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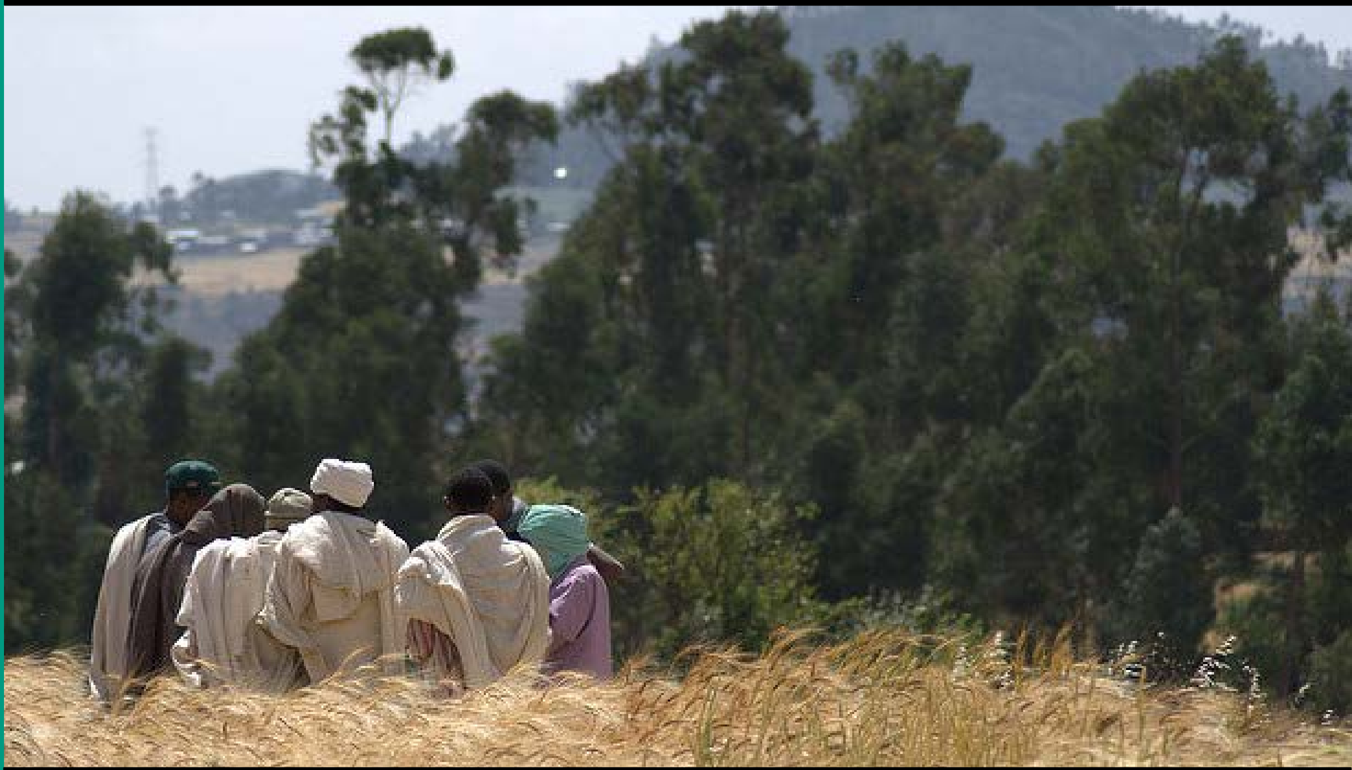

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Adoption of agricultural technologies in the semi-arid northern Ethiopia: A Panel Data Analysis

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Abstract

Agricultural technology change is required in developing countries to increase the robustness to climate-related variability, feed a growing population, and create opportunities for market-oriented production. This study investigates technological change in the form of adoption of improved wheat, drought-tolerant teff, and cash crops in the semi-arid Tigray region in northern Ethiopia. We analyze three rounds of panel data collected from smallholder farms in 2005/2006, 2009/2010 and 2014/2015 with a total sample of 1269 households. Double-hurdle models are used to assess how the likelihood (first hurdle) and intensity of technology adoption (second hurdle) are affected by demographic, weather, and market factors. The results indicate that few smallholders have adopted the new crops, those that have adopted the crops only plant small shares of their land with the new crops, and that there has been only a small increase in adoption over the ten-year period. Furthermore, we find that high population density is positively associated with the adoption of improved wheat, and previous period's rainfall is positively associated with the adoption of drought-tolerant teff. The adoption of cash crops is positively associated with landholding size and access to irrigation. The policy implications of these results are that the government should increase the improved wheat diffusion efforts in less population dense areas, make sure that drought-tolerant teff seed is available and affordable after droughts, and promote irrigation infrastructure for production of cash crops.

Keywords: Semi-arid areas, climate risk, new crop varieties, double-hurdle, northern Ethiopia.

