-Neighbor Matching Estimates

The propensity score (pscore) estimates were not our primary interest and, as a result, we did not include these results here. However, results from nearest neighbor method are discussed briefly. The propensity score models controlled for the plot and household characteristics are available in tables A.2A and A.2T. The balancing property was satisfied for all variables used for the computation of the propensity score.

The matching results reported in tables A.3A and A.3T are estimates of the average treatment effect (*ATT*) on the treated (conservation investment), which in our setting corresponded to the average effect on yield of plots from conservation. The outcome variable is the log of value of crop production per hectare. Our estimates demonstrated the existence of a positive, additional significant log-yield premium for conserved plots, compared to non-conserved plots in low-rainfall areas (Tigray region) of the Ethiopian highlands. However, we could not find any significant differences in yields between conserved and non-conserved plots in high-rainfall areas (Amhara region) of the Ethiopian highlands. The mean difference was negative and statistically insignificant.

6.2 Stochastic Dominance Analysis Estimates

The estimates of the SDA were based on matched observations to control for impact of other inputs on production, apart from stone bunds. Figures 2 and 3 show the cumulative density function for yields obtained on conserved and non-conserved plots. As the graph illustrates, the yield cumulative distribution with conservation is to the left of the without-conservation yield distribution for Tigray, indicating that yield with conservation first order stochastically dominated the yield distribution without conservation. The results implied that the chance of getting higher yield is higher for plots with conservation than plots without conservation, given the same probability. However, we did not see this dominance for the Amhara region dataset. These results agreed with the propensity-score nearest-neighbor matching estimates.

6.3 Estimates of the Probit Model

Although our dataset was very rich in information concerning plot-, household-, and village-related variables, nothing really prevented the possibility that, even after controlling for these characteristics and using matched observations, there might still be some other omitted variables responsible for some residual correlation between the error term in the probit model and the error term in the yield equations. The objective of probit model was to generate a regressor (inverse mills ratio) that took this correlation into account and which would enable us to obtain unbiased estimates.

Tables A.4A and A.4T in the appendix present the parameter estimates of the stone-bund adoption decision equation used in the endogenous SR model. The probit models estimates were based on matched observations. We presented two sets of results corresponding to a pooled probit model using the Mundlak approach and to the standard pooled probit model without the Mundlak approach. (We referred to this as the traditional approach, where we did not assume any correlation between household fixed effects and regressors.) The probit model results were not of primary interest in this paper. As indicated above, we used this model to drive the correction factor (inverse mills ratio), and thus did not describe them extensively. There were not as many significant parameters as in pscore estimation in each type of specification. This was perhaps not a surprising result since, in the probit estimation, we considered a comparable sample of plot observations (similar characteristics) obtained from the propensity-score nearest-neighbor matching method. Once we had comparable sample plots based on plot and household characteristics, this sample was likely to be relatively homogeneous with respect to observed characteristics.

When we looked at estimates based on the Mundlak approach, we found that some of the coefficients of the mean values were statistically significant. We were also able to reject the null hypothesis that all coefficients of the mean values (the vector γ) are simultaneously equal to zero.[14] This evidence supported the existence of correlation between explanatory variables and unobservable household fixed effects. This model was significant compared to the traditional random effects model.

6.4 Switching Regression Estimates

Tables A.5A and A-6A, and A.5T and A.6T present the linear random effects regression estimates of the treatment effect. The linear regression estimates were based on matched observations to control for possible bias to the regression estimates induced by observed household characteristics, apart from controlling for selection bias introduced by unobservables effects. We estimated both exogenous and endogenous switching regression models. In each case, the dependent variable in the analysis was the log of value of crop production per hectare. We used pooled cross-section OLS regression to estimate the endogenous SR model following Wooldridge (1995). The exogenous SR model estimated using correlated random effects models (Mundlak approach) and the standard random effects models (traditional approach). When we looked at the correlated random effects output, we found that some of the coefficients associated with the parameter vector γ were statistically significant. The chi-square test statistics rejected the null hypothesis that all coefficients of the mean values are equal to zero for all models (but not for model 1 of table A.5A). This confirmed the correlation between explanatory variables and unobservable farm-specific effects. We did not report the coefficients of each mean variable but they are available on request. The variance of the unobserved effects was also greater than zero, which confirmed the appropriateness of the use of random effects estimation instead of pooled OLS regressions.

