Environment for Development

Discussion Paper Series

March 2017 ■ EfD DP 17-03

The Tilling of Land in a Changing Climate

Panel Data Evidence from the Nile Basin of Ethiopia

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Abstract

Empirical studies point to reduced tillage as a means to increase yields and reverse land degradation. A relatively neglected avenue of research concerns why farmers increase tillage frequencies. Using household plot–level panel data from the Nile Basin of Ethiopia, this article applies a random effects ordered probit endogenous switching regression model to empirically investigate the impact of weather events and other conditioning factors on farmers' choice of tillage intensity and the effect of changing tillage frequencies on differences in farm returns. Results indicate that, while low-frequency tillage is more likely in drier areas, plot-level shocks (such as pests and diseases) are key variables in the choice of high-frequency tillage. Adoption of a low-till approach leads to increasing farm returns in low-moisture areas but high-frequency tillage provides higher returns in high-rainfall areas. Understanding how farmers' tillage options correlate with climatic conditions and farm economies is salient for developing effective adaptation and mitigation plans.

Key Words: tillage intensity, climate change, farm return, random effect, endogenous switching regression, Ethiopia

JEL Codes: Q01, Q12, Q16, Q18

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Hailemariam Teklewold and Alemu Mekonnen*

1. Introduction

Soil tillage has long been one of the key components of smallholder farming systems, although reduced or zero tillage is being increasingly promoted as part of conservation agriculture as a sustainable agricultural practice (Ding et al. 2009; Kassie et al. 2015; Teklewold et al. 2013). Conventional tillage, which uses the traditional ox-plow with subsequent repeated tillage, is aimed at loosening the soil, controlling weeds and enhancing the penetration of moisture deep into the soil (Temesgen et al. 2008). However, there is a great concern that excessive tillage is a leading cause of high levels of surface runoff and soil erosion from arable fields, contributing to losses of soil and water, plant nutrients and organic matter (Hoogmoed et al. 2004). Soil erosion by water or wind due to intensive cultivation, deforestation and overgrazing represents the most important soil degradation process and affects more than 1 billion hectares globally (FAO 2003). A similar soil degradation trend, with annual levels ranging from 16 to over 300 ton per hectare, is observed in Ethiopia (Tesfaye et al. 2014). Intensive tillage also tends to engender accelerated oxidative breakdown of organic matter, with accelerated release of increased volumes of CO2 to the atmosphere, which have the potential to contribute to greenhouse gas emission (Lal et al. 1998; Kassam et al. 2009). IPCC (2001) reported that land use and land cover change and agricultural practices contribute about 20 percent of the global annual emission of carbon dioxide.

The agricultural and resource management literature has thoroughly documented the biophysical benefits of a minimum tillage system, a key component of conservation

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This study was financed by the International Development Research Centre (IDRC) under the project "Adaptation to Increase Resilience to Climate Change in Ethiopian Agriculture (IDRC Project Number: 107745-001)." Logistical support for this study from the Environment and Climate Research Center (ECRC) of the Environment and Development Initiative (EfD) at the Ethiopian Development Research Institute (EDRI) is also gratefully acknowledged.

agriculture.[1] With its capacity for moisture conservation, reduced tillage is an important climate change adaptation strategy that farmers can use as a means to increase crop-water use efficiency to stabilize the variability of yield which is particularly important in dry land farming (Ding et al. 2009; McCarthy et al. 2011; El-Shater et al. 2016; Grabowski et al. 2016). Less frequent tilling promotes the sequestration of carbon in agricultural soils, leading to improved soil organic carbon and subsequently promoting soil fertility and enhancing yields (Wilman 2011).

The synergies between adaptation and mitigation due to reduced tillage are attractive because they offer the chance to make more efficient use of limited resources for reducing the effect of climate damage. Low-tillage agriculture offers mitigation potential by increasing the ability of soil to store carbon while simultaneously enriching the soil (Paustion et al. 1995). A similar study found that, under sub-tropical conditions, zero-tillage increases soil carbon from 0.1 to 0.7 metric tons per hectare per year. Lal (2004) also shows that the carbon equivalent (CE) emissions for different tillage methods are 35.3 kg CE/ha for the conventional till method of seedbed preparation and 7.9 kg CE/ha for minimum till.

Despite the aforementioned benefits, uptake of reduced tillage by smallholder farmers in developing countries remains sluggish and a number of important constraints to widespread adoption have been highlighted (Kassam et al. 2009; Andersson and D'Souza 2013; Tessema et al. 2015; Grabowski et al. 2016; Ngoma et al. 2016). There is also growing evidence that the benefits from conservation agriculture come from the interaction of reduced tillage with mulching and crop rotations (Thierfelder et al. 2013). However, in a situation where there are various market imperfections and institutional failures, competition for resources among alternative uses in the crop-livestock mixed farming system is an important factor limiting the diffusion of conservation agriculture, through constraining on-farm labor use and retention of crop residue (Valbuena et al. 2009; Magnan et al. 2011; Baudron et al. 2014; Tessema et al. 2015). Specifically, farmers have to make trade-offs between using crop residue for soil mulching and livestock feeding.

[1] Conservation agriculture, constituting a set of principles such as reduced tillage with minimum soil disturbance, permanent soil cover through retention of crop residues, and crop diversification, has been promoted as an important resource management strategy to sustainably increase crop yields and alleviate land degradation problems (FAO 2014).

In many parts of the developing world, conventional tillage in smallholder farming systems typically includes a sequence of soil plowings, from 2 to 12 passes, to get a fine seedbed for ease of crop germination (Hobbs and Gupta 2003; Mouazen et al. 2007) and as a means of weed control, both before and after the crop has emerged, which allows for higher farm productivity (Hobbs et al. 2008; Givens et al. 2009). For instance, in Ethiopia, wheat and teff[2] farm land is prepared by ox-plow three to five times before planting (Ito et al. 2006; Temesgen et al. 2008). Agronomic research results in Ethiopia also indicate that grain yield increased with an increasing number of plowings (IAR 1998). While low tillage facilitates the intensification of crop production, due in part to reduced land preparation time, as well as reduced risk of soil erosion, low tillage also permits a greater accumulation of weeds, which increases labor demand for weeding or reliance on agro-chemical weed control (Chan and Pratley 1998; Uri 1998; Fuglie 1999; Knowler and Bradshaw 2007; Teklewold et al. 2013).

A relatively neglected avenue of research concerns farmers' actual options for tillage frequency, as well as short-term productivity differences due to repeated cultivation. Previous empirical studies have examined the determinants and impacts of reduced tillage, considering farmers' tillage options to be limited to the dichotomous choice of whether or not to switch to a long-term no-till regime (Kassie et al. 2015; Kassie et al. 2010; Teklewold et al. 2013; Wilman 2011; Grabowski et al. 2016; Ngoma et al. 2016). While these studies concluded that reduced tillage increases farm productivity, they are imposing an *a priori* restriction that this effect is constant across the number of times that a farmer tills. To the best of our knowledge, empirical evidence on the heterogeneous effect of tillage frequency on farm economies is scarce, and discussions of the implications of such evidence are virtually non-existent. For this reason, our paper aims to fill this gap in the literature. In addition, despite the recent evidence that drought significantly increases the adoption of soil and water conservation systems (Asfaw et al. 2016), understanding the ways in which climatic conditions affect the intensity of tillage is badly lacking. Therefore, we wonder how household, farm and climate characteristics affect tillage frequency, and how the farm return is impacted due to differences in tillage frequency. By using an ordered selection equation instead of a binary selection equation, we are able to take into account the extra information available from observing tillage frequencies. Thus, instead of only correcting for systematic

[2] Teff (*Eragrostis tef*) is a fine grain predominantly grown in Ethiopia.

differences between those who till and those who do not till, we also take into account unobserved differences among those who use different tillage intensities, to better understand individual farmers' decisions and the impact of changing tillage on farm economies.

