The impact of adaptation practices on crop productivity in northwest Ethiopia: an endogenous switching estimation

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ABSTRACT

Climate change and variability adversely affect smallholder farmers in developing countries, including Ethiopia. In response, farmers are adopting various adaptation strategies. However, there is a paucity of studies examining whether or not these responses benefit farmers in increasing crop productivity. Cognizant of this fact and its policy importance, this study empirically analyzes the impact of adaptation strategies on crop productivity in northwest Ethiopia. We collected data through household survey questionnaire, focus group discussion and key informant interview. We also analyzed time-series climate data to see how crop yield responds to climate variability. The empirical model employs the endogenous switching regression. Climate information and distance to market are validated as instrumental variables. The model revealed that farmers who adopted adaptation strategies would have gained lower yield if they had not adopted them; and those who did not adopt a strategy would have gained higher yield than if they had. Improved seed, contact with development agents (DAs), urea, compost and rainfall are significantly associated with the likelihood of increasing yield. The results also show systematic difference where age is inversely related with adapters and vice versa for non-adapters. Hence, adaptation interventions should consider these heterogeneities.

1. Introduction

Research shows that climate change and variability (CCV) have brought substantial welfare loss especially for smallholder farmers (Komba and Muchapondwa 2018). The Food and Agricultural Organization (FAO 2014) reported that the number of African food crises per year has tripled in the last three decades. Agricultural production in many African countries is severely compromised where yield from rain-fed agriculture is reduced by up to 50% (Intergovernmental Panel for Climate Change (IPCC) 2014). Moreover, climate change reduces the area of land suitable for rain-fed agriculture by an average of 6%, and total agricultural Gross Domestic Product of the continent by 2–9% (TerrAfrica 2009; Edwards 2010). Specific to Sub-Saharan Africa, two-thirds of the population’s livelihood relies on agriculture. Worse is that the per capita demand for cereal crops in Sub-Saharan Africa has increased by approximately 4.9% per year up to 2020 (Rosegrant et al. 2001). However, climate change also generates the ‘carbon fertilization effect’ leading to plant growth caused by elevated levels of carbon dioxide, especially for some crops such as Wheat, Rice and Soybean (Collier, Conway, and Venables 2008). As a result, the IPCC report of 2014, mentioned the difficulty of generalizing the impact of climate change on global agricultural productivity.

Ethiopia is one of the agrarian Sub-Saharan African countries dominated by subsistence farmers with less than two hectares of land (Agricultural Transformation Agency (ATA) 2014). The transformation towards a more manufacturing and industrially oriented economy is underway. The success is determined by the productivity of smallholder farmers that account 95% of the national agricultural output where 75% is consumed at the household level (World Bank (WB) 2006). Agriculture is heavily dependent on natural rainfall, where irrigation accounts for just under 1% of the total cultivated land in the country (Di Falco, Kohlin, and Yesuf 2012).

Although agriculture is expected to play a key role in ensuring food security and overall economic development, its performance is primarily constrained, amongst other things, by degradation, unreliable weather conditions and underdeveloped technology. The livelihood of many millions of farmers in Ethiopia is critically challenged by CCV. The country’s agricultural
production has increased but per capita cereal yield remains stagnant (World Bank 2010). About 16 major
national droughts occurred since the 1980s and recently
in 2015 and 2017 about 10 and 5 million people, respect-
ively, were critically challenged by drought (Alemu and
Tamene et al. 2006; Kebede and Mesele 2014). Thus, a
large area of the country is already experiencing a
major deficit in food production and is plagued by
food insecurity (Di Falco, Veronesi, and Yesuf 2011).
One of the ways out of these challenges is the enforce-
ment of adaptation strategies that substantially minimize
current and future climate change and contribute to
food security (Di Falco and Veronesi 2018; Khanal et al.
2018). The most commonly cited climate change adap-
tation strategies include adjustment of planting and har-
vesting time, diversification, improved crop variety,
adoptive soil and water conservation practices (SWC),
irrigation, agroforestry, planting trees, development of
early warning system and so forth (Deressa et al. 2009;
Di Falco 2014; Mengistu, Bewket, and Lal 2015; Amare
and Simane 2018; Antwi-Agyei et al. 2018; Khanal et al.
2018; Komba and Muchapondwa 2018; Nigussie et al.
2018; Teklewold, Mekonnen, and Kohlin 2019).
Numerous studies have established empirical evidence
on the association of various variables with climate
change adaptation and crop production. Natural, physical,
financial, social and institutional capitals play an important
role in climate change adaptation and production (Bedeke
et al. 2018). For instance, large land size provides the
opportunity for diversification (Bedeke et al. 2018).
Farmers endowed with fertile land less likely invest in
SWC (Shiferaw et al. 2014; Bedeke et al. 2018). Moreover,
farmers who own gentle slope land less likely construct
SWC due to its less exposure for erosion (Kassie et al.
2013; Asrat and Simane 2017). The early adoption of sus-
tainable land management practices (stone bund, soil
bund, gars strips) increases crop yield as compared to
later years adoption, but its adoption decreases with
increased distance from the market (Asrat and Simane
2017). Access to financial capital plays a pivotal role in
reducing the financial constraints of farmers and pro-
motes the adoption of irrigation facilities and other
inputs such as fertilizer (Di Falco 2014; Wainaina, Tongruki-
sawattana, and Qaim 2016). Moreover, family size, farm
experience, education (see Khanal et al. 2018) and
farmers’ access to information reduces the climate risk
through informing adaption practices (Deressa et al.
2009; Kassie et al. 2013; Khanal et al. 2018). The institu-
tional services provided by extension agents positively
influence the adoption of climate change adaptation
strategies through knowledge and confidence building
(Bedeke et al. 2018). Family size, access to extension and
owning more livestock increases the likelihood of adap-
tation and food security (Amare and Simane 2018).
Numerous studies have also examined the impact of
climate change adaptation on crop productivity and
income (see e.g. Asrat and Simane 2017; Mohammed
et al. 2017; Teklewold and Mekonnen 2017; Amare and
Simane 2018; Di Falco and Veronesi 2018; Gorst,
Dehlavi, and Groom 2018; Khanal et al. 2018; Nonvide
2018; Wekesa, Ayuya, and Lagat 2018; Cholo et al.
2019). However, the current study differs from these
studies in at least four areas. Firstly, the combination
of adaptation strategies under consideration differs as
this study focuses on improved seed, diversification, irriga-
tion and modifying planting and harvesting time.
These practices are properly screened by farmers as
major responses to the changing climate in the study
area. Secondly, the employed econometric models
widely differ. Most of the previous studies employed
the propensity score matching (see, for instance, Kassa
et al. 2013; Asrat and Simane 2017; Amare and Simane
2018). This approach is widely criticized for its lack of
accounting the unobservable characteristics of farmers.
Thirdly, most of the previous studies estimate the
impact of adaptation strategies by aggregating crops
and income. To the best of the researchers’ knowledge,
crop level estimation was conducted by Gorst, Dehlavi,
and Groom (2018) at the macro level in Pakistan; Mohammed et al. (2017) in north Ethiopia; and Bedeke
et al. (2018) in southern Ethiopia. Estimating the impact
of adaptation for each crop is important for the fact
that each crop might grow in different seasons and the
farm management options likely play an important part
in determining how productive these crops are (Gorst,
Groom, and Dehlavi 2015). Different crops respond
differently to climate change, so having a separate analy-
sis is important. Commonly cited researchers such as Seo
and Mendelsohn (2008) for Africa, Teklewold et al. (2017),
Yesuf et al. (2008), Deressa and Hassan (2010) and Di
Falco, Veronesi, and Yesuf (2011, 2012) in Ethiopia have
investigated the impact of adaptation practices on aggre-
gated crop and income. Moreover, the last 4 studies were
conducted at the sub-regional level in the Nile River
basin based on the same data set of 1000 households col-
lected more than a decade ago. As a result, these are dated,
aggregated and have little relevance for addressing
specific area adaptations to climate change. Hence, there
is a need to conduct the study in specific agro-ecological
zones and socioeconomic groups as the effect of climate
change and its adaptation strategies varies thereof.
Fourthly, there are contradictory findings about the
impact of adaptation interventions in the Ethiopian
highlands that call for context-specific research. Several studies such as Pender and Gebremedhin (2006), Adgo, Teshome, and Mati (2013), Asrat and Simane (2017) and Gorst, Dehlavi, and Groom (2018) indicate that practice has a significantly positive impact on crop yield, whereas other studies such as Kassie et al. (2008), found that adopting adaptation structures reduces crop yield as compared to the non-conserved land in the high rainfall areas of Ethiopian highlands. Antwi-Agyei et al. (2018) in Ghana also found that livelihood diversification and intensification, and irrigation deliver maladaptive outcomes that could exacerbate future vulnerabilities. Moreover, Cholo et al. (2019) in southern Ethiopia evidenced that terracing decrease the probability of being food secure. Little is known about whether or not adaptation practices adopted by farmers in less developed countries support farm productivity (Khanal et al. 2018). Thus, the current study will shed some light on this by investigating the impact of adopting adaptation strategies in previously unresearched areas of northern Ethiopia. This study estimates the impact of adaptation practices on the yield of staple crops, Maize and Teff, during one harvesting season in 2016. These crops were selected because they occupy a large share of cultivation and are a major staple food in the community. The general objective of this research is to analyze the impact of adaptation practices on the productivity of major staple crops in Rib watershed. It also purports to examine the determinants of crop yield. The findings of this study are relevant to literature and policy makers in two ways. Firstly, this research will contribute to the literature by linking adaptation strategies and crop productivity and providing feedback as to whether or not the farming community is benefiting from adopting adaptation strategies. Unlike previous studies, this research will shed some light by estimating the impact of adaptation practices for each of the major crops using endogenous switching regression (ESR). Secondly, local level empirical evidence is important as interventions will also vary thereof.