Our parameter of interest was the mean-yield gap between conserved plots and non-conserved plots. The impact of each explanatory variable on yield was not of primary interest to us, so we did include the impact of each explanatory variable on mean yield.

[14] The results of mean variables were not reported; instead, we reported the joint significance of these variables to conserve space. Results are available from authors on request.

The predicted yield values from each regression were used to examine the mean yield gap between conserved and non-conserved plots. As indicated in table A.7A, the mean yield difference between conserved and non-conserved plots was not statistically significant for the Amhara region, although it was positive and statistically significant for the Tigray region in each specification.[15] This result was in line with the propensity-score nearest-neighbor matching estimates and stochastic dominance analysis.

From the results obtained using the three methods above, it seems that soil and water conservation is more productive in low-rainfall areas than in high-rainfall areas, as a result of greater benefits of moisture conservation in low-rainfall areas. (In high-rainfall areas, moisture conservation can contribute to water logging problems, as well as weeds and pests.) This finding is consistent with findings of other studies of conservation impacts in the Ethiopian highlands (Herweg 1993; Pender and Gebremedhin 2006; Benin 2006). In high-rainfall areas, moisture conservation with physical structures may not be important, but choosing appropriate conservation measures and placing them properly (e.g., diversion ditches) could help soil protection during extreme rainfall.

6.5 Variance Regressions

We followed the same estimation procedure for variance regressions as in yield regressions. We estimated the yield variance impact of conservation using a sub-sample of farmers who adopted conservation technology and a pooled sample of matched observations—although pooling adopters and non-adopters was rejected statistically. In each case, the dependent variable in the analysis was the square of residuals. Tables A.8A and A.8T, and A.9A and A.9T contain the results from the exogenous and endogenous switching variance regression models. Although some coefficients of the mean values were significant, the test for joint significance turned out to be insignificant in each model. We did not discuss the impact of each regressor on variance of yield as we did in yield regression estimates because our primary interest was to determine the impact of stone bunds on variance of yield. In each specification, the binary and continuous stone-bund indicator variables did not demonstrate that stone bund reduced yield variance in both regions. However, in the Amhara region, the binary variable

[15] The result was robust when potential endogenous regressors included in each specification as well as using random effects model for endogenous SR model. Results are available from authors on request.

turned out to be significant in the traditional approach (see model 4 of table A.8A). Its significance level, however, disappeared when selection due to unobserved effects was controlled for. This result should also be interpreted with caution since the impact of binary variable on risk was investigated using pooled matched observations (conserved and non-conserved plots), although the Chow test statistics rejected estimation of pooling both conserved and non-conserved plots.

The normalized second order stochastic dominance (NSOSD) analysis also did not support the hypothesis that soil conservation constituted a risk-reducing production strategy, compared to the situation without soil conservation (figures 4 and 5). To observe adequately risk effects, it may be important to have panel data (repeated observations from the same households and plots over time) on the impact of technologies on yield.

7. Summary and Conclusion

The primary objective of this paper was to investigate the effect of stone bunds on mean yield and variance of yield using multiple plot observations per household in low- and high-rainfall areas of the Ethiopian highlands. Our analysis incorporated the propensity score matching method, stochastic dominance analysis, and exogenous and endogenous switching regression methods. The switching regressions and stochastic dominance analysis were based on matched observations obtained from estimation of the propensity-score nearest-neighbor matching method. This helped compare plots with conservations measures (conserved) and plots without conservation measures (non-conserved) with the same distribution of observed characteristics. Unlike the previous studies, in this paper the impact of stone bunds on yield and variance of yield estimated controlling for simultaneously possible selection bias to the regression estimates, induced by observed and unobserved individual characteristics, using matched observations from propensity-score nearest-neighbor matching methods and the control function approach in the spirit of Heckman’s two-step approach. We also used the technique proposed by Wooldridge to estimate the endogenous switching regression model. In order to tackle the issue of potential endogeneity that arises due to the correlation between household fixed effects and the explanatory variables, we used Mundlak’s approach, where the unobserved effects were parameterized as a linear function of the mean of plot-varying explanatory variables.

The estimates from the three methods tell a consistent story. Stone bunds are productive in low-rainfall areas, compared to high-rainfall areas. We found statistically significant and positive impact of stone bunds in low-rainfall areas. However, this impact was not observed in high-rainfall areas. These results were consistent across methods and specifications. In addition to the productivity characteristics of stone bunds, their contribution to production risk is important in explaining their use by farm households. The results indicated that stone bunds have no statistically significant impact on reducing production risk in either setting, low- or high-rainfall areas. This result was robust to different methods and specifications.