In this paper, we address three methodological issues that have not received much attention in the literature. Firstly, from a data point of view, our analysis uses a comprehensive household and plot-level panel data set with detailed farm characteristics and rich socio-economic information, combined with a set of geo-referenced weather variation indicators. This helps us to control unobserved heterogeneity and to examine the role of various socio-economic, biophysical and weather variables in determining variation in the frequency of tillage among farmers, as well as the effect of tillage intensity on farm households' income. Second, because land preparation is costly, farmers may decide to reduce frequency of land preparation in poor growing seasons. In other words, the data on farm outcomes could be non-random and estimation using ordinary least squares could be biased. Furthermore, we observe frequency of tillage, and thus a conventional sample selection approach is not applicable. We overcome this issue by using a recent development in econometrics – a random effects ordered probit endogenous switching regression – and extend the binary sample selection process (till or not till) to ordinal sample selection to control potential sample selection bias in multiple tillage options, in order to disentangle the effects of additional tillage (Bourguignon et al. 2007). Third, the moisture-conserving effect of reduced tillage implies that weather variation is an additional driver determining tillage, given that farmers respond to the impacts of climate change on their production base and land management. Given the lack of evidence on the potential effects of increased frequency of extreme weather events on tillage intensities in the Sub-Saharan African countries at large, our detailed study of Ethiopia is important to account for its potential for climate change adaptation and mitigation for smallholder agriculture.

2. Study Areas, Data Sources, and Sampling Procedure

The current study is based on plot-household level data from the farm household survey conducted as part of the "Adaptation to Increase Resilience to Climate Change in Ethiopian Agriculture" project, which was implemented by the Environment and Climate Research Center at the Ethiopian Development Research Institute. The survey was conducted from March to May, in both 2013 and 2015. The target population is drawn from the five regions in the Blue Nile Basin of Ethiopia: Amhara, Oromia, Tigray, Benshangul-Gumuz and the Southern Nations and Nationalities People's (SNNP) Region. The basin covers about two-thirds of the country's land mass and contributes nearly 40 percent of its agricultural products and 45 percent of its surface water (Erkossa et al. 2014). The areas selected represent different agro-ecological settings, with altitudes ranging from 800 to over 3000 meters above sea level. The farming system of the basin can be broadly categorized as a mixed crop-livestock farming system, where over 98 percent of the area is covered by annual crops (Erkossa et al. 2014). We thus limit our analysis to the annual crop plots, where repeated plowing is common.

The sampling frame considered the traditional typology of agro-ecological zones in the country. These are *Dega* (cool, humid, highlands), *Weina-Dega* (temperate, cool sub-humid, highlands), *Kolla* (warm, semi-arid lowlands), and *Bereha* (hot and hyper-arid). The sampling frame selected *woredas*[3] in such a way that each class in the sample matched the proportions for each class in the entire Nile basin. Accordingly, the survey was carried out in a total of twenty *woredas* from the five regional states (three from Tigray, three from Benshangul-Gumuz, six from Amhara, seven from Oromia, and one from SNNP). This resulted in a random selection of 50 farmers from each *woreda* and a total sample size of 1000 households. After cleaning inconsistent responses and attrition (due to people moving away or passing away), the sample for this study is composed of a total of 4365 farming plots for 929 farm households in 2013, while the follow-up survey in 2015 covers 921 households[4]. In both years, a structured questionnaire was prepared, and data were collected from household heads using trained and experienced enumerators with knowledge of the local language.

As part of the household survey, we collected data on household characteristics, including asset endowments, quantity of livestock, crops produced, agricultural practices used, and methods and frequency of land preparation and other farming operations. Information was gathered on farmers' perceptions about farm characteristics, including slope, fertility and depth of the soil, and different types of plot-level shocks affecting crop production. The survey also recorded geo-referenced household-level latitude and longitude coordinates using hand-held Global Positioning System (GPS) devices, which

[3] A *woreda* is an administrative division equivalent to a district. It is the third-tier administrative unit in Ethiopia, after region and zone.

[4] The attrition (less than 1%) is relatively small given the sample size. This is true attrition: either the household left the village or the respondent passed away.

allow for the linking of household-level data to historical temperature and precipitation data.

3. Methodological Approach

3.1. Conceptual Framework

Building on the economic theory of the agricultural household model, this paper aims to examine the determinants of a household's decision on tillage intensity and to quantify the effect of tillage frequency on farm returns. Conceptually, differences in farm income due to tillage are attributable to: 1) Observable differences in the characteristics of farm households with different tillage intensities. For example, farms having lower intensity of tillage tend to have good soil, and good soil is usually associated with higher farm productivity. 2) Unobservable self-selection. For example, people may choose higher intensity of tillage simply because they want to use less farm labor for weeding or get rid of excessive soil moisture, and they regard tillage as the proper method for doing so. Sorting out the relative importance of these factors helps us understand the implications of the rising trend of policy intervention favoring reduced tillage, as well as the associated complementary practices such as weed control packages. For example, if the productivity difference stems solely from self-selection, then the trend of intervention towards reduced tillage simply reflects the fact that more people are choosing to have higher productivity, suggesting that reduced till itself is not solely a reason for the rising of productivity. Conversely, if people with similar characteristics behave differently under different tillage intensities, then the rising trend of intervention towards reduced till may have a profound impact on farm productivity.

Therefore, we propose a new panel data sample selection model for estimating the impact of tillage intensity of farm earnings through a comparison of net farm income from different tillage frequencies, where both the selection and the income equation contain individual effects, which are allowed to be correlated with the observable variables.

3.2. Empirical Model

We model farmers' choice of tillage frequency and the outcome variable (net farm income per hectare) in a random effects ordered probit endogenous switching regression framework, based on a panel of farm-plot level data (Dubin and McFadden 1984; and Bourguignon et al. 2007). This framework has the advantage of evaluating the various tillage frequencies and also captures self-selection bias (Mansur et al. 2008; Wu and Babcock 1998). The rationale behind the endogenous switching regression model is that the choice of tillage frequency may not be random; instead, farmers may endogenously self-select into tillage choice decisions, so decisions are likely to be influenced by unobservable characteristics (for example, expectation of yield gain from adoption, managerial skills, motivation) that may be correlated with the outcomes of interest.