2. Materials and methods

2.1. Description of study area

The study was conducted in Amhara Region, south Gondar Zone, Rib watershed. It is located between 10°43' and 11°53' N latitude and 37°47' and 37°54'E. It has a drainage area of about 1586 km². The landscape of the watershed is highly rugged with a high mountain range on the south and closely dispersed hills and escarpments in the central and northern parts of the watershed (Water Works Design and Supervision Enterprise (WWDSE) 2008) (Figure 1). According to Central Statistical Authority projection for 2014 (2013), about 181,813 households share the watershed. Woina-Dega and Dega are the dominant traditional agro-climate zones of the watershed. June, July, August and September are the rainy seasons.

2.2. Data source, collection methods and sampling

The study is based on on across-sectional survey that followed a qualitative and quantitative mixed approach. Primary data were collected through a household survey questionnaire, key informant interview and focus group discussion (FGD). The questionnaire was designed to gather information about the household demographic and social characteristics, adaptation practice and yield. The questionnaire was completed by interviewing the heads of farm households because most interviewees cannot read and write. Face-to-face key informant interviews with kebele1 development agents2 (DAs), Woreda3 and the zone heads of agriculture and rural development provided the specific village-level challenges and achievements of the adaptation strategies. Five FGDs with farmers and one with DAs were conducted. Development agents and farmers shared their experiences of the trend of rainfall and temperature and whether they are really benefiting from adaptation practices. The rainfall and temperature secondary data were collected from the National Meteorological Agency.

In order to select sample households, the research followed a multistage sampling technique. Firstly, Rib watershed was stratified into Dega and Woina Dega traditional agro-climatic zones. Then, within each agro-climatic zone, Kebeles were randomly selected and the sample size was determined proportional to the climate zone’s household size. The complete list of the farm households was collected from the Kebele administration. Then the sampling unit households were selected through systematic random sampling. With these procedures, according to Kothari (2004), the sample size from the finite population was determined to be 383 (see Table 1).

2.3. Theoretical framework

The theoretical framework for technology adoption is the random utility model where farmers choose a strategy that provides the highest utility among the given alternatives. This utility is not directly observed, rather it is observed through the farmers’ choice. Suppose that there are two choices, j and k and the farm household’s utility of two choices respectively be denoted by $U_j$ and
The common formulation of the linear random utility model is given as:

\[ U_j = \beta_j'X_i + \varepsilon_j \quad \text{and} \quad U_k = \beta_k'X_i + \varepsilon_k, \]

The observed choice between the two reveals which one provides the greater utility. If the derived utility of adapting option \( j \) is greater than the utility from other options, say \( k \), the household decides to use option \( j \). Hence, the observed indicator equals 1 for \( U_j > U_k \) and 0 otherwise.

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Where \( U_j \) and \( U_k \) have perceived utilities of adaptation methods \( j \) and \( k \), respectively; \( X_i \) is vector of explanatory variables affecting the perceived desirability of the method, \( \beta_j \) and \( \beta_k \) are parameters to be estimated, \( \varepsilon_j \) and \( \varepsilon_k \) are residuals assumed to be IID (Greene 2003).

### 2.4. Econometric model specification: ESR

There are various econometric models for estimating the impact of climate change adaptation on crop yield. The most widely used models and techniques for the cross-sectional survey are simple comparison of mean of adapters and non-adapters, ordinary least square by regressing adaptation as a binary variable and propensity score matching. However, these approaches assume that adaptation is exogenously determined, while it is endogenous (Di Falco and Veronesi 2018; Khanal et al. 2018). If adaptation was assigned randomly, its impact on yield can be easily estimated with the comparison of adapters and non-adapters. However, if the farmers who adopt the strategy have different characteristics from the non-adopters, the comparison between the two groups might be biased. For the fact that adapters were not assigned randomly, it is very likely that the estimate of the simple OLS be biased (Madalla 1983). It is usually difficult to model unobservable characteristics, for instance, skill and motivation of the farmer (Gorst, Groom, and Dehlavi 2015). It is very likely to have a correlation that the skilled farmer adapt and gain better
productivity, and hence the impact of adaptation might be overestimated due to this omitted unobservable. The other option that the existing literature widely used is the propensity score matching. It requires unconfoundedness where all the variables that affect the treatment and the outcome must be observed (Caliendo and Kopeinig 2008), assuming no selection bias due to unobserved characteristics. However, unobservable characteristics are unavoidable in the adaptation and production framework. Thus, matching helps control only for observable differences, not unobservable differences. As a result, the best model for resolving the selection bias issue is the ESR. It is possible to estimate the impact of adaption on yield by correcting the selection bias. Thus, the endogenous switching approach is far better than OLS in cases where unobservable factors simultaneously affect the adaptation decision and the productivity of farmers.