JEL Classification: O33; Q12; Q16; R34

1. Introduction

Adoption of improved agricultural technologies is an important means of adapting to climate change, improving agricultural productivity, and facilitate the transition from subsistence agriculture to market-oriented agriculture (Bezu et al., 2014; De Janvry & Sadoulet, 2002; Mendola, 2007; Minten & Barrett, 2005; Yu et al., 2011; Zilberman et al., 2012). Among the technologies adopted by farmers in the Ethiopian highlands are improved wheat, drought-tolerant teff, and cash crops (Belay et al., 2006; Shiferaw et al., 2014; Wale & Chianu, 2015). In this paper, we investigate to what extent farmers in the semiarid Tigray region of Ethiopia have adopted improved wheat, drought-tolerant teff, and cash crops, and which factors explains the adoption and intensity of adoption.

Technology diffusion often takes years and can best be captured using panel data. However, most studies on the adoption of improved wheat in semi-arid agriculture in Ethiopia use cross-sectional data (Kelemu, 2017; Kotu et al., 2000; Lobell et al., 2005; Matuschke et al., 2007; Shiferaw et al., 2014; Tesfaye et al., 2016). One of few studies including a time dimension is Abera (2008), who use cross-section household data from 2001 with recall data back to 1997, and estimate factors affecting adoption of improved wheat in northern and west Shewa zones of Ethiopia. He analyzes how farmer and farm characteristics are correlated with adoption and intensity of adoption, but does not cover important supply-side constraints that need attention.

Studies of drought-tolerant teff in Ethiopia include Wale and Chianu (2015) and Belay et al. (2006). Wale and Chianu (2015) examine farmers' demand for drought-tolerant teff using cross-sectional data. The study of Belay et al. (2006) use data from an experiment on village demonstration plots, including 41 farmers in 2002 and 2003, and find that farmers adopt drought-tolerant teff varieties when there is limited rainfall. To the best of our knowledge, empirical studies of the adoption of drought-tolerant teff using rich panel data from semi-arid agriculture are missing.

Adoption of cash crops is mainly associated with access to irrigation and has a dual advantage. First, irrigation and adoption of cash crops typically allow the smallholders to harvest more than one time per year, which lead to improved land productivity. Second, the adoption of cash crops leads to improved output market integration and increased income. Ethiopia has adopted smallholders' commercialization as part of its economic transformation strategy (Gebremedhin et al., 2009). The development of irrigation reduces the production risk in semi-arid areas and expansion of public investments in infrastructures improve market access. This has improved agricultural productivity and enhanced market participation by Ethiopian smallholders (Gebregziabher et al., 2009; Hailua et al., 2015).

The main contribution of this study is threefold: First, we provide new insight into the development in adoption of the three improved agricultural technologies improved wheat, drought-tolerant teff and cash crops in Tigray, Ethiopia. Second, we provide new insight into factors affecting the likelihood of adoption and intensity of adoption for these improved agricultural technologies. Third, we discuss policy implications for how to best integrate and reap the benefits from the promotion of improved wheat, drought-tolerant teff and cash crops, given their importance for food productivity, food security, and market integration.

2. Survey design and data

The data is collected in Tigray in northern Ethiopia. The region is semi-arid and exhibits high population pressure, seasonal and erratic rainfall, relatively low agricultural potential, and limited access to sizeable markets. The data used in this study come from three rounds of farm household surveys conducted in 2005/2006, 2009/2010 and 2014/2015 production seasons (Table 1).

The panel sample is based on a survey conducted in 1998/1999 using a two-stage sampling technique and described in Hagos and Holden (2003). In the first stage, communities were selected from the rural districts of the region to reflect differences in agricultural potential, population density, agro-ecology, market access, and access to irrigation. In the second stage, 25 households were randomly sampled from a list of farm families in the selected communities for detailed interviews. Most of the technologies of interest for this study were introduced in the study region after year 2000, and we use data from the three survey rounds in 2006, 2010 and 2015, each covering the previous year cropping seasons. Over time some households dropped out of the sample and new were added, resulting in an unbalanced household panel.

To examine farmers' technology adoption decisions, we use information on household and farm characteristics including land and non-land endowments, farm-level population pressure, indicators of access to infrastructure (market-place and road), and rainfall at community level. We construct long-term average annual rainfall, variation (standard deviation) in average annual rainfall, and one and two-year lagged annual rainfall at the community level from the monthly satellite record of the African Rainfall Climatology Version 2 (ARC2) for the years 2003-2014[2].

Presuming that access to technology differs according to the features of agro-ecology and accessibility of public services, we divide the households into three access-to-agricultural-technologies groups. The first access group is households residing in the mid- and highland agro-ecology with access to improved wheat (Group 1). In Ethiopia wheat is a mid- and highland crop (Doss et al., 2003; Kotu et al., 2000) and is distributed to households in this agroecology. The second access group is households who live in drought-affected agro-ecologies with access to drought-tolerant teff (Group 2). Promotion of the adoption of drought-tolerant teff is an important strategy for adapting to the changing climate in these areas. The third access group is households who live in communities with access to irrigation and, thereby, are able to grow cash crops (Group 3). Access to irrigation such as a dam or ground-water that can be used to grow crops facilitate the adoption of cash crops. We will later refer to these three regionally determined access groups as the households with access to improved wheat, access to drought-tolerant teff, and access to cash crops, respectively.