Tillage Frequency Choice Model

In the first step, we model the choice of frequency of tillage using the random effect ordered probit model. In a multiple tillage setting, farmers are assumed to compare the expected utility under each number of tillings and choose the tillage intensity that provides the highest expected utility. The model involves a latent variable for tillage frequency function (h*). We assume that the i^{th} farm household $(i = 1,\ldots, N)$ decides to choose a number of tillings at time t $(t = 1, \ldots, T)$ based on the maximization of an underlying utility function:

$$h_{it}^{*} = z_{it}\delta + \gamma_i + u_{it} \quad i = 1, \ldots, N;\ t = 1, \ldots, T \qquad (1)$$

Because the utility level of individual farmer h_{it}^{*} is unobserved, the observed level of tillage h_{it} is assumed to be related to the latent variable h_{it}^{*} for $h_{it} = 1, 2, \ldots J$ categories of tillage (McKelvey and Zavoina 1975). Furthermore, z_{it} are vectors of explanatory variables for the tillage frequency choice equation. δ represents unknown parameter vectors to be estimated and γ is a random individual-specific effect, which is possibly correlated with z_{it}. u_{it} are unobserved disturbances, which are assumed to follow a normal distribution with mean zero and variances $\sigma_{u,t}$ and are assumed to be uncorrelated with z_{it}.

Moreover, if the unobserved individual effects are correlated with the explanatory variables in the first step, then the random effects ordered probit may give inconsistent results. This is likely to be the case because unobserved individual effects (such as skills, motivation and social characteristics) are likely to influence the choice of tillage frequency. Our econometric approach exploits the panel nature of our data to control for this prospect, building on the correlated random effect estimation approaches originally developed by Mundlak (1978) and now widely applied to non-linear panel data estimation (see Wooldridge 2002).The correlated random-effects framework parameterizes the individual-specific effect in the selection equation (1) as a linear function of the mean of time-varying controls, as a proxy for removing the time-invariant individual effects.[5] This approach mimics the identification strategy of fixed-effects estimation that can be applied to nonlinear models.[6]

Outcome Equations

In the second step, the relationship between the outcome variable and a set of control variables X (plot, household and location characteristics) is estimated by a fixed effect model for the chosen tillage frequency. The outcome equation for each tillage category j is given as:

$$y_{itj} = x_{it}\beta_j + \varepsilon_{itj} \qquad \text{if } h_{it} = j \text{ for j= 1, . . . , J} \qquad (2)$$

where y_{itj}'s is the outcome variable of the i^{th} farmer for tillage category j at time t and the error term $(\varepsilon_{itj}\text{'s})$ is distributed with $E(\varepsilon_{itj}|x,z) = 0$ and $\operatorname{var}(\varepsilon_{itj}|x,z) = \sigma_j^2$. y_{itj} is observed if and only if tillage j is used. The error term ε_{it} comprises unobservable individual effects α_i and idiosyncratic effect e_{it}.

For the selection bias, assume the error terms for the selection and outcome equations can be decomposed into an individual effect (α and γ) and an idiosyncratic effect (e_{it} and u_{it}), where each error component is assumed to be normally distributed and correlated with the component of the same dimension as in the other equation. If the e_{it}'s and u_{it}'s are not independent, the OLS estimates in Equation (2) will be biased. A consistent estimation of α_j requires inclusion of the selection correction terms of the alternative choices in (2). From the estimation results of Equation (1), we derive the Inverse Mills Ratio (IMR)[7] variables that will be added as additional explanatory variables in the second-stage outcome equations. The second-stage equation of the multinomial endogenous switching regression in (2) is specified as:

$$y_{itj} = x_{it}\beta_j + \sigma_j\hat{\lambda}_{itj} + \varepsilon_{itj} \qquad \text{if } h_{it} = j \text{ for j= 1, . . . , J} \qquad (3)$$

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[5] Discussion of the application of Mundlak (1978) to panel data selection models is found in Wooldridge (1995). Mundlak (1978) showed that, in linear panel data models, such a correlated random-effects strategy is identical to fixed-effects estimation.

[6] The result indicates that the null hypothesis (that all coefficients of the mean of plot-varying covariates are jointly statistically equal to zero) is rejected (Table 4). Hence, the result supports the presence of correlation between unobserved household fixed effects and observed covariates.

[7] The inverse Mill's Ratio (λ_{itj}) is defined as the ratio between the standard normal probability distribution function and the standard normal cumulative distribution function evaluated at each $z_{it}\delta$ for h_{itj}.

where σ_j is the parameter of coefficients for $\hat{\lambda}_{itj}$ showing the covariance between $\varepsilon's$ and $u's$.

Self-selection models that are estimated in a two-stage procedure have been criticized for being sensitive to misspecification (Wu and Babcock 1998). The lack of identification is particularly a problem when variables affecting the choice decisions (z_{it}) are the same as those affecting the subsequent outcome equations (x_{it}). This is because, though the correction term (λ_{itj}) is non-linear, this may not be sufficient in some cases and may lead to problems of multicollinearity (Khanna 2001; Wu and Babcock 1998). Accordingly, to enable identification, we established a set of selection instruments hypothesized to directly affect the tillage frequency choice decisions but not the outcome variables. Examples include number of oxen owned and social capital (number of relatives in and outside the village, and number of groups of which the household is a member). These are included in the selection equations but not in the net farm income outcome equations. We conduct a simple post-estimation test to check the validity of the instruments. The results confirm that, in nearly all cases, these variables are jointly significant in the tillage choice equations but not in the net income regression equations. A simple correlation analysis between these instruments and the outcome variable also shows that there is insignificant correlation.

Estimation of Average Effects of Tillage

The average treatment effect on the treated (ATT) is the estimand that is most commonly of interest to obtain an unbiased estimate of the average effect of more rounds of tillage. The ATT answers the question of how the average outcome would change if everyone who used a lower tillage frequency had instead used a higher tillage frequency. We define low-till as zero or one tilling, and high-till as two or more rounds of tilling.

In observational studies, where control over the assignment of the frequency of tillage is less likely, the tillage choice status is likely to be dependent on outcomes and thus a biased estimator of the average effect of tillage on the population. However, the ATT is used to compare the expected net farm income in the case of high-frequency tillers with the counterfactual income of low-frequency tillers. The expected net farm income under the actual and counterfactual hypothetical cases is computed as follows, by applying Equation (3):

Average net income for actual high-frequency tillers:

$$E(y_{itj} \mid h_{it} = j) = x_{itj}\beta_j + \sigma_j\lambda_{itj} \tag{4}$$

Counterfactual net income if high-frequency tillers had decided to low till:

$$E(y_{it1} \mid h_{it} = j) = x_{itj}\beta_1 + \sigma_1\lambda_{itj} \tag{5}$$

Equation (4) represents the expected outcome of high-frequency tillers that were actually observed in the sample, whereas Equation (5) denotes the counterfactual expected outcome if high-frequency tillers had opted for low-till. These expected values are used to compute unbiased estimates of the effects of tillage frequency. The average effect of tillage conditional on high-tillage users (the ATT) is defined as the difference between Equations (4) and (5):

$$ATT = (y_{itj} \mid h_{it} = j) - E(y_{it1} \mid h_{it} = j) = x_{it}(\beta_j - \beta_1) + \lambda_{itj}(\sigma_j - \sigma_1) \tag{6}$$

4. Model Specification

To select a comprehensive set of drivers that are known to affect farmers' decisions on tillage frequency, we explore a rich set of literature on technology adoption (D'Souza et al. 1993; Fuglie 1999; Neill and Lee 2001; Arellanes and Lee 2003; Gebremedhin and Scott 2003; Lee 2005; Bandiera and Rasul 2006; Marenya and Barrett 2007; Knowler and Bradshaw 2007; Ricker-Gilbert and Jayne 2009; Wollni et al. 2010; Kassie et al. 2010, 2011; Holden and Lunduka 2012; Arslan et al. 2013; Asfaw et al. 2016). Based on these empirical works and economic theory, we have summarized household, plot, and climate variables in our empirical specifications. These include input and output market access, household composition, education, asset ownership (including livestock ownership), various sources of income, participation in credit and off-farm activities, social capital and networks (membership in formal and informal organizations), current shocks/stresses experienced in crop production, participation in extension services, type of crops produced, land tenure, temperature, intensity and variability of rainfall. A wide range of plot-specific attributes such as soil fertility, depth, slope, farm size in hectares, walking distance of plot from residence, and detailed agricultural practices are also considered in the empirical specification. Table 1 provides the definitions of the variables used in our analysis and the mean values for the entire sample for the 2013 and 2015 cropping seasons. Below, we focus on describing those variables that are not common in the adoption and impact literature.