Our findings have the following implications. First, the productivity impact of stone bunds is agro-ecology-specific. This highlights the importance of developing and disseminating agro-ecology-specific soil conservation technologies to increase agricultural productivity, instead of blanket recommendations of similar conservation measures. For instance, in high-rainfall areas, moisture conservation using physical structures may not be important, but choosing and properly placing appropriate conservation measures (e.g., diversion ditches) could help protect soil during extreme rainfall. Second, the risk-reducing benefits of stone bunds are insignificant. This may affect the willingness of risk-averse farmers to make conservation investments, especially when yield improvements due to conservation occur in the future—i.e., with some delay—and returns are often negative in the short run. However, to make a robust conclusion on the impact of stone bunds on risk, we suggest further research based on a time-series, cross-sectional household survey because single-cross-sectional survey data may not clearly show yield variability.

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Appendices

Figures

Figures 2–5

Figure 2. Impact of stone bunds on Crop yield in Tigray region

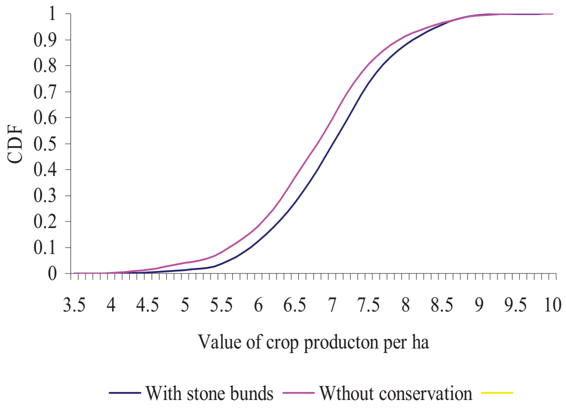


Figure 3. Impact of stone bunds on crop yield in Amhara region

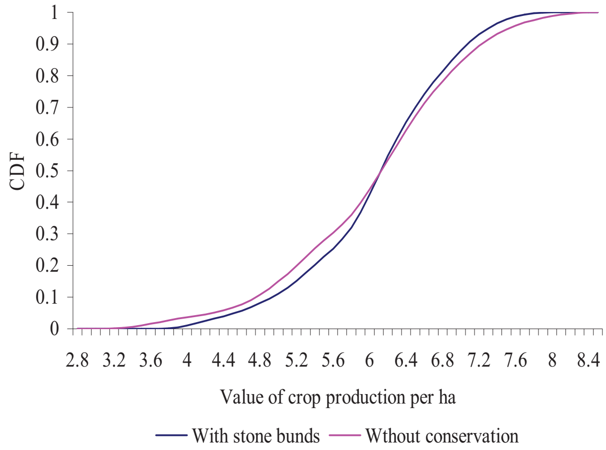


Figure 4. Impact of stone bunds on yield variability in Tigray Region

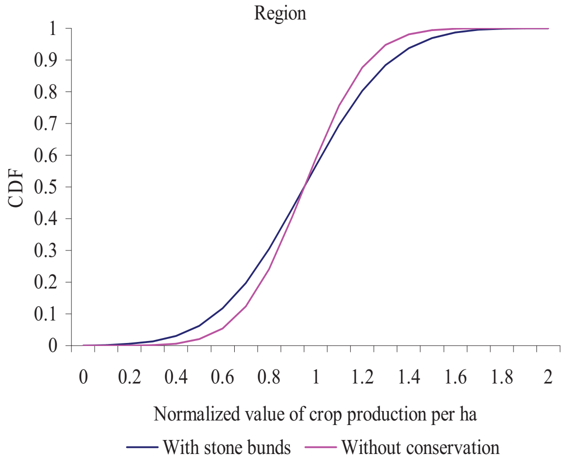
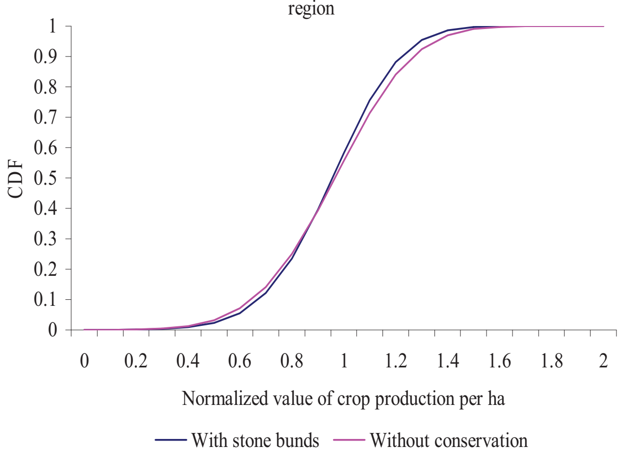