### 2.5. The endogenous selection and switching regression model

The switching regression was modeled in two stages (Di Falco, Veronesi, and Yesuf 2011; Gorst, Dehlavi, and Groom 2018). The first is the selection model for climate change adaptation denoted with the binary variable. That is, let \( A^*_i \) be the latent variable that captures the expected benefits from the adaptation choice with respect to not adapting. The latent variable is specified as:

\[
A^*_i = Z_{i0} + \eta_i \quad \text{with} \quad A_i = \begin{cases} 
1 & \text{if } A_i > 0 \\
0 & \text{otherwise}
\end{cases} \tag{1}
\]

that is farm household \( i \) will choose to adapt \( (A_i = 1) \) some strategies in response to long-term changes in mean temperature and rainfall, if \( A^*_i > 0 \), and 0 otherwise. \( Z \) represents an \( n \times m \) matrix of explanatory variables and \( a \) is an \( m \times 1 \) vector of model parameters to be estimated, and \( \eta \) is an \( n \times 1 \) vector of normally distributed mean zero random error terms.

The second stage is the outcome equation (yield measured as quintal per hectare) that split the endogenous model into two (Lokshin and Sajaia 2004). That is running a separate regime or production function for the decision of adapting and not to adapt.

Regime 1 to adapt \( y_{1i} = X_{1i} \beta_1 + \epsilon_{1i} \) if \( A_i = 1 \), \tag{2}

Regime 2 not to adapt \( y_{2i} = X_{2i} \beta_2 + \epsilon_{2i} \) if \( A_i = 0 \), \tag{3}

where \( y_{1i} \) and \( y_{2i} \) respectively represent crop yield for adapters and non-adapters measured as kg/hectare. \( X_i \) is the list of explanatory variables that consists of inputs, climate variables and household characteristics. \( \epsilon_{1i} \) and \( \epsilon_{2i} \) are the error terms for adapters and non-adapters, respectively.

In this switching regression model, the selection bias would manifest itself in the error terms \( \epsilon \) and \( \eta \). As far as the unobserved variables are not captured by the explanatory variables, the error terms of the production and selection equation are correlated \( \text{corr} (\epsilon, \eta) \neq 0 \). The error terms \( \eta_i, \epsilon_{1i} \) and \( \epsilon_{2i} \) follow a trivariate normal distribution with zero mean and the covariance matrix is specified as:

\[
\text{Cov}(\eta, \epsilon_{1i}, \epsilon_{2i}) = \begin{bmatrix}
\sigma^2_{\eta} & \sigma_{1\eta} & \sigma_{2\eta} \\
\sigma_{1\eta} & \sigma^2_{1\epsilon} & \sigma_{1\epsilon} \\
\sigma_{2\eta} & \sigma_{1\epsilon} & \sigma^2_{2\epsilon}
\end{bmatrix},
\]

where

- The variance of the error terms in the selection equation and the two production regimes 1 and 2 is respectively denoted by \( \sigma^2_{\eta}, \sigma^2_{1\epsilon} \) and \( \sigma^2_{2\epsilon} \).
- The covariance of the selection equation error term \( \eta \) and the production regimes 1 \( \epsilon_{1i} \) and 2 \( \epsilon_{2i} \) is respectively \( \sigma_{1\eta} \) and \( \sigma_{2\eta} \).
- The dot (.) shows that the regimes 1 and 2 outcomes cannot be simultaneously observed for a farmer and hence the covariance is not present (Madalla 1983).
- In the presence of selection bias, the expectations of the error terms for the two regime equations are different from zero.

\[
E[\epsilon_{1i}|A_i = 1] = \sigma_{1\epsilon} \frac{\Phi(Z_{i0})}{\Phi(Z_{i0})} = \sigma_{1\epsilon} \lambda_{1i}, \tag{4}
\]

\[
E[\epsilon_{2i}|A_i = 0] = -\sigma_{2\epsilon} \frac{\Phi(Z_{i0})}{1 - \Phi(Z_{i0})} = \sigma_{2\epsilon} \lambda_{2i}, \tag{5}
\]

where

- \( \Phi(.) \) is the standard normal probability distribution.
- \( \Phi(.) \) is the standard normal cumulative distribution.

\( \lambda_{1i} \) and \( \lambda_{2i} \) are interpreted as inverse Mills ratios (Heckman 1979) where these were incorporated in the production right side equations for capturing any selection bias.

The correlation between the error terms of the production and the selection equations are shown as the correlation coefficients

\[
\rho_1 = \frac{\sigma_{1\eta}}{\sigma_{1\epsilon}}, \tag{6}
\]

\[
\rho_2 = \frac{\sigma_{2\eta}}{\sigma_{2\epsilon}}. \tag{7}
\]

The significance of the estimated covariances of \( \rho_{1\eta} \) and \( \rho_{2\eta} \) reflect that the decision to adapt and yield are correlated, that reject the null hypothesis of sample selectivity bias. This highlights the importance of endogenous
The impact of adaptation practice on productivity is estimated using the endogenous regression model where the adapters are considered as the treatment group ($A_i = 1$) with the estimation of their counterfactual. The observed outcomes for adapters and the non-adapters are presented below following the works of (Di Falco, Veronesi, and Yesuf 2011; Alem, Eggert, and Ruhinduka 2015; Gorst, Groom, and Dehlavi 2015). Thus, the observed yield for adapters and the non-adapters is:

$$ATT = E[y_{1i}|A_i = 1] - E[y_{2i}|A_i = 1]$$

$$= X_0b_1 + \sigma_1A_i$$

The treatment effect of adaptation

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Adapter $E[y_{1i}|A_i = 1] = X_0b_1 + \sigma_1A_i$, \hspace{1cm} (8)

Non-adapters $E[y_{2i}|A_i = 0] = X_2b_2 + \sigma_2A_i$, \hspace{1cm} (9)

In a similar fashion, the equation for the counterfactual yield of adapters and the non-adapters is:

$$Adapter \text{ counterfactual } E[y_{1i}|A_i = 1] = X_0b_2 + \sigma_2A_i$$

$$Non-adapters \text{ counterfactual } E[y_{2i}|A_i = 0] = X_2b_1 + \sigma_1A_i$$

Then the average treated impact of yield for those is computed as:

$$ATT = E[y_{1i}|A_i = 1] - E[y_{2i}|A_i = 1]$$

$$= X_0(b_1 - b_2) + (\sigma_1 - \sigma_2)A_i$$

And the predicted impact of adaptation on yield for non-adapters (untreated) is:

$$ATU = E[y_{1i}|A_i = 0] - E[y_{2i}|A_i = 0]$$

$$= X_2(b_1 - b_2) + (\sigma_1 - \sigma_2)A_i$$

3. Results and discussion

3.1. Socioeconomic and demographic characteristics of respondents

About 80% of sampled farmers are married, 5% not married, 8.6% divorced and 6.8% widowed. The majority of respondents (98.7%) are Orthodox Christians while the remaining (1.3%) are Muslims. The education profile of households’ show that 38.7% are illiterate, 53.5% can read and write and 7.8% have completed primary school and above. Females headed about 19% of the respondents’ and none of them have joined the level of primary school. The age distribution shows that 12.3% are below 34 years, 73.1% between 35 and 59, and 14.6% above 60 years of age. The average land size and TLU is respectively 1.22 and 3.8 hectare. The key informants’ minimum level of education is diploma and the maximum is bachelor’s degree with an average experience of six years.