There has been relatively little research on the effects of climate and other farm-related shocks (such as droughts, water-logging, untimely or uneven distribution of rainfall, and incidence of pests and diseases) on tillage. Climatic variables are included to show how differences in seasonal temperature and precipitation influence farmers' choice of combination of adaptation practices and the resulting farm income. Temperature and rainfall data for each parcel were interpolated from meteorological stations near the study areas over the years 2000-2014. The Thin Plate Spline method of spatial interpolation was used to impute the parcel-specific rainfall and temperature values using geo-referenced information such as elevation, longitude and latitude.[8] It is expected that higher temperatures and shortfall of rainfall increase the use of moisture-conserving practices such as reduced tillage.

In addition, in order to identify heterogeneity in the monthly pattern of rainfall, we used Oliver's (1980) Precipitation Concentration Index (PCI),[9] analyzed at seasonal scale. This index is constructed for the major cropping season, April-September. The PCI value varies across the areas under study, ranging from values higher than 16 in Tigray to lower than 11 in Benshangul-Gumuz. This indicates a much higher concentration of growing season rainfall in Tigray than in Benshangul-Gumuz. Greater riskiness, shown in higher rainfall heterogeneity, is expected to increase the use of reduced tillage as an agricultural water management practice.

It should be recognized that, in developing countries like Ethiopia, meteorological stations are sparse and hence reliable rainfall data at micro-level is scarce (Demeke et al. 2011). Hence, in addition to the objective rainfall data, we also considered self-reported rainfall shocks. We followed Quisumbing (2003) to construct the subjective rainfall index based on respondents' rainfall satisfaction in terms of timeliness, amount, and distribution. The individual rainfall index was constructed to measure the farm-specific experience related to rainfall in the preceding seasons, based on such questions as

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[8] The Thin Plate Spline is a physically-based, two-dimensional interpolation scheme for arbitrarily spaced tabulated data. The spline surface represents a thin metal sheet that is constrained not to move at the grid points, which ensures that the generated rainfall and temperature data at the weather stations are exactly the same as data at the weather station sites that were used for the interpolation (see Wahba 1990). This method is one of the most commonly used to create spatial climate data sets (e.g., Di Falco et al. 2011; Deressa et al. 2010). Its strengths are that it is readily available and relatively easy to apply, and that it accounts for spatially varying elevation relationships. Given that our area of study is characterized by significant terrain features, the choice of the Thin Spline method is reasonable.

[9] The PCI is described as: $\mathrm{PCI} = 50\,\mathrm{X}\left[\sum r_m^2 / \left(\sum r_m\right)^2\right]$, where r_m is the amount of rainfall in the m^{th} month. The PCI is a powerful indicator of temporal distribution of precipitation; as the precipitation becomes more concentrated, the value increases. PCI values of less than 10 indicate uniform monthly distribution of rainfall (low precipitation concentration); values between 11 and 15 indicate moderate precipitation concentration; PCI between 16 and 20 indicates irregular distribution; and values above 21 indicate very high precipitation concentration (strong irregularity) (Oliver 1980).

whether rainfall came on time at the start of the growing season, whether there was enough rain at the beginning of and during the growing season, whether the rain stopped on time and whether there was rain at harvest time. Responses to each of these questions (either yes or no) were coded as favorable or unfavorable rainfall outcomes. By averaging over the number of questions asked (five questions), we created an index that provides a value close to one for the best outcome and zero for the worst outcome.

We also created a farm-level shocks index capturing the most common shocks affecting crop production: pest and disease pressure; drought; flood; hailstorm; and erratic rainfall. Based on agronomy and climate literature, these shocks are hypothesized to affect the choice of intensity of land preparation. Farmers' responses to the presence of each of these shocks (either yes or no) were coded as unfavorable or favorable disturbance outcomes. By averaging over the number of shocks about which we asked (five questions), we created an index that provides a value close to one for the highest level of shocks.

To account for the effect of farm features on tillage practices, we include several plot-specific attributes, including soil fertility,[10] soil depth,[11] plot slope,[12] spatial distance of the plot from farmer's home (in minutes walking) and choice of crops grown. On average, 75 percent of land owners operate on about four parcels, each about 0.25 ha, and these plots are often not spatially adjacent (as far as 15 minutes walking time from the farmer's residence). The variable distance to plot is an important determinant of adaptation practices through its effect on increasing transaction costs on the farthest plot, particularly costs for transporting bulky materials/inputs associated with tillage practices.

5. Results

5.1. Characterizing Tillage Frequency

As a prelude to the econometric analysis, we provide some descriptive insights on the frequency distribution of repeated cultivation over time. We measure tillage intensity by the number of oxen-plow passes on the farm from the last season's harvest to planting

[10] The farmer's perception of each plot's soil fertility is ranked as "poor", "medium" or "good."

[11] The farmer's perception of each plot's soil depth is ranked as "deep", "medium deep" or "shallow."

[12] The farmer's perception of each plot's slope is ranked as "flat", "medium slope" or steep slope."

time. The literature usually refers to a "low till" operation when there is only one plow pass or zero tillage. Fig. 1 display the frequency distribution of the number of tillings during the 2013 and 2015 cropping season in our data set. We see that the frequency of tillage in 2013 and 2015 is not constant. This means we observe changes in tillage frequencies between 2013 and 2015, where there is a decline of low till and an increase of high-frequency tillage. The distributions in 2013 are left-skewed while the 2015 distributions are relatively skewed to the right. The mode is two plowing passes in 2013 (observed on about 40 percent of the plots) and three plowing passes in 2015 (observed on about 34 percent of the plots). Few plots (about 9 percent) are under a low-till system (zero tillage or only one pass). Farmers report higher frequencies of tillage (more than two passes) on 80 percent of the plots in 2015 and on 60 percent of the plots in 2013.