Figure 5. Impact of stone bunds on yeild variability in Amhara region



Tables

Table A.1A Descriptive Statistics of Variables for the Amhara Region

Variables	Mean 1 (std. error)	Mean 2 (std. error)	Mean 3 (std. error)	Mean 4 (std. error)
Value of crop production per hectare	636.029 (632.525)	620.771 (522.673)	594.331 (443.078)	660.345 (622.603)
Male household head	0.954	0.974	0.983	0.961
Family size (total number of members)	6.802 (2.563)	6.571 (2.262)	6.591 (2.156)	6.542 (2.418)
Age of household head (years)	44.689 (12.340)	46.711 (12.224)	47.151 (12.183)	46.052 (12.295)
Livestock holding in TLU	2.918 (2.391)	2.391 (1.777)	2.332 (1.774)	2.479 (1.783)
Education level (years)	2.614 (3.378)	2.602 (3.258)	2.603 (3.186)	2.600 (3.372)
Total farm land holding (hectares)	1.766 (1.235)	1.389 (0.734)	1.393 (0.717)	1.382 (0.761)
Credit access	0.445	0.388	0.384	0.394
Extension frequency contact	1.707 (1.522)	1.938 (1.536)	1.957 (1.511)	1.910 (1.576)
Participation in off-farm activity	0.261	0.305	0.306	0.303
Plot size (hectares)	0.386 (0.351)	0.416 (0.270)	0.431 (0.276)	0.393 (0.260)
Plot slope (degree)	5.547 (5.964)	8.114 (6.947)	8.034 (5.609)	8.232 (8.589)
Black soil plots	0.310	0.354	0.358	0.348
Brown soil plots	0.274	0.333	0.362	0.290
Gray soil plots	0.070	0.106	0.086	0.135
Deep soil plots	0.237	0.150	0.138	0.168
Medium soil plots	0.538	0.587	0.591	0.581
Moderately eroded plots	0.315	0.530	0.556	0.490
Severely eroded plots	0.095	0.119	0.108	0.135
Clay soil plots	0.122	0.070	0.078	0.058
Loam soil plots	0.431	0.372	0.362	0.387
Sandy soil plots	0.118	0.150	0.147	0.155

Variables	Mean 1 (std. error)	Mean 2 (std. error)	Mean 3 (std. error)	Mean 4 (std. error)
High fertile plots	0.104	0.041	0.039	0.045
Medium fertile plots	0.697	0.724	0.724	0.723
Plots in middle slope position	0.273	0.432	0.422	0.445
Plots in bottom slope position	0.147	0.196	0.207	0.181
Plots not on slope	0.440	0.189	0.181	0.200
Waterlogged plots	0.109	0.111	0.095	0.135
Gully plots	0.048	0.057	0.052	0.065
Altitude (m.a.s.l.)	2350.388	2409.912	2377.013	2459.155
Plot distance to residence (minutes)	17.026	15.729	15.233	16.471
Plot distance to main road (minutes)	143.274	172.437	173.534	170.794
Plot distance to market (minutes)	78.438	85.817	86.224	85.206
Population density per km^2	0.429	0.457	0.456	0.460
Annual rain fall (mm)	1981.108 (594.800)	1920.181 (654.720)	1851.093 (601.234)	2023.591 717.115)
Fertilizer use (kg per hectare	32.940 (71.240)	20.512 (54.305)	14.769 (40.470)	29.107 (69.360)
Seed use (kg per hectare)	40.379 (171.389)	55.448 (283.770)	61.738 (347.515)	46.033 (143.310)
Labor use (man-days per hectare)	33.303 (39.974)	31.620 (31.052)	33.274 (31.038)	29.145 (31.008)
Rented-in plots	0.108	0.057	0.052	0.065
Improved seed use dummy	0.091	0.059	0.043	0.084
Reduced tillage plots	0.146	0.266	0.284	0.239
N	1365	387	232	155