3.2. Overview of CCV induced risks and adaptation strategies

Most of the farmers surveyed reported the warming of temperature, excessive rain in July and August, the
occurrence of drought and shift in rainfall entry and exit time. The multidimensional challenges induced by CCV, as reported by farmers, are thematically ranked in decreasing order as yield decrease 92%, drying of streams and water shortage 55.7%, crop diseases 37.6%, weeding expansion 42%, animal diseases 34.7%, loss of some crop species in the agronomy 27.7%, heavy flooding 24.8% and road destruction 21%; where \(N = 314\), with multiple response set.

Farmers took various short-term coping and long-term adaptive responses to these challenges. The major short-term coping strategies were food consumption decrease (73.5%), sale of livestock (69.7%), any aid (21.1%), migration as labor (35%), borrowing (53.3%), previous store (30.9%) and other solutions (7.6%). Percentages equal more than 100 as a farmer has a likelihood of using more than one coping strategy.

Moreover, farmers use various adaptation strategies. Among these use of the improved seed, diversification, irrigation and modifying planting and harvesting time were identified as common adaptation strategies in the study area. About 80% of sampled farmers practiced any of the adaptation strategies. As a diversification, farmers rear livestock and sow a combination of crops for minimizing the expected risks. The other adaptation strategy in the area is use of improved water and drought-resistant crops. Water resistant rice was introduced to the frequently-flooded Fogera plain. In the area, drought-resistant crops such as finger millet are preferred for times of severe drought but have longer growth periods than other crops. River-diverted irrigation and water harvesting through collecting surface runoff in wells covered by geomembrane were also encouraged by the government. However, water harvesting failed to achieve its objective due to a tear in the geomembrane, the water gets warm, is not suitable for crops and is labor demanding. The application of irrigation also requires access to water, irrigable land and

| Table 2. Description of variables and hypothesis for the outcome variable. |
|---------------------------------------------------------------|
| No. | Explanatory variables with codes | Definition and measurement | Expected. sign |
|-----|---------------------------------|-----------------------------|----------------|
| 1   | Demographic characteristics     |                             |                |
|     | EDUC                           | Education in years          | Continuous     |
|     | HHSIZE                         | Household size              | Head count     |
|     | SEX                            | Gender of the head of the household | 1 if male and 0 otherwise |
|     | AGE                            | Age of the household head   | Continuous     |
|     | EXP                            | Farm experience in years    | Continuous     |
| 2   | Assets/wealth                   |                             |                |
|     | FRMSZE                         | Farm size in hectare        | Continuous     |
|     | FRMY                           | Farm income in a year       | Continuous     |
|     | NFRMY                          | Nonfarm income in a year    | Continuous     |
|     | RADO                           | Radio ownership             | 1 if yes; and 0 otherwise |
|     | MOBLE                          | Mobile ownership            | 1 if yes; and 0 otherwise |
|     | TLU                            | Tropical Livestock Unit     | TLU            |
| 3   | Institutional factors          |                             |                |
|     | CREDIT                         | Credit access               | 1 if there is and 0 otherwise |
|     | EXTN                           | Extension access frequency with DA (experts) | 1 if None; 2 if weekly; 3 if per two-three weeks; 4 if monthly and above |
|     | DEMO                           | Demonstration site availability | 1 if available 0 otherwise |
| 4   | Social capital                 |                             |                |
|     | F_F_EXTN                       | Farmer to farmer extension   | 1 yes; and 0 otherwise |
|     | NEIGBOR                        | Number of neighbors         | Headcount      |
|     | COOP                           | Membership in cooperative    | 1 member and 0 otherwise |
| 5   | Infrastructure                 |                             |                |
|     | HOME_FARMDSTCE                 | Average distance between home and farm in minutes | Continuous |
| 6   | Land characteristics           |                             |                |
|     | FRMSLP                         | Farmers perceived slope of the farm | 1 if gentle, 2 if moderate, 3 if steep |
|     | SOIL                           | Farmers’ reported soil fertility | 1 if Fertile, 2 if moderate, 3 if degraded |
| 7   | Environmental factors          |                             |                |
|     | AGRO_CLIMATE                   | Traditional climate zone    | 1 if Dega, and 0 WoinaDega |
|     | RF                             | Average rainfall of 1980–2015 | +/- |
|     | Temp                           | Average temperature of 1980–2015 | +/- |
|     | Drought                        | If experienced drought in 2016 | 1 if experienced and 0 otherwise |
|     | Flood                          | Flood severity on cropland  | 1 if severely affected and 0 otherwise |
| 8   | Instruments for adaptation      |                             |                |
|     | DSTCE_Mkt                      | Distance markets in minutes | Continuous     |
|     | CLI_INFO                       | Have information on climate change | 1 if there is and 0 otherwise |

Notes: The table shows the definition and measurement of the variables. The variables are the determinants of adaptation and crop yield. The instrumental variables are hypothesized as determinants of adaptation only.
3.3. Impact of adaptation strategies on the productivity of major staple crops, Maize and Teff: ESR estimation

In this section, we start by discussing the determinants of crop yield (see Table 3) and then we look at the impact of adaptation strategies on the productivity of Maize and Teff (see Table 4). The adaptation strategies that do not have a clear and immediate relationship with crop yield such as a shift from crop to livestock were not considered in the definition of adaptation that links with yield. These kinds of exclusions are common in studies, for instance, in Pakistan. Gorst, Groom, and Dehlavi (2015) excluded income diversification in impact measurements. The third column in Table 3 presents the OLS estimation of Maize, yield used as the dependent variable. The regression estimation for Teff is not reported (to save space) but is available from the authors upon request. It is regressed with sets of explanatory variables including adaptation to climate change as a dummy variable. The coefficient of adaptation for both Maize and Teff is positive and statistically insignificant. Insignificant adaptation on yield in the OLS was also found by Di Falco, Veronesi, and Yesuf (2011), showing that adaptation is an exogenously determined endogenous variable.

The insignificance of the adaptation coefficient in OLS implies that there is no yield difference between adapters and non-adapters. Accepting this result is misleading due to its bias and inconsistent reporting that OLS yield equations did not account for the potential endogeneity. There is a mean yield difference between adapters and non-adapters tested using the unpaired T-test. However, this is not conclusive as there is a need to control various factors. Thus, the ESR model is considered with the selection instruments. The Wald test of independence is statistically significant at \( p < .00094 \). It indicates the presence of selection bias and the need to run separate models for adapters and non-adapters. The ESR model instruments are jointly validated as strong predictors for adaptation but not for production \( (\text{chi}^2 (3) = 14.70 \, \text{Prob} > \text{chi}^2 = 0.0021 \, \text{for Maize}; \, \text{and Chi}^2 (3) = 9.47 \, \text{and Prob} > \text{chi}^2 = 0.023 \, \text{for Teff}).