The cross-classifying matrix shows a statistically significant correlation in a household's tillage frequencies between the 2013 and 2015 cropping season. However, there is also a dynamic aspect of mobility over time of in terms of the tillage intensity status of a given farm plot, which is described using the tillage transition matrix shown in Table 2. The percentage of immobility, with the same tillage frequency, ranges from 12 percent (i.e., 12 percent of plots received five or more times plowing in both years) to 34 percent (i.e., 34 percent of plots received three times plowing in both years). Of the ten percent of farming plots that received low tilling (less than two passes) in 2013, only 15 percent of those plots continued with low-till operations in 2015, while more than 58 percent of the plots with low till in 2013 changed to high tillage frequency ***(two or more passes).*** Similarly, 27 percent of the plots were plowed three times in 2013. Of these plots, about 34 percent still received three passes of plowing in 2015, 24 percent received less than three passes in 2015, and about 42 percent received more than three passes in 2015. The change in households' tillage frequency status between 2013 and 2015 is also confirmed by the high Chi-squared value [χ_1^2 (16)=60.39; p=0.000], which allows us to reject the null hypothesis of independent tillage intensities between the two years at the 1 percent significance level. The results support the evidence of alternating tillage frequency as a common practice among farm households (Wilman 2011).

We also provide the frequency distributions of tillage intensity for the three categories of the amount of rainfall in the growing season (Table 3). The result indicates a gradual decrease of low-till operations as one moves from the low-rainfall tercile to the highest tercile. Conversely, repeated tillage is more common in the high-rainfall tercile than in the low-rainfall tercile. In 2013, for instance, just fewer than 40 percent of plots in the low-rainfall tercile but 66 percent of the plots in the high rainfall tercile were plowed more than twice. Similarly, in 2015, the share of plots under high tillage (three or more passes) is 68 percent in low-rainfall areas and 75 percent in high-rainfall areas. This also confirms that the share of plots with repeated tillage increased over time in both low-rainfall and high-rainfall conditions. Table 3 further shows that high frequency of tillage is more dominant in areas where rainfall variability is lower, while the share of plots with a low number of tillings is high in low-rainfall areas. We find prima facie support for the oft-cited assertion that, because low-tillage conserves soil moisture, its adoption is one strategy that agricultural producers can use to reduce the risk associated with a low amount of rainfall and high precipitation variability (Asfaw et al. 2016; Ngoma et al. 2016).

6. Econometric Results

6.1. Determinants of Tillage Intensity

We model the first stage random effects ordered probit models with five ordered categories of tillage participation: from low till (zero or one plowing) to high tillage frequency (up to five passes of plowing). The results of the first stage analysis – the estimation of the pooled and random effects ordered probit model of how much tillage to pursue – is presented in Table 4. The qualitative results of the two models in terms of the sign and significance of variables are almost the same, despite the significance of the random effects. A likelihood ratio test of the random effects ordered probit model against the ordered probit model [χ_1^2 =402; p=0.000] suggests that we can reject the null hypothesis of no variability and shows that there is enough variability between plots to favor a random-effects ordered probit regression over a standard ordered probit regression. The discussion of results is then based on the random effects ordered probit model. The Wald test that all regression coefficients are jointly equal to zero is also rejected [$\chi^2(65) = 1413$; p = 0.000], suggesting the model fits the data reasonably well.

One assumption on which the ordered probit method is based is zero covariance between two observations. With panel data, as used in this paper, this amounts to the assumption that the error term of the individual farm households is uncorrelated over time. If uncorrelated, the effect of clustering on tillage frequency is assumed to be similar for all farmers. It might well be, however, that the tillage frequency of individual farmers is correlated over time. The result shows that the null hypothesis (that the inter-temporal correlation coefficient is zero) is rejected $[\rho = 0.147\ (p = 0.000)]$, suggesting that the individual variance component is not negligible and consequently the random effects model is justified. For about 85 percent of the farm plots, the tillage frequency changes over time. For the remaining 15 percent of the farm plots, the frequency of tillage in the previous year equals the frequency of tillage in the later year.

The effect of climatic shocks, represented by mean temperature and rainfall and variability of rainfall variables, indicates that farmers choose different tillage intensity depending on the climate they face, holding other variables constant (Table 4). The role of both temperature and precipitation in determining the choice of intensity of tillage reveals the direct bio-physical effect of climate change on changing tillage as an adaptation practice. We find a positive effect of the amount of rainfall on the intensity of tillage. The result provides empirical evidence to show that farmers generally follow a low-till production system by reducing the frequency of tillage to conserve the available moisture on-farm for a weather shock, represented by the average of the shortage of rainfall. The result is in agreement with other studies, which also have observed that tillage frequency in semi-arid areas where there is a shortage of rainfall is lower than in higher rainfall areas (Tarekegne et al. 1996; Ngoma et al. 2016). Yadeta et al. (2001) observed tillage frequency ranging from three passes in Nazareth (a low-rainfall area in Ethiopia) to 12 passes in western Wellega (a high-rainfall area in Ethiopia). We also provide evidence on the importance of rainfall distribution in determining tillage frequency. As expected, the parameter estimate for rainfall variability is found to be negatively associated with tillage frequency, implying that the higher the variability of rainfall during the growing season, the lower the frequency of tillage.

With regard to temperature, we find a negative correlation between mean growing season temperature and choice of tillage frequency. For instance, in communities with elevated temperature during the growing season, farmers generally reduce the frequency of tillage to keep moisture in the soil. The result also points to the inverted U-shaped relationship between tillage frequency and temperature. The quadratic climate coefficients are significant, implying that the tillage choice response function to temperature is nonlinear. These results imply that reduced tillage is an important land management system in low-rainfall areas, supporting the hypothesis that farmers traditionally adapted to climate risk by changing their practices (Shiferaw et al. 2014). The low-till adaptation practices function as in-situ conservation of the available moisture in order to support effective plant growth and reduce crop failure. These findings also confirm the notion that climate variability is one of the critical “drivers of choice of land management methods" in many smallholder agrarian households as a method to improve agricultural water productivity in rainfed systems (Ngoma et al. 2106).

The effect of rainfall and plot-level shocks in determining the tillage intensity is as anticipated. The rainfall satisfaction index is found to be negatively and significantly associated with tillage frequency. The results suggest that the probability of reducing tillage intensity is high in areas/years where rainfall is perceived to be favorable in terms of timing, amount and distribution. On the other hand, the probability of tillage intensity is positively and significantly influenced by plot-level disturbances. In the presence of plot-level shocks (such as pests, disease and weeds), farmers increase tillage frequency as a control method.

The parameter estimates for credit constraints are positive and significant. We followed the approach of Feder et al. (1990) to construct a credit-access variable. This measure of credit tries to distinguish between farmers who choose not to use available credit and farmers who do not have access to credit. In our study, credit-constrained farmers are defined as those who need credit but are unable to get it. The estimation results reveal that the frequency of tillage increases for credit-constrained households. This suggests that farmers who need credit but are unable to find it face liquidity constraints for the purchase of agro-chemicals and are more likely to increase tillage as a means for controlling weeds and pests.

The effect of extension services on the practice of reducing tillage is indeterminate *a priori*. Although Ethiopia's Climate Resilient Green Economy strategy advocates conservation agriculture (with zero or reduced tillage as one component) as one of the climate change adaptation options (FDRE 2011), still farmers are advised by extension agents about frequent land preparation starting from the onset of rain. The latter is to soften the surface soil and prepare a good seedbed to allow easier seeding of crops. The estimation results show that contact with extension agents has a positive and significant effect on reducing tillage intensity. This is similar to the findings of El-Shater et al. (2016) who found a positive effect of extension services on the adoption of zero-tillage in Syria.