Notes: Standard errors for dummy variables were not reported.
m.a.s.l = meters above sea level
TLU = tropical livestock units
Mean 1 = Refers to mean and standard errors (se) of variables from total sample before matching
Mean 2= Refers to mean and se of variables from matched sample (after matching)
Mean 3 = Refers to mean and se of variables with conservation of matched sample
Mean 4 = Refers to mean and se of variables without conservation of matched sample

Table A.1T Descriptive Statistics of Variables for the Tigray Region

Variables	Mean 1 (std. error)	Mean 2 (std. error)	Mean 3 (std. error)	Mean 4 (std. error)
Value of crop production per hectare	1774.252 (2372.698)	1546.902 (616.026)	1634.152 (1682.932)	1367.216 (1456.234)
Plots in middle slope position	0.219	0.278	0.305	0.223
Plots in bottom slope position	0.238	0.265	0.262	0.272
Plots not on slope	0.430	0.311	0.274	0.386
Gently sloped plots	0.304	0.382	0.409	0.327
Steeply sloped plots	0.089	0.128	0.147	0.089
Deep soil plots	0.372	0.367	0.356	0.391
Medium soil plots	0.421	0.477	0.493	0.446
Brown soil plots	0.142	0.172	0.188	0.139
Gray soil plots	0.226	0.257	0.252	0.267
Red soil plots	0.393	0.387	0.382	0.396
Loam soil plots	0.353	0.413	0.416	0.406
Clay soil plots	0.314	0.299	0.308	0.282
Sandy soil plots	0.102	0.121	0.113	0.139
Moderately eroded plots	0.285	0.332	0.358	0.277
Severely eroded plots	0.066	0.095	0.101	0.084
Stone-covered plot	0.236	0.322	0.351	0.262
Mildly waterlogged plots	0.083	0.070	0.065	0.079
Severely waterlogged plots	0.030	0.019	0.019	0.020
Fenced plots	0.048	0.052	0.060	0.035
Gully plots	0.035	0.042	0.046	0.035
Plot distance from residence (hours)	0.315	0.292	0.275	0.326
Improved seed plots	0.045	0.045	0.053	0.030
Rented-in plots	0.157	0.113	0.106	0.129
Reduced tillage plots	0.125	0.126	0.137	0.104
Burning-to-prepare plots	0.094	0.118	0.115	0.124
Mixed / intercropped plots	0.139	0.152	0.161	0.134
Irrigated plots	0.037	0.011	0.010	0.015
Participation in off-farm activity	0.265	0.275	0.293	0.238
Credit access	0.711	0.736	0.736	0.738
Member of rural institutions	0.170	0.181	0.192	0.158

Variables	Mean 1 (std. error)	Mean 2 (std. error)	Mean 3 (std. error)	Mean 4 (std. error)
Extension contact	0.177	0.181	0.195	0.153
Distance to market (hours)	2.843	3.077	3.126	2.976
Male household head	0.900 (12.765)	0.896 (12.422)	0.909 (12.182)	0.871 (12.868)
Household size (total number of family members)	5.961 (2.052)	6.061 (1.990)	6.091 (1.988)	6.000 (1.998)
Education of household head (1–2 grade)	0.081	0.091	0.094	0.084
Education of household head (3+ grade)	0.063	0.053	0.050	0.059
Oxen (number)	1.410 (.917)	1.341 (0.874)	1.320 (0.876)	1.386 (0.869)
Other cattle (number)	3.585 (.686)	3.275 (.525)	3.221 (3.514)	3.386 (3.553)
Small ruminant (number)	5.868 (9.105)	5.531 (8.851)	5.750 (8.796)	5.079 (8.970)
Pack animals (number)	0.979 (1.459)	0.914 (1.467)	0.923 (1.492)	0.896 (1.419)
Radio in household	0.190	0.194	0.197	0.188
Household savings	0.546	0.510	0.519	0.490
Total own farm size	1.067 (0.828)	1.077 (.921)	1.072 (1.018)	1.087 (0.683)
Fertilizer use (kg per hectare)	41.187 (95.395)	40.449 (103.343)	44.300 (112.555)	32.518 (80.825)
Seed use (kg per hectare)	154.500 (238.414)	125.886 (144.042)	125.897 (139.368)	125.864 (153.580)
Altitude (m.a.s.l.)	2177.611 (340.992)	2166.701 (332.611)	2176.334 (322.351)	2146.861 (352.800)
Annual rain fall (mm)	649.318 (101.677)	654.642 (98.960)	655.720 (95.712)	652.422 (105.545)
Population density per km^2	140.609 (68.925)	147.480 (72.718)	150.410 (74.535)	141.447 (68.611)
N	1019	618	416	202