Table 3. Parameters estimates of adaptation and crop productivity equations (Maize in ln of yield).

| Explanatory variables            | 2 | 3 | 4 | 5 |
|----------------------------------|---|---|---|---|
| Marital status (married)         | 0.1156**(0.236) | 0.0134(0.026) | 0.0052(0.031)* | 0.0059(0.043) |
| AGE                              | -0.005(0.008) | 0.0004(0.001) | -0.002*(0.001) | 0.0021(0.002) |
| Education                        | 0.059(0.198) | 0.0029(0.023) | -0.0076(0.026) | -0.0038(0.040) |
| Household size                   | 0.0503(0.055) | -0.0011(0.006) | 0.0002(0.007) | -0.0011(0.01) |
| Credit                           | 0.1118(0.199) | 0.0078(0.023) | 0.0089(0.027) | -0.0026*(0.04) |
| TLU                              | 0.195*** (0.05) | 0.0028(0.006) | 0.0085**(0.006) | 0.0163(0.01) |
| Urea/ha                          | 0.0008(0.001) | 0.0001(0.001) | 0.0038**(0.002) |
| Soil erosion (high)              | -0.0086(0.018) | -0.0309(0.020) | 0.0632(0.032) |
| Seed type (improved)             | 0.0050(0.022) | 0.0507**(0.025) | 0.0731*(0.04) |
| Soil fertility degraded          | -0.0608(0.025) | -0.0402(0.026) | -0.0649(0.05) |
| Farm size                        | 0.0004(0.020) | -0.0222(0.023) | 0.0335(0.033) |
| Soil type                        | 0.0318**(0.014) | 0.0134(0.016) | 0.0636**(0.023) |
| Contact DA                       | -0.074**(0.035) | -0.078**(0.043) | -0.0945(0.05) |
| Working days                     | -0.0011(0.001) | -0.0006(0.002) | -0.0030(0.002) |
| Agro-climate zone                | -1.716***(0.53) | 0.0106(0.050) | 0.2042(0.164) | 0.5647(0.065) |
| Compost                          | -0.51**(0.31) | 0.0230(0.025) | 0.0364(0.031) | 0.0495**(0.035) |
| Insecticide use                  | -0.0110(0.029) | 0.0051(0.032) | 0.0014(0.048) |
| Temperature                      | 0.219**(0.051) | -0.0004(0.006) | 0.0068(0.007) | -0.026**(0.010) |
| Rainfall (rainy season)          | 0.0009**(0.001) | 0.002**(0.0001) | 0.002**(0.0001) | 0.002**(0.0001) |
| Drought                          | 0.593(0.231)* | -0.0062(0.025) | -0.0248(0.030)* | -0.0218(0.047) |
| Flood                            | 0.761(0.211) | -0.0062(0.025) | -0.0120(0.032)* | -0.0211(0.038) |
| Demonstration site               | 0.8405(0.191) |                      |                      |                      |
| Constant                         | -5.68**(1.209) | 0.587*** (0.169) | 0.598*** (0.224) | 0.925(0.303)*** |
| Distance to market               | 0.0120**(0.007) |                      |                      |                      |
| Climate information              | 0.616*** (0.23) |                      |                      |                      |
| Adaptation                       |                      |                      |                      |                      |
| /ln0                             | 0.049(0.027) |                      |                      |                      |
| /ln1                             |                      |                      |                      |                      |
| Number of obs                    | 282 | 282 | 282 | 282 |
| Wald ch2(21)                     | 818.49; | Log likelihood = 16.759549; | Prob > ch2 = 0.00000 |
| F(22, 259)                       | 104.62; | Prob > F = 0.0000; | Adj R^2 = -.089 |
| LR test of indep. eqns.:ch2(2)    | 9.34 | Prob > ch2 = 0.0094 |

Notes: The table shows adaptation is statistically insignificant in the OLS estimation. However, the ESR estimation, that accounts the potential endogeneity, shows the heterogeneity of the factors that affect the yield of adapters and non-adapters.

***p < .01, **p < .05, *p < .1. Standard errors in parentheses.
Table 4. Average expected yield (kg/hectare) and net crop income; treatment and heterogeneity effects.

| Crop          | Farm households (r1) | Adapt (c1) | Not to adapt (c2) | Adaptation effects (c3) |
|---------------|-----------------------|------------|-------------------|-------------------------|
| Maize         | That adapted (r2)     | 21.29(798) | 18.5(755)         | ATT = 2.79(1.1)**       |
|               | That did not adapt (r3)| 21(901)   | 17.9(10)          | ATU = 3.1(1.3)**        |
|               | Heterogeneity (r4)    | 0.29(0.05)**| 0.6(1.2)          | −31(2.5)                |
| Teff          | That adapted (r5)     | 14.2(32)   | 9.5(11)           | ATT = 4.7(34)****       |
|               | That did not adapt (r6)| 19.4(1.4) | 14.6(52)          | ATU = 4.8(1.2)**        |
|               | Heterogeneity (r7)    | −5.2(95)** | −5.1(45)          | −1.5(39)*****           |
| Net Crop income/ha in Birr | That adapted (r8) | 5205(39)  | 3312(15)          | ATT = 1893(42)****      |
|               | That did not adapt (r9)| 6294(175) | 2642(16)          | ATU = 3652(176)****     |
|               | Heterogeneity (r10)   | −1089*     | 670               | −1759***                |

Notes: The row (r2) and (r5) of Table 4, respectively report the adapters’ actual yields of Maize and Teff and the yields that would have been produced if the farm households had not adapted. The row (r3) presents the non-adapters yield of Maize and the yield that would have been produced if the farm households had adapted.

***p < .01, **p < .05, *p < .1. Standard errors in parentheses.

And whether the instruments are correlated with the unobservables is indirectly checked using the falsification test as indicated by Di Falco, Veronesi, and Yesuf (2011). The falsification test for Maize and Teff respectively shows (F (3, 82) = 2.12 Prob > F = 0.1033; F (3, 85) = 0.69 and Prob > F = 0.559) that the instruments are not statistically significant drivers of productivity.

3.3.1. Determinants of crop yield

Table 3 presents the ESR model’s estimation for Maize. The second, fourth and fifth columns of the table show the outputs of the selection equation, and outcome equations for adapters and non-adapters, respectively. Climate variables, household and plot characteristics played a statistically significant role for yield. The variables that are significantly associated with Maize yield are age, seed type, TLU, credit, contact with DAs, urea, compost, soil type, rainfall and temperature. Farm size, credit access, soil fertility, marital status, compost use and agro-climatic zone have statistically significant associations with Teff yield. There are some variables, for instance, age that affect adapters and non-adapters differently. Such differences in the sign of coefficients reflect the presence of heterogeneity between adapters and non-adapters (Di Falco, Veronesi, and Yesuf 2011; Khanal et al. 2018).

Being married creates more likelihood of yield as compared to being unmarried for adapters. Marriage provides privilege, acceptance and power in the local culture. Findings show that an increase in age is associated with a lower likelihood of productivity for adapters and higher productivity for non-adapters, the difference might emanate from the experience or availability of labor for managing the farm. The t-test shows that there is a statistically significant age difference between adapters and non-adapters at P < .05. The association of age with adaptation and productivity is controversial in the literature. It is empirically supported that crop productivity decreases with age (Asfaw, Di Battista, and Lipper 2016), for the fact that older persons might be risk-averse and become more reluctant, and may have a shorter planning horizon in cases where the benefit of adaptation is not immediate. As a result, one could find a negative relationship between age and some adoption practices such as soil conservation practices (Shiferaw and Holden 1998). Whereas, younger farmers are more likely to be, on average, more educated with longer planning horizons and thus may engage in adaptation to climate change that results in increased production. On the other hand, age can be positively associated with adaptation and production (Maddison 2006) as a result of superior farm experience. The model revealed that the use of improved seed improves the likelihood of increasing yield. Similarly, Bedeke et al. (2018) showed that in the face of climate change, drought-resistant-improved seed, along with chemical fertilizer, increases farm productivity and net economic returns. Improved seed is justified by farmers as the preferred option among the list of agricultural adaptation practices in the upper Blue Nile basin (Nigussie et al. 2018). Similarly, Di Falco, Veronesi, and Yesuf (2011) found that seed is significantly associated with the increase in yield for those adapters, while labor and fertilizer for non-adapters.