Social capital as measured by a household's participation in a number of rural institutions significantly influences the choice of tillage frequency. One would expect the positive role played by such local institutions in adopting low tillage systems. Member households of these institutions are in a better condition to access information about the benefits of reducing tillage and to obtain financial resources for the purchase of agro-chemicals for the control of pests and diseases, which must be controlled in some other way in the case of reduced tillage (Teklewold et al. 2013). However, contrary to our expectation, participation in rural associations carries an unexpected sign. This might corroborate the dark side of social capital, as in Di Falco and Bulte (2011), where social capital may reduce incentives for hard work and induce inefficiency, such that farmers may exert less effort in control of weeds and pests and hence substitute frequency of tillage as a pest control method.

Bio-physical characteristics are also found to be important determinants of the choice of tillage frequency. As expected, plot access, as measured by residence-to-plot distance, has a negative impact on the frequency of tillage. Farmers are more likely to apply a greater number of tillings on nearby plots. The plot distance is an important determinant of tillage intensity because of increased transaction costs on the farthest plot, particularly the cost of transporting bulky materials/inputs. Plots grown with cereal crops (such as maize, wheat and teff) are more likely to receive repeated cultivation than other types of crops (such as legumes). Farmers are also more likely to increase plowing frequency if the plot is planned for growing improved crop varieties.

6.2. Impacts of Tillage Intensity

As stated above, in the second stage, we estimate the fixed effects regression on net crop income for each tillage frequency level, taking care of the selection bias correction terms from the first stage. We don’t present the second stage estimation results here for the sake of space. However, it is worth mentioning that a good number of variables in the fixed effects model have shown significant correlation with the outcome variable and that there are differences between the outcome equations’ coefficients among the different tillage frequencies. This illustrates the heterogeneity in the sample with respect to crop net income. The intra-class correlation in the fixed effects model indicates that more than 90 percent of the variance in the net income equation is due to differences across panels. This means that the variation in each equation coming from cross-sectional data is higher than that occurring across time. Hence, we can say that the higher proportion of the variation in the model is caused in part by individual heterogeneity.

From the fixed effects regression estimates, we derive the unconditional and conditional average effect of the choice of various tillage frequencies.[13] The unconditional average effect is presented in Table 5. The unconditional average effects compare net farm income from the choice of frequent tillage (more than one plowing) relative to low-till practice (zero or one tillage). The result indicates that farmers using repeated tillage earn higher net crop income, on average, than low-tillage users. This approach, however, would drive misleading conclusions, because the approach doesn't consider that the difference in the outcome variable may be caused by observable and unobservable characteristics. Therefore, the unconditional estimates would yield biased and inconsistent estimates.

We compute the true average tillage effects of net crop income under actual and counterfactual conditions by comparing the net farm income variable of farm households who practiced a high frequency of tillage with the outcome variables that would have been found if the households had practiced minimum tillage (zero or one tillage). This is done based on Eq. (6). Table 6 reports the aggregate size of the effects. In order to determine the average tillage effects for high-tillage users, we compare columns A and B of Table 6. Column C presents the impact of various tillage frequencies on net crop income, computed as the difference between columns A and C. Results show the adoption of more than one round of tillage provides higher net farm income compared with low-tillage practices, defined as zero or one tillage (Table 6). In all counterfactual cases, farm households that actually use more than one round of tillage would have earned lower income if they had not used more than one round of tillage. Importantly, compared with low tillage, the effect of tillage (two or more times) shows a similar trend on farm income as tillage frequency increases. The greatest farm income (3.7 thousand birr per hectare) is obtained from four rounds of tillage. Compared with low tillage, plowing the farm more than four times still increases farm income by 11 percentage points. But this productivity-enhancing effect of tillage declines when tillage exceeds four rounds of tillage.

Table 7 shows the net farm income effect of additional tillage. Farm income from adoption of three-times tillage is significantly higher (17.5 thousand birr per hectare)

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[13]As a robustness check, we replicate our estimation procedure using the pooled model specification and estimate the average treatment effects. The results don't change much (detailed estimation results from the pooled multinomial endogenous switching regression is available from the authors upon request).

compared with farm income with only two-times tillage (15.8 thousand birr per hectare). Similarly, the potential additional gains of farm income from using four rounds of plowing are statistically significantly higher by 14 percentage points compared with three rounds of tillage. The results from more than four tillings show a similar trend compared with four rounds of tillage; the net income effect (1.1 thousand birr per hectare) is positive and significant but with a decreasing trend from tillage beyond four passes. The results show the nonlinear effects of tillage intensity on farm income.

We also report and discuss the conditional average effects of tillage on net farm income disaggregated by quartiles of growing season rainfall intensity. Unlike either of the previous results, Table 8 presents the decomposition analysis, which enables us to partition the farm return differences with a different frequency of tillage across quantiles of rainfall amount. This helps test potential heterogeneous effects of the frequency of tillage across quantiles of the rainfall amount. Overall, we find that lower frequency of tillage provides higher returns at the lower quantile of the rainfall amount. The additional tillage effect from two rounds of plowing is about 3.2 thousand birr per ha in the lower tail of rainfall intensity, while this effect is about 1.7 thousand birr per hectare in the upper tail of the rainfall amount. The results agree with Suddick et al. (2010), who state that low tillage decreases evaporation and increases in-situ soil moisture retention, which can increase yields in drought years.

In contrast, we find opposite effects of tillage on the fourth quantile of the rainfall distribution, i.e., higher net income using higher frequency of tillage is obtained at the higher tail of the rainfall amount. This implies again that reducing tillage might conserve moisture in low-rainfall areas. The result corroborates the substantial agronomic evidence that argues that reduced or zero tillage offers opportunities to farmers in terms of soil and moisture conservation. While the effects of reduced tillage on yield were significant in drier areas where moisture is the major limiting factor, increased tillage frequency also helps farmers avoid excess soil moisture in high-rainfall areas (Kimble et al. 2007; Ngoma et al. 2016). The asymmetric effects of tillage intensity on farm productivity in different agro-ecological regions raises a concern about the relevance of blanket recommendations or one-size-fits-all approaches.

7. Conclusions

This study examines the determinants of households' decisions on tillage frequency and quantifies the effect of tillage frequency on farm income. We use a farm household-plot level panel data collected in 2013 and 2015. We employ a random effect ordered probit endogenous switching regression to estimate net farm income for each level of frequency of tillage.

The results show the nonlinear effects of tillage intensity on farm income. Compared with low tillage (zero or one passes), tilling two or more times a year increases farm income, more so as tillage frequency increases. But this productivity-enhancing effect of tillage declines when tillage frequency is greater than four rounds of tillage. In relation to rainfall, we find that, while lower frequency of tillage provides higher returns at the lower quantile of the rainfall amount, higher net income with higher frequency of tillage is generated at the higher tail of the rainfall distribution.

We found that high frequency of tillage is more dominant in areas where rainfall variability is lower. The share of plots with low frequency of tillage is high in low-rainfall areas. The results support the idea that, because low-tillage conserves soil moisture, its adoption is one strategy agricultural producers can use to reduce their risk associated with a low amount of rainfall and high precipitation variability. The results also reveal that changing tillage frequency over time is common among farm households. This has implications affecting the climate mitigation potential of low-tillage, which is often promoted as a method to improve the ability of agricultural soil to store carbon while simultaneously enriching the soil.