Mean 1 = Refers to mean and standard errors (se) of variables from total sample before matching
Mean 2= Refers to mean and se of variables from matched sample (after matching)
Mean 3 = Refers to mean and se of variables with conservation of matched sample
Mean 4 = Refers to mean and se of variables without conservation of matched sample
Note: We did not report standard errors for dummy variables.
m.a.s.l. = meters above sea level

Table A.2A Propensity Score Estimates of Stone Bunds Adoption in Amhara Region

Explanatory variables	Coefficients (std. error)	Explanatory variables	Coefficients (std. error)
Plot slope (degree)	0.024 (0.008)***	Reduced tillage plots	0.229 (0.124)*
Black soil plots	0.285 (0.135)**	Male household head	0.726 (0.296)**
Brown soil plots	0.253 (0.133)*	*Ln* (total number of family members)	-0.153 (0.142)
Gray soil plots	0.275 (0.191)	*Ln* (age of household head)	0.666 (0.208)***
Deep soil plots	-0.026 (0.168)	Livestock holding (in TLU)	-0.062 (0.027)**
Medium-deep soil plots	0.115 (0.128)	Education level (years)	0.012 (0.015)
Moderately eroded plots	0.571 (0.108)***	*Ln* (total farm size in hectares)	-0.444 (0.122)***
Severely eroded plots	0.056 (0.177)	*Ln* (plot altitude in m.a.s.l)	0.279 (0.345)
Clay soil plots	-0.286 (0.184)	*Ln* (population density)	0.029 (0.085)
Loam soil plots	-0.141 (0.112)	Off-farm activity participation	0.027 (0.114)
Sandy soil plots	-0.146 (0.152)	Credit access	0.096 (0.104)
High fertile plots	-0.249 (0.242)	Extension frequency contact	0.114 (0.033)***
Medium fertile plots	0.133 (0.130)	*Ln* (rainfall in mm)	-1.025 (0.211)***
Plot distance to residence	-0.004 (0.002)	Irrigated plots	-0.695 (0.303)**
Plot distance to market	0.001 (0.001)*	Plot in bottom slope position	-0.030 (0.164)
Plot distance to main road	0.001 (0.000)**	Plot not on slope	-.472 (0.157)***
Ln (plot size in hectares)	0.249 (0.170)	Waterlogged plots	0.087 (0.156)

Explanatory variables	Coefficients (std. error)	Explanatory variables	Coefficients (std. error)
Plot in middle slope position	0.016 (0.142)	Gully plots	-0.162 (0.227)
Rented-in plots	-0.210 (0.196)	Square of log of plot area	-0.086 (0.061)
LR chi2	312.366***	Constant	1.524 (2.191)
Pseudo R2	0.2545	N	1320

Notes: p<0.10, ** p<0.05, *** p<0.01
m.a.s.l. = meters above sea level
TLU = tropical livestock units

Table A.2T Propensity Score Estimates of Stone Bunds Adoption in the Tigray Region

Explanatory variables	Coefficients (std. error)	Explanatory variables	Coefficients (std. error)
Male household head	0.102 (0.165)	Brown soil plots	0.188 (0.193)
Ln (household head age)	0.379 (0.165)**	Gray soil plots	0.051 (0.191)
Ln (total number of family members)	0.223 (0.120)*	Red soil plots	-0.227 (0.181)
Education grade (1–2)	0.142 (0.179)	Loam soil plots	0.213 (0.181)
Education grade (3+)	-0.114 (0.204)	Clay soil plots	0.247 (0.184)
Oxen (number)	-0.070 (0.058)	Sandy soil plots	0.474 (0.221)**
Other cattle (number)	-0.015 (0.017)	Moderately eroded plots	0.104 (0.108)
Small ruminants (number)	-0.002 (0.005)	Severely eroded plots	0.246 (0.195)
Pack animals (number)	0.006 (0.040)	Stone-covered plot	0.390 (0.113)***
Radio in household	0.094 (0.129)	Mildly waterlogged plots	0.007 (0.170)
Household savings	0.011 (0.103)	Severely waterlogged plots	-0.194 (0.292)
Ln (rainfall in mm)	1.110 (0.347)***	Plot distance from residence (hours?)	-0.581 (0.135)***
Ln (altitude in m.a.s.l.)	0.627 (0.366)*	Distance to market	0.058 (0.024)**
Ln (population density)	0.298 (0.110)***	Gully plots	0.173 (0.252)
Total own farm size	-0.080 (0.059)	Rented-in plots	-0.400 (0.134)***
Ln (plot size in hectares)	0.386 (0.062)***	Participation in off-farm activity	0.171 (0.108)
Plots in middle slope position	-0.095 (0.169)	Credit access	0.079 (0.107)