Farmers that contact with DAs at least per two weeks have less likelihood of increasing yield as compared with those who contact later than the aforementioned time. The access of extension agents is supposed to provide information that enhances the use of adaptation strategies (Amare and Simane 2018; Bedeke et al. 2018) and hence crop productivity and food security. Having credit access has the likelihood of reducing yield for non-adapters. The FGD participant farmers described how they were usually involved in off-farm activities for repaying credit and spent less time on the farm. Usually, in the rainy season, farmers use the credit for immediate consumption rather than for farm investment. If unable to repay the credit, farmers are obliged.
to sell their livestock, which forces them into a vicious cycle of challenges. This goes against the findings of several studies (Wainaina, Tongruksawattana, and Qaim 2016; Bedeke et al. 2018; Gorst, Dehlavi, and Groom 2018; Nonvide 2018; Teklewold, Mekonnen, and Kohlin 2019) that argue adoption of improved varieties, fertilizer and SWC practices increase with the access of microcredit services.

The use of urea and compost increase the likelihood of Maize yield for non-adaptors. This is attributed to the fact that manure and crop residue reduce the cost of fertilizer while retaining soil fertility and moisture (Bedeke et al. 2018). This result is consistent with Asfaw, Di Battista, and Lipper (2016) and Di Falco, Veronesi, and Yesuf (2011) who found that the use of fertilizer and manure are significantly associated with increases in yield. The model reveals that sowing in black (fertile) soil is significantly associated with the higher yield for non-adapters. That is because of sowing in poor soil results in lower yields and net crop income (Asrat and Simane 2017; Bedeke et al. 2018). Nonvide (2018) in Benin also found that farmers who have fertile land had a higher yield compared to those who perceived the soil as poor. Increasing farm size has the likelihood of reducing yield for both adapters and non-adapters. This is probably associated with lack of proper management of farmland.

The increase in summer rainfall has the likelihood of increasing Maize yields for both adapters and non-adaptors while temperature has the likelihood of reducing yields for non-adaptors. Conversely, the increased temperature has the likelihood of increasing Teff yields for adapters and reducing for non-adaptors. Such differences in the sign of the coefficient of variables emerge from the difference in the response of crops to temperature, characteristics of the farmland in retaining moisture and access to irrigation. As most of the farmers surveyed largely depend on rainfall, the results also show the critical importance of the summer season rainfall (Asfaw, Di Battista, and Lipper 2016). Gorst, Dehlavi, and Groom (2018) also found that climate variables significantly affect crop yields in Pakistan. Both temperature and rainfall coefficients are low for both production functions. The coefficient of climate variables may be high if there is not enough variation in the data under consideration (Gorst, Groom, and Dehlavi 2015). The number of droughts experienced by farmers is found to increase the likelihood of adaptation. Similarly, Khanal et al. (2018) in Nepal found that households affected by drought or flood in the last five years were more likely to use adaptation practices. Farmers in the Dega agro-climate zone have greater likelihood of Teff yields, for both adapters and non-adapters. This is because more rain and wetter Dega is conducive for Teff yields.

**3.3.2. Impact of adaptation on crop yield**

As shown in Table 4, the impact of adaptation on crop yields is determined by differencing column (c1) and column (c2). The results portray that adaptation grants higher yields as compared with not adapting, which is consistent with several studies (for example Asrat and Simane 2017; Mohammed et al. 2017; Bedeke et al. 2018; Di Falco and Veronesi 2018; Gorst, Dehlavi, and Groom 2018; Khanal et al. 2018; Nonvide 2018; Wekesa, Ayuya, and Lagat 2018). That is, farmers who actually adopted would have gained lower if they had not adapted; and those farmers who actually did not adapt would have gained higher if they had adapted (counterfactual).

The heterogeneity shows that non-adapter’s counterfactual yield is higher than the actual adapters. For Maize and Teff, adapters would have produced 2.8 and 4.7 quintal/ha less if they would have not adapted, respectively. The actual Teff yield of non-adapters exceeds adapters that might be due to systematic differences in farm characteristics, for instance, comparative soil characteristics as shown in Table 5.

The impact of adaptation on aggregated net crop income/hectare is reported in Table 4. Crop income is net of inputs (fertilizer, seed, pesticide, insecticide and labor costs). However, land value was not considered due to the absence of an open land market in the area. The OLS estimation reveals the significant positive effect of adaptation for aggregated net crop income at $P < .044$. The estimation with the endogenous switching model shows that adapters would have earned less income if they had not adapted; and non-adapters would have earned more if they had adapted. Similar studies, for instance, Teklewold et al. (2017) found that the joint use of agricultural water management, improved crop variety and/or fertilizer has positive associations with net farm income.

**Table 5.** T-test on soil attributes of adapters and non-adapters for teff.

| Soil characteristics         | Adapters | Non-adapters | Difference |
|------------------------------|----------|--------------|------------|
| Rated average soil fertility | 1.86(0.049) | 1.99(0.045) | .13*(0.071) |
| Soil erosion                 | 2.31(0.057) | 2.10(0.053) | .21** (0.081) |

Source: Researchers survey (2016).

Notes: Soil fertility (1 refers degraded, 3 very fertile); soil erosion (1 low; 3 severe). The table shows the statistically significant difference in degree of soil erosion and fertility between adapters and non-adapters.

**4. Conclusion and policy implications**

The majority of the farming community has experienced gradual warming of temperatures and declining but
unpredictable rainfall across consecutive years. The major short-term coping strategies to CCV were decreasing food consumption, selling livestock, receiving aid, migration, borrowing and the use of stored crops. While the use of improved seed, diversification, irrigation and modifying planting and harvesting time were identified as the major adaptation strategies in the study area. Using an ESR model this study looked at whether or not these adaptation strategies increase yields of staple crops; especially Maize and Teff. The model revealed that age, seed type, contact with DAs, urea, compost, agro-climate zone, farm size, credit access, soil type, soil fertility, marital status, rainfall and temperature are significantly associated with crop yield. Except for contact with DAs and credit, the coefficient of all variables is in line with the hypothesis. Farmers with access to credit have less likelihood of increasing yields as it is not used for farm investment. Two important conclusions are drawn from this study. Firstly, adapters have benefited from increased crop productivity. Secondly, the model showed a systematic difference (heterogeneity) between adapters and non-adapters. This can be revealed by the various controlled variables. For instance, for Maize, increase in age is associated with a lower likelihood of productivity for adapters and higher productivity for non-adapters. Moreover, being single (non-married), soil erosion and infertile soil have a likelihood of reducing yields for adapters, but not for non-adapters. Three important policy implications are derived from this study. First, the heterogeneous association of a factor on adapters and non-adapters implies the importance of considering these heterogeneities during intervention. Second, ownership of productive assets (for instance, livestock) and access to climate information played a pivotal role in determining adaptation. As a result, planning and implementation of adaptation strategies should enhance and consider asset formation and devising access to climate information to increase the awareness of farmers. This increases adaptation and hence crop production. Third, access to credit is negatively associated with crop production. Interventions should revisit how credit is accessed, used and returned by farmers.