The study shows that increasing farm productivity due to tillage is beneficial to the farmer. But this is at a cost to him and the environment, and the natural resource base on which farming depends (Hobbs et al. 2008). This is a challenge for crop production in the next decade: to produce more food from less land by making more efficient use of natural resources and with minimal impact on the environment.

The purpose of changing tillage frequency generally falls into the following three categories: to achieve improved productivity, a private economic decision for the individual farm households; to improve the welfare (lifestyle) of the household, a private non-economic decision for the farm households; and/or to improve or preserve the environment and the natural resource base, a decision with possible benefits or costs to the society. While we address the first category in this study, the latter two points may be an area of future research.

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Appendix: Tables and Figures

Table 1. Description and Summary Statistics of the Variables Used in the Regression

Variables	Descriptions	2013		2015		Total	
Gender	Sex of the head (1=if female)	0.09		0.12		0.10	
Age	Age of the head, years	50.12	(12.52)	51.81	(12.73)	51.00	(12.66)
Familysize	Familysize	7.91	(2.30)	8.21	(2.40)	8.07	(2.36)
Education	Householdheadeducation, years	1.76	(3.00)	1.75	(2.93)	1.76	(2.96)
Farmsize	Farm size, ha	1.82	(1.39)	2.00	(1.39)	1.92	(1.39)
Ox	Numberof oxen owned	1.64	(1.15)	1.83	(1.57)	1.74	(1.39)
Offarm	1= if off-farm labor participation	0.22		0.19		0.20	
Credit	1=ifcreditconstraint	0.59		0.44		0.52	
Expenditure	Annualhouseholdexpenditure, Birr	3711.14	(6620.27)	5337.33	(5112.66)	4555.99	(5940.93)
Distoutmkt	Distance to output markets, km	10.45	(4.82)	9.68	(3.80)	10.05	(4.34)
Disinputmkt	Distance to input markets, km	10.51	(4.26)	10.42	(1.86)	10.46	(3.24)
Extcont	1=if extension contact (at least once in a month)	0.63		0.96		0.80	
Infoclimate	1=if farmer is well informed about climate change	0.75		0.79		0.77	
Relative	Number of relatives in and outside the village	29.24	(34.16)	20.96	(30.20)	24.93	(32.43)
Totgroup	Number of groups the household is a member	6.28	(2.16)	3.93	(2.33)	5.06	(2.54)
Rainindex	Rainfall disturbance index (1=best)	0.53	(0.24)	0.18	(0.07)	0.35	(0.25)
Plotindex	Plot level disturbance index (0=best)	0.25	(0.22)	0.06	(0.06)	0.15	(0.19)
Plotdist	Plot distance from residence, min	12.14	(16.28)	14.57	(17.37)	13.40	(16.91)
Tenure	1=if own the plot	0.83		0.85		0.84	
Dark	1=if dark soil type plot	0.37		0.37		0.37	
Red	1=if red soil type plot	0.44		0.44		0.44	
Higfert	1=if highly fertile soil plot	0.35		0.38		0.37	
Medfert	1=if medium fertile soil plot	0.54		0.51		0.52	
Flatslp	1=if flat slope plot	0.65		0.61		0.63	
Medslp	1=if medium slope plot	0.31		0.36		0.34	
Depdpth	1=if deep depth soil plot	0.44		0.48		0.46	
Meddpth	1=if medium depth soil plot	0.47		0.41		0.44	
Improvedvar	1=if grow improved crop varieties	0.24		0.24		0.24	
Maize	1=ifgrowmaize	0.60		0.20		0.39	
Wheat	1=ifgrowwheat	0.12		0.15		0.13	
Tef	1=ifgrowtef	0.09		0.19		0.14	
Rainfall	Average annual rainfall, mm (2000-2013)	779.68	(262.14)	804.21	(276.22)	792.42	(269.81)
Temperature	Averagemonthlytemperature, 0^{C} (2000-2013)	19.82	(2.52)	19.97	(2.59)	19.90	(2.56)
PCI	Percepitationconcentrationindex	10.26	(2.42)	20.58	(5.13)	15.62	(6.56)
Elevation	Altitude (meter above sea level)	2244.54	(420.48)	2227.44	(416.68)	2235.65	(418.57)
Observations (Household/plots)		929/4365		921/4697			

* Numbers in parentheses are standard deviations.

Table 2. Transition Matrix for Changing Tillage Frequency

		Tillage frequency in 2015 (%)					Total in 2013 (%)
		1	2	3	4	5	
Tillage frequency in 2013 (%)	1	14.57	27.73	26.89	17.37	13.45	9.67
	2	8.43	20.34	32.64	23.76	14.83	39.54
	3	7.49	16.75	33.69	27.39	14.68	26.64
	4	6.44	17.01	32.87	26.44	17.24	11.89
	5	9.71	23.40	29.80	24.72	12.36	12.26
Total in 2015 (%)		8.60	19.84	33.85	24.02	13.69	

Table 3. Distribution of Tillage Frequency Based on Amount of Rainfall in the Growing Season

Rainfall in the growing season		Year	Tillage frequency (%)				
			1 or less	2	3	4	5 or more
Total amount (mm)	1st tercile (<505)	2013	10.39	48.34	28.15	6.19	6.93
		2015	11.35	20.27	40.6	20.34	7.44
	2nd tercile (505-783)	2013	9.08	31.53	26.39	17.1	15.9
		2015	8.52	19.99	23.57	27.59	20.34
	3rd tercile (>783)	2013	8.21	44.72	24.34	10.19	12.55
		2015	5.47	19.91	32.55	25.85	16.23
Variability (PCI)	1st tercile (<13)	2013	8.94	36.34	26.48	14.12	14.12
		2015	9.69	22.14	27.65	23.73	16.79
	2nd tercile (13 - 21)	2013	8.2	38.87	25.72	13.36	13.85
		2015	4.66	17.81	27.7	29.82	20
	2nd tercile (>21)	2013	10.93	48.37	27.24	6.28	7.18
		2015	12.32	20.64	41.44	19.25	6.36

Table 4. Parameter Estimates of the Ordered Probit Model with Mundlak's Approach for Tillage Intensities