Explanatory variables	Coefficients (std. error)	Explanatory variables	Coefficients (std. error)
Plots in bottom slope position	-0.175 (0.168)	Member of rural institutions	0.175 (0.132)
Plots not on slope	-0.499 (0.168)***	Extension contact	0.091 (0.130)
Deep soil plots	0.133 (0.128)	Reduced tillage plots	0.048 (0.146)
Medium soil plots	0.272 (0.130)**	Irrigated plots	-0.704 (0.347)**
Gently sloped plots	0.280 (0.128)**	Constant	-15.155 (3.943)***
Steeply sloped plots	0.345 (0.192)*	LR chi2	278.892***

Notes: p<0.10, ** p<0.05, *** p<0.01
m.a.s.l. = meters above sea level

Table A.3A Propensity-Score Nearest-Neighbor Matching Estimates of the Effects of Stone Bunds on Crop Yield in the Amhara Region

N. conserved plots	N. without conserved plots	ATT	Standard error	t
232	155	-0.084	0.110	-0.758

Note: the numbers of treated (conserved) and controls (non-conserved) refer to actual nearest neighbor matches. Matched variables are indicated in table A.2A.

Table A.3T Propensity-Score Nearest-Neighbor Matching Estimates of the Effects of Stone Bunds on Crop Yield in the Tigray Region

N. conserved plots	N. without conserved plots	ATT	Standard error	t
416	202	0.355	0.100	3.555

Note: the numbers of treated (conserved) and controls (non-conserved) refer to actual nearest neighbor matches. Matched variables are indicated in table A.2T.

Table A.4A Pooled Probit Estimates of Determinants of Stone Bunds Adoption in the Amhara Region

Explanatory variables	With Mundlak approach	Without Mundlak approach	Explanatory variables	With Mundlak approach	Without Mundlak approach
Plot distance to market	-0.004 (0.006)	0.001 (0.001)	*Ln* (plot size in hectares)	0.052 (0.174)	0.159 (0.125)
Plot distance to main road	-0.002 (0.004)	0.000 (0.000)	Plot in middle slope position	-0.278 (0.262)	-0.119 (0.191)
Plot slope (degree)	0.001 (0.019)	-0.002 (0.012)	Plot in bottom slope position	-0.308 (0.312)	-0.039 (0.222)
Black soil plots	-0.188 (0.236)	0.108 (0.188)	Plot not on slope	-0.124 (0.322)	-0.071 (0.232)
Brown soil plots	-0.124 (0.273)	0.179 (0.199)	Waterlogged plots	0.109 (0.308)	-0.169 (0.243)
Gray soil plots	-0.870 (0.330)***	-0.293 (0.249)	Gully plots	0.051 (0.358)	-0.142 (0.320)
Deep soil plots	-0.071 (0.314)	-0.236 (0.235)	*Ln* (rainfall in mm)	-0.656 (0.343)*	-0.494 (0.300)*
Medium soil plots	-0.094 (0.248)	-0.066 (0.176)	Male household head	0.603 (0.642)	0.571 (0.553)
Moderately eroded plots	-0.013 (0.213)	0.174 (0.157)	*Ln* (total number of family members)	-0.033 (0.216)	-0.029 (0.200)
Severely eroded plots	0.013 (0.321)	0.070 (0.257)	*Ln* (household head age)	0.397 (0.307)	0.277 (0.288)
Clay soil plots	-0.328 (0.362)	0.230 (0.274)	Livestock (in TLU)	0.003 (0.048)	-0.031 (0.045)
Sandy soil plots	-0.717 (0.303)**	-0.051 (0.208)	Education level (continuous)	0.017 (0.023)	0.009 (0.022)
High fertile plots	0.286 (0.488)	-0.095 (0.369)	*Ln* (total farm size in hectares)	-0.109 (0.211)	-0.076 (0.167)
Medium fertile plots	0.205 (0.273)	0.005 (0.188)	*Ln* (plot altitude in m.a.s.l.)	-0.091 (1.254)	-0.150 (0.468)
Plot distance to residence	0.002 (0.005)	-0.001 (0.004)	*Ln* (population density)	-0.157 (0.165)	-0.079 (0.145)