5. The research is not interested to analyze the determinants of climate change adaptation as the topic is properly addressed by other researches.

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Data deposition

Data sharing is not applicable for this article, for no datasets were generated. The authors have no right to dispose of the data as the climate data is owned by the Ethiopian meteorological agency.

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References

Adgo, E., A. Teshome, and B. Mati. 2013. “Impacts of Long-Term Soil and Water Conservation on Agricultural Productivity: The Case of Anjeni Watershed, Ethiopia.” Agricultural Water Management 117: 55–61.

Alem, Y., H. Eggert, and R. Ruhinduka. 2015. “Improving Yield Through Climate-Friendly Agriculture: The Case of the System of Rice Intensification.” Paper presented on at 13th International Conference on the Ethiopian economy co-organized by Ethiopian economic association, Addis Ababa, Ethiopia July 23–25, 2015.

Alemu, T., and A. Mengistu. 2019. “Impacts of Climate Change on Food Security in Ethiopia: Adaptation and Mitigation Options: A Review.” In Climate Change-Resilient Agriculture and Agroforestry, 397–412. Cham: Springer.

Amare, A., and B. Simane. 2018. “Does Adaptation to Climate Change and Variability Provide Household Food Security? Evidence from Muger Sub-Basin of the Upper Blue-Nile, Ethiopia.” Ecological Processes 7 (1): 13.

Antwi-Agyei, P., A. J. Dougill, L. C. Stringer, and S. N. A. Codjoe. 2018. “Adaptation Opportunities and Maladaptive Outcomes in Climate Vulnerability Hotspots of Northern Ghana.” Climate Risk Management 19: 83–93.

Asfaw, S., F. Di Battista, and L. Lipper. 2016. “Agricultural Technology Adoption Under Climate Change in the Sahel: Micro-Evidence from Niger.” Journal of African Economies 25 (5): 637–669. doi:10.1093/jae/ejw005.

Asrat, P., and B. Simane. 2017. “Household-and Plot-Level Impacts of Sustainable Land Management Practices in the Face of Climate Variability and Change: Empirical Evidence from Dabus Sub-Basin, Blue Nile River, Ethiopia.” Agriculture and Food Security 6 (1): 61.
ATA (Agricultural Transformation Agency). 2014. Annual Report Transforming Agriculture in Ethiopia 2013/14. Addis Ababa, Ethiopia.

Bedeku, S., W. Vanhove, M. Gezahegn, K. Natarajan, and P. Van Damme. 2018. “Adoption of Climate Change Adaptation Strategies by Maize-Dependent Smallholders in Ethiopia.” NIAS – Wageningen Journal of Life Sciences 88: 96–104. doi:10.1016/j.njas.2018.09.001.

Caliendo, M., and S. Kopeinig. 2008. “Some Practical Guidance for the Implementation of Propensity Score Matching.” Journal of Economic Surveys 22 (31): 72.

Central Statistical Agency. 2013. Population Projection of Ethiopia for All Regions at Wereda Level from 2014–2017. Addis Ababa, Ethiopia: Central Statistical Agency.

Cholo, T. C., L. Fleskens, D. Sietz, and J. Peerlings. 2019. “Land Fragmentation, Climate Change Adaptation, and Food Security in the Gamo Highlands of Ethiopia.” Agricultural Economics 50 (1): 39–49.

Collier, P., G. Conway, and T. Venables. 2008. Climate Change and Africa.” Oxford Review of Economic Policy 24 (2): 337–353.

Daniel, D. 2001. Soil and Water Conservation Manual/Guideline for Ethiopia. Soil and Water Conservation Team, Natural Resources Management and Regulatory Department. Addis Ababa: Ministry of Agriculture.

Deressa, T., and R. H. Hassan. 2010. “Economic Impact of Climate Change on Crop Production in Ethiopia: Evidence from Cross-Section Measures.” Journal of African Economies 18 (4): 529–554.

Deressa, T., R. M. Hassan, C. Ringler, T. Alemu, and M. Yesuf. 2009. “Determinants of Farmers’ Choice of Adaptation Methods to Climate Change in the Nile Basin of Ethiopia.” Global Environmental Change 19 (1): 248–255.

Di Falco, S. 2014. “Adaptation to Climate Change in Sub-Saharan Agriculture: Assessing the Evidence and Rethinking the Drivers.” European Review of Agricultural Economics 41 (3): 405–430. doi:10.1093/erae/jbu014.

Di Falco, S., G. Kohlin, and M. Yesuf. 2012. “Strategies to Adapt to Climate Change and Farm Productivity in the Nile Basin of Ethiopia.” Climate Change Economics 3 (2): 1250009.

Di Falco, S., and M. Veronesi. 2018. “Managing Environmental Risk in Presence of Climate Change: The Role of Adaptation in the Nile Basin of Ethiopia.” In Climate Smart Agriculture, Natural Resource Management and Policy (Vol. 52), edited by L. Lipper, N. McCarthy, D. Zilberman, S. Asfaw, and G. Branca, 497–526. Cham: Springer.

Di Falco, S., M. Veronesi, and M. Yesuf. 2011. “Does Adaptation to Climate Change Provide Food Security? A Micro-Perspective from Ethiopia.” American Journal of Agricultural Economics 93 (3): 829–846. doi:10.1093/ajae/aar006.

Edwards, S. 2010. Ethiopian Environment Review No. 1. Addis Ababa, Ethiopia: Forum for Environment.

FAO. 2014. Climate-smart Agriculture and Resource Tenure in Sub-Saharan Africa: A Conceptual Framework. Washington, DC: FAO.

Gorst, A., A. Dehlavi, and B. Groom. 2018. “Crop Productivity and Adaptation to Climate Change in Pakistan.” Environment and Development Economics 23 (6): 679–701.

Gorst, A., B. Groom, and A. Dehlavi. 2015. Crop Productivity and Adaptation to Climate Change in Pakistan. London: Center for Climate Change, Economics and Policy, ESRC Research Center.

Greene, W. H. 2003. Econometric Analysis. 5th ed. Upper Saddle River, NJ: Prentice Hall.

Harmer, N., and S. Rahman. 2014. “Climate Change Response at the Farm Level: A Review of Farmers’ Awareness and Adaptation Strategies in Developing Countries.” Geography Compass 8 (11): 808–822. doi:10.1111/gec3.12180.

Heckman, J. 1979. “Sample Selection Bias as a Specification Error.” Econometrica 47: 153–161.

IPCC. 2014. Climate Change 2014: Impacts, Adaptation, and Vulnerability. IPCC WGII AR5: Summary for Policy Makers. Rome: IPCC.

Jahnke, H. E. 1982. Livestock Production Systems and Livestock Development in Tropical Africa. Vol. 35. Kiel: Kieler Wissenschaftsverlag Vauk.

Kassa, Y., F. Beyene, J. Haji, and B. Legesse. 2013. “Impact of Integrated Soil and Water Conservation Program on Crop Production and Income in West Harerghze Region.” International Journal of Environmental Monitoring and Analysis 1 (4): 111–120.