Variables	Random effects		Pooled ordered probit	
	Coefficient	Std. error	Coefficient	Std. error
Gender	0.015	0.058	0.024	0.040
Age	0.003*	0.002	0.002*	0.001
Family size	-0.002	0.008	0.004	0.005
Education	0.010	0.007	0.004	0.004
Farmsize	-0.021	0.013	-0.024**	0.010
Ox	0.004	0.014	0.011	0.010
Offarm	0.167***	0.035	0.159***	0.029
Credit	0.111***	0.027	0.117***	0.023
Expenditure (10^{-5})	0.303	0.257	0.270	0.207
Distoutmkt	0.002	0.003	0.002	0.003
Disinputmkt	0.007	0.005	0.004	0.004
Extcont	-0.109***	0.040	-0.059*	0.033
Infoclimate	-0.024	0.035	-0.043	0.029
Relative	-0.0002	0.0005	0.00004	0.0004
Totgroup	0.065***	0.007	0.050***	0.006
Rainindex	-0.298***	0.084	-0.214***	0.070
Plotindex	0.326***	0.093	0.254***	0.078
Plotdist	-0.004***	0.001	-0.004***	0.001
Tenure	-0.020	0.037	-0.021	0.037
Dark	-0.080**	0.038	-0.044	0.034
Red	0.077**	0.037	0.077**	0.033
Higfert	0.201***	0.051	0.182***	0.051
Medfert	0.103**	0.047	0.097**	0.047
Flatslp	-0.017	0.077	-0.027	0.076
Medslp	-0.037	0.077	-0.043	0.076
Depdpth	0.026	0.054	0.016	0.054
Meddpth	0.025	0.052	0.014	0.051
Improvedvar	0.125***	0.031	0.107***	0.028
Maize	0.315***	0.031	0.306***	0.030
Wheat	0.407***	0.039	0.381***	0.038
Tef	0.760***	0.038	0.697***	0.037
Rainfall	0.006*	0.003	0.0005	0.003
Rainfall-square(10^{-5})	-0.058	0.274	-0.034	0.255
Temperature	-26.929***	3.746	-22.913***	3.584
Temperature-square	0.615***	0.092	0.512***	0.087
PCI	0.021*	0.013	0.016	0.013
Rainfall X PCI (10^{-4})	0.400**	0.200	0.435**	0.194
Elevation	-0.0001	0.0002	-0.0001	0.0002
Year-2015	-0.248	0.290	-0.191	0.272
Constant	-290.39***	38.587		
μ_1	-289.14***	38.586	-251.70***	37.121
μ_2	-288.17***	38.585	-250.53***	37.120
μ_3	-287.40***	38.585	-249.63***	37.120
μ_4	0.172***	0.016	-248.92***	37.120
N	9041			
Joint significance of location variables: χ^2 (19)	288.33***		526.25***	
Joint significance of time varying variables: χ^2 (8)	19.04***		34.65***	
Joint significance of selection instruments: χ^2 (3)	77.72***			
Model significance	Waldχ^2 (65)=1413***		LR χ^2 (65) = 1959***	
σ_u^2	0.172*** (0.016)			
LR test vs. Oprobit regression: $\chi^2(4)$ = 402.01 Prob>χ^2 = 0.0000				

Note: *, ** and *** indicate statistical significance at 10, 5 and 1% level.

Table 5. The Unconditional Average Net Farm Income Effect of Tillage Frequencies (Results from Fixed Effect Estimation)

Number of tillage	Net farm income (Birr/ha)	Tillage effects
1 or less	13610.82 (118.03)	-
2	15165.42 (126.97)	1554.60(173.35)***
3	17780.10(148.35)	4169.27 (189.58)***
4	16455.73 (182.01)	2844.90(216.93)***
5 or more	14526.38(126.42)	915.55(172.95)***

Note: figures in parenthesis are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level, respectively.

Table 6. Average Expected Net Farm Income (Birr/ha) and Conditional Tillage Frequency Effects (Results from Fixed Effect Estimation)

Outcome	Tillage status		Tillage Effects (C)
	High frequency tillage, (j= 2, 3, 4,5) (A)	One tillage, (j=1) (B)	
$E(Q_{jit} \mid T=2)$ - $E(Q_{1it} \mid T=2)$	12741.62 (205.40)	11532.03 (186.65)	1209.589 (277.54)***
$E(Q_{jit} \mid T=3)$ - $E(Q_{1it} \mid T=3)$	17523.96 (256.24)	13880.62 (215.96)	3643.34 (335.11)***
$E(Q_{jit} \mid T=4)$ - $E(Q_{1it} \mid T=4)$	16048.97 (364.83)	12301.05 (105.91)	3747.91 (293.01)***
$E(Q_{jit} \mid T=5)$ - $E(Q_{1it} \mid T=5)$	18769.97 (403.84)	17545.47 (407.23)	1223.50 (573.13)***

Note: 'j' represents tillage frequency; figures in parentheses are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level.

Table 7. Average Expected Net Farm Income (Birr/ha) and Additional Tillage Effects (Results from Fixed Effect Estimation)

Outcome	Tillage status		Additional Tillage Effects (C)
	More tillage, (j= 2, 3, 4, 5) (A)	Lower tillage, (j=1, 2, 3, 4) (B)	
$E(Q_{2it} \mid T=2)$ - $E(Q_{1it} \mid T=2)$	12741.62 (205.40)	11532.03 (186.65)	1209.59 (277.54)***
$E(Q_{3it} \mid T=3)$ - $E(Q_{2it} \mid T=3)$	17523.96 (256.24)	15805.00 (235.21)	1718.96 (347.83)***
$E(Q_{4it} \mid T=4)$ - $E(Q_{3it} \mid T=4)$	16048.97 (364.83)	14061.23 (171.41)	1987.74 (358.18)***
$E(Q_{5it} \mid T=5)$ - $E(Q_{4it} \mid T=5)$	19497.97 (429.84)	18403.37 (538.03)	1094.60 (688.59)***

Note: 'j' represents tillage frequency; figures in parentheses are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level.

Table 8. Average Expected Net Farm Income (Birr/ha) and Additional Tillage Effects (Results from Fixed Effect Estimation)

Outcome (Rainfall quantile)	Tillage status		Additional Tillage Effects (C)
	More tillage, (j= 2, 3, 4, 5) (A)	Lower tillage, (j=1, 2, 3, 4) (B)	
$E(Q_{2it} \mid T=2)$ - $E(Q_{1it} \mid T=2)$			
I	13143.18 (347.88)	9923.89 (253.80)	3219.29 (430.62)***
II	10543.96 (319.21)	10653.11 (322.15)	-109.14 (453.52)
III	-	-	-
IV	16416.7 (552.38)	14726.78 (502.00)	1689.91 (746.42)***
$E(Q_{3it} \mid T=3)$ - $E(Q_{2it} \mid T=3)$			
I	11273.22 (263.06)	10795.54 (233.00)	477.67 (351.42)***
II	14108.07 (368.88)	11911.92 (378.68)	2196.15 (528.65)***
III	20915.57 (766.33)	11595.23 (333.57)	9320.33 (835.79)***
IV	25933.43 (438.76)	22001.32 (609.81)	3932.10 (751.26)***
$E(Q_{4it} \mid T=4)$ - $E(Q_{3it} \mid T=4)$			
I	9604.691 (277.74)	11787.58 (188.59)	-2182.89 (472.40)***
II	16240.82 (535.88)	13527.76 (310.89)	2713.06 (599.81)***
III	23899.78 (961.98)	15220.29 (435.00)	8679.485 (914.86)***
IV	20936.87 (280.79)	15905.86 (371.23)	5031.012 (642.14)***
$E(Q_{5it} \mid T=5)$ - $E(Q_{4it} \mid T=5)$			
I	13565.50(434.48)	10346.00(522.10)	3219.51 (679.23)***
II	19294.24 (760.21)	15202.05 (396.56)	4092.18 (857.42)***
III	19060.25 (677.82)	13639.13 (357.34)	5421.12 (766.25)***
IV	19981.03 (987.01)	13031.44 (764.69)	6949.59 (1248.58)***

Note: 'j' represents tillage frequency; figures in parentheses are standard errors; *, ** and *** indicate statistical significance at 10%, 5% and 1% level; Rainfall quantiles: I=less than 620 mm; II= 620 – 720mm; III=720-1094 mm; and IV= greater than 1094 mm.

Figure 1. Frequency Distribution of Tillage Intensity