Explanatory variables	With Mundlak approach	Without Mundlak approach	Explanatory variables	With Mundlak approach	Without Mundlak approach
Constant	2.443 (3.291)	3.654 (2.953)	Model test (Wald chi2)	77.748**	25.743
Pseudo R2	0.1180	0.0400	N	387	387
Joint hypothesis test for significance of mean values [chi2]	44.06***				

Notes: p<0.10, ** p<0.05, *** p<0.01
Figures in parentheses are standard errors.
m.a.s.l. = meters above sea level
TLU = tropical livestock units

Table A.4T Pooled Probit Estimates of Adoption of Stone Bunds in the Tigray Region

Explanatory variables	With Mundlak approach	Without Mundlak approach	Explanatory variables	With Mundlak approach	Without Mundlak approach
Ln (plot size in hectares)	0.256 (0.098)***	0.143 (0.078)*	Distance to market	0.012 (0.033)	0.031 (0.034)
Plots in middle slope position	0.130 (0.238)	-0.013 (0.188)	Male household head	0.212 (0.225)	0.264 (0.208)
Plots in bottom slope position	0.063 (0.236)	-0.092 (0.187)	*Ln* (household head age)	0.295 (0.226)	0.305 (0.218)
Plots not on slope	-0.200 (0.273)	-0.200 (0.191)	*Ln* (total number of family members)	0.058 (0.165)	0.046 (0.158)
Deep soil plots	-0.191 (0.183)	-0.055 (0.162)	Education of household (1–2 grade)	0.219 (0.225)	0.144 (0.211)
Medium soil plots	-0.273 (0.184)	0.040 (0.168)	Education of household (3+ grade)	-0.071 (0.278)	-0.210 (0.269)
Gently sloped plot	0.101 (0.203)	0.190 (0.143)	Oxen (number)	-0.015 (0.074)	-0.072 (0.071)
Steeply sloped plot	0.255 (0.289)	0.249 (0.224)	Other cattle (number)	-0.007 (0.021)	-0.007 (0.020)
Brown soil plots	-0.013 (0.319)	0.212 (0.224)	Small ruminant (number)	0.003 (0.008)	0.006 (0.008)
Gray soil plots	-0.242 (0.332)	0.055 (0.204)	Pack animals (number)	-0.023 (0.048)	0.000 (0.048)
Red soil plots	-0.309 (0.286)	-0.049 (0.183)	Radio in household	-0.036 (0.168)	0.052 (0.160)
Loam soil plots	-0.374 (0.261)	-0.115 (0.212)	Household savings	0.050 (0.152)	0.095 (0.137)
Clay soil plots	0.058 (0.317)	0.036 (0.223)	*Ln* (rainfall in mm)	0.431 (0.544)	0.475 (0.514)
Sandy soil plots	0.021 (0.377)	-0.096 (0.252)	*Ln* (plot altitude in m.a.s.l.)	0.683 (0.534)	0.527 (0.508)
Moderately eroded plots	-0.099 (0.172)	0.081 (0.125)	*Ln* (population density)	0.117 (0.160)	0.163 (0.148)
Severely eroded plots	-0.193 (0.311)	0.014 (0.216)	Total own farm size	-0.041 (0.072)	-0.023 (0.073)

Explanatory variables	With Mundlak approach	Without Mundlak approach	Explanatory variables	With Mundlak approach	Without Mundlak approach
Stone-covered plot	-0.321 (0.211)	0.164 (0.133)	Gully plots	0.124 (0.296)	0.189 (0.284)
Mildly waterlogged plots	-0.477 (0.275)*	0.005 (0.214)	Plot distance from residence	-0.486 (0.208)**	-0.328 (0.163)**
Severely waterlogged plots	-0.169 (0.455)	0.013 (0.377)	Wald chi2	116.237***	44.223
Constant	-10.358 (6.034)*	-8.758 (5.586)	Pseudo R2	0.1111	0.0521
N	618	618			
Joint hypothesis test for significance of of mean values (chi2)	51.99***				

Notes: * p<0.10, ** p<0.05, *** p<0.01
Figures in parentheses are standard errors.