Kassie, M., M. Jaleta, B. Shiferaw, F. Mmbando, and M. Mekuria. 2013. “Adoption of Interrelated Sustainable Agricultural Practices in Smallholder Systems: Evidence from Rural Tanzania.” Technological Forecasting and Social Change 80 (3): 525–540.

Kassie, M., J. Pender, M. Yesuf, G. Kohlin, R. Bluffstone, and E. Mulugeta. 2008. “Estimating Returns to Soil Conservation Adoption in the Northern Ethiopian Highlands.” Agricultural Economics 38: 213–232.

Kebede, W., and N. Mesele. 2014. “Farmers’ Adoption of Soil and Water Conservation Technology: A Case Study of the Bokole and Toni Sub-Watersheds, Southern Ethiopia.” Journal of Science and Development 2 (1): 35–48.

Khanal, U., C. Wilson, B. L. Lee, and V. N. Hoang. 2018. “Climate Change Adaptation Strategies and Food Productivity in Nepal: A Counterfactual Analysis.” Climatic Change 148 (4): 575–590.

Komba, C., and E. Muchapondwa. 2018. “Adaptation to Climate Change by Smallholder Farmers in Tanzania.” Agricultural Adaptation to Climate Change in Africa 129 (168): 129–168. Routledge in Association with GSE.

Kothari, C. R. 2004. Research Methodology: Methods and Techniques. 2nd ed. Ansari Road, Daryaganj. New Delhi: New Age International.

Lobell, D. B. 2014. “Climate Change Adaptation in Crop Production: Beware of Illusions.” Global Food Security 3 (2): 72–76.

Lokshin, M., and Z. Sajaia. 2004. “Maximum Likelihood Estimation of Endogenous Switching Regression Models.” The Stata Journal: Promoting Communications on Statistics and Stata 4: 282–289.

Madalla, G. 1983. Limited Dependent and Qualitative Variables in Econometrics. Cambridge: Cambridge University Press.

Maddison, D. 2006. “The Perception of and Adaptation to Climate Change in Africa.” CEEPA. Discussion paper No. 10, Centre for Environmental Economics and Policy in Africa, University of Pretoria, Pretoria.

Mengistu, D., W. Bewket, and R. Lal. 2015. “Conservation Effects on Soil Quality and Climate Change Adaptability of Ethiopian Watersheds.” Land Degradation & Development 27 (2016): 1603–1621. doi:10.1002/ldr.2376.
Mohammed, A., T. Tana, P. Singh, A. Molla, and A. Seid. 2017. “Identifying Best Crop Management Practices for Chickpea (Cicer arietinum L.) in Northeastern Ethiopia Under Climate Change Condition.” *Agricultural Water Management* 194: 68–77.

Nigussie, Y., E. van der Werf, X. Zhu, B. Simane, and E. C. van Ierland. 2018. “Evaluation of Climate Change Adaptation Alternatives for Smallholder Farmers in the Upper Blue-Nile Basin.” *Ecological Economics* 151: 142–150.

Nonvide, G. M. A. 2018. “A Re-examination of the Impact of Irrigation on Rice Production in Benin: An Application of the Endogenous Switching Model.” *Kasetsart Journal of Social Sciences*, 1–6. doi:10.1016/j.kjss.2017.12.020.

Pender, J., and B. Gebremedhin. 2006. “Land Management, Crop Production, and Household Income in the Highlands of Tigray, Northern Ethiopia: An Econometric Analysis.” In *Strategies for Sustainable Land Management in the East African Highlands*, edited by John Pender, Frank Place, and Simeon Ehui, 107–140. Washington, DC: IFPRI.

Rosegrant, M. W., M. S. Paisner, S. Meijer, and J. Witcover. 2001. *Global Food Projections to 2020: Emerging Trends and Alternative Futures*. Washington, DC: International Food Policy Research Institute.

Seo, S., and R. Mendelsohn. 2008. “Measuring Impacts and Adaptations to Climate Change: A Structural Ricardian Model of African Livestock Management.” *Agricultural Economics* 38 (2): 151–165.

Shiferaw, B., and S. T. Holden. 1998. “Resource Degradation and Adoption of Land Conservation Technologies in the Ethiopian Highlands: A Case Study in Andit Tid, North Shewa.” *Agricultural Economics* 18 (34): 233–247.

Shiferaw, B., K. Tesfaye, M. Kassie, T. Abate, B. M. Prasanna, and A. Menkir. 2014. “Managing Vulnerability to Drought and Enhancing Livelihood Resilience in Sub-Saharan Africa: Technological, Institutional and Policy Options.” *Weather and Climate Extremes* 3: 67–79. doi:10.1016/j.wace.2014.04.004.

Tamene, L., S. Park, R. Dikau, and Vlekg PIlg. 2006. “Reservoir Siltation in the Semi-Arid Highlands of Northern Ethiopia: Sediment Yield-Catchment Area Relationship and a Semi-Quantitative Approach for Predicting Sediment Yield.” *Earth Surface Processes and Landforms* 31 (11): 1364–1383.

Teklewold, H., and A. Mekonnen. 2017. “The Tilling of Land in a Changing Climate: Empirical Evidence From the Nile Basin of Ethiopia.” *Land Use Policy* 67: 449–459.

Teklewold, H., A. Mekonnen, and G. Kohlin. 2019. “Climate Change Adaptation: A Study of Multiple Climate-Smart Practices in the Nile Basin of Ethiopia.” *Climate and Development* 11 (2): 180–192.

Teklewold, H., A. Mekonnen, G. Kohlin, and S. Di Falco. 2017. “Does Adoption of Multiple Climate-Smart Practices Improve Farmers’ Climate Resilience? Empirical Evidence From the Nile Basin of Ethiopia.” *Climate Change Economics* 8 (1): 1750001. doi:10.1142/S2010007817500014.

TerrAfrica. 2009. “The Role of Sustainable Land Management for Climate Change Adaptation and Mitigation in Sub-Saharan Africa.” Issue Paper, TerrAfrica, Regional Sustainable Land ManagementTerrAfrica Partnership.

Wainaina, P., Tongruksawattana, S., Qaim, M. 2016. “Tradeoffs and Complementarities in the Adoption of Improved Seeds, Fertilizer, and Natural Resource Management Technologies in Kenya.” *Agricultural Economics*. 47 (3), 351–362. doi:10.1111/agec.12235.

Water Works Design and Supervision Enterprise and TAHAL Consulting Engineers. 2008. *Lake Tana Sub-basin four Dams Project, Final Feasibility Report for Rib Dam Project*. Vol.8: Watershed Management Study Report.

Wekesa, B. M., O. I. Ayuya, and J. K. Lagat. 2018. “Effect of Climate-Smart Agricultural Practices on Household Food Security in Smallholder Production Systems: Micro-Level Evidence From Kenya.” *Agriculture and Food Security* 7 (1): 80.

World Bank. 2006. *Ethiopia: Managing Water Resources to Maximize Sustainable Growth. A World Bank Water Resources Assistance Strategy for Ethiopia*. BNPP Report TF050714. Washington, DC.

World Bank. 2010. *Economics of Adaptation to Climate Change Ethiopia*. Washington, DC.

Yesuf, M., S. Di Falco, T. Deressa, C. Ringler, and G. Kohlin. 2008. “The Impact of Climate Change and Adaptation on Food Production in Low-Income Countries, Evidence from the Nile Basin, Ethiopia.” IFPRI Discussion Paper 00828.