3. Theoretical framework

Household's adoption decision of new technology is usually modeled as a choice between traditional and new technology. A farm household adopts the new agricultural technology when the expected benefit from adoption is higher than without adoption (Amare et al., 2012; Bezu et al., 2014; Ma & Shi, 2015). More recently, the literature has started to investigate constraints that could cause only partial adoption across and within farms.

The theoretical framework of this study builds on the state-contingent partial adoption framework for new technologies in a risk exposed economy, as in Holden and Quiggin (2017). Partial and state-contingent adoption reflects that household choices may be affected by factors such as stochastic weather events, market imperfections in input and output markets, limited knowledge about the performance of new technologies under different states of nature, limited availability and high cost of technologies, and heterogeneity in farm and household characteristics.

Climate change and climate risk may affect technology adoption as illustrated by the state-contingent production approach (Holden & Quiggin, 2017). This approach states that farmers' adoption decision depends on their perception of risk associated with the choice of the new technology relative to alternative technologies and the states of nature that may be realized after adoption decisions are made. Limited knowledge of the performance of new technologies under alternative states of nature may be one constraint. Partial adoption and exposure to different states of nature can over time help farmers build realistic and more accurate expectations about alternative technologies and thereby influence the adoption and adaptation process. Hence, households exposed to earlier weather shocks and who are risk-averse are more likely to choose a less risky technology such as drought-tolerant crop varieties when they have developed their knowledge about these (Amare et al., 2012; Antle, 1987; Holden & Quiggin, 2017).

Another research string important for our study is the literature on technology diffusion. Pan et al. (2018) investigate how technology diffusion processes affect farmers' adoption decisions. They find that factors making it easy to learn about the benefits of new technologies have a positive impact on adoption rates. Examples of such factors are extension services, field demonstrations, market integration, and viewing and learning from other farmers. Other studies also point to learning externalities, social learning diffusion, communication patterns, and following successful neighbors' practices as drivers of technology diffusion (Conley and Udry, 2005; Genius et al., 2010). In total, these studies point in the direction of a gradual increase in adoption of improved agricultural technologies over time, if they are available and affordable.

Based on the theoretical framework, we propose the following hypotheses for testing:

H1. There is a gradual increase in the adoption and intensity of adoption of the three improved agricultural technologies over the ten-year time period.

H2. Improved wheat is more likely to be adopted in areas with high population pressure and by more land-constrained households (high farm level population pressure).

H3. Drought-tolerant teff is more likely to be adopted in areas with more rainfall variability and in areas exposed to recent rainfall shocks (droughts).

H4. Cash crops are more likely to be adopted in areas with good market access (short distance to markets).

4. Estimation Method: Double-hurdle Model

The technology adoption literature proposes various econometric methods that can be used in modeling the behavior of households' demand for new agricultural technology and identify the factors that can explain adoption decisions (Heckman, 1979; Maddala & Nelson, 1975; Wooldridge, 2010). We present results based on Cragg's double-hurdle models that allow variables to have different effects on adoption and intensity of adoption. In the first hurdle, we estimate a probit model to determine the probability that the households adopt the new agricultural technologies. In the second hurdle, we use a truncated regression model to determine the intensity of the adoption. We estimate the double-hurdle models for the adoption of the three technologies separately using the subsample that has access to the respective technologies.

We first run parsimonious models with the key explanatory variables of interest: household level and average community-level population pressure (family size/farm size), average community level rainfall and rainfall variability over the last 12 years, one and two years lagged deviations from average rainfall, distance to market, and farm-level access to irrigation in the case of cash crops. We then assess the robustness of these results by including additional household control variables with and without a Correlated Random Effects (CRE) approach (see elaboration below). The control variables include household head characteristics (gender, age, age squared, and literacy status), family labor (number of adult males and females), household resource endowments (number of oxen, mobile phone ownership (dummy), and size of owned land). Two year-dummies are also included to capture change over time (2010 and 2015). We will refer to these control variables by the vector X.

We specify the following Craggit double-hurdle model:

Hurdle 1: Probability of adoption, binary probit

$$P(w_{ijt} = 1) = \alpha_p P_{ijt} + \alpha_r R_{ct} + \alpha_d D_{ct} + (\alpha_n X_{ijt} + \gamma_n \bar{X}_{ij}) + u_i + e_{ijt} \quad (1)$$

Hurdle 2: Intensity of adoption, truncated regression model

$$Y_{ijt} = \beta_p P_{ijt} + \beta_r R_{ct} + \beta_d D_{ct} + \left(\beta_n X_{ijt} + \delta_n \bar{X}_{ij}\right) + \mu_i + \varepsilon_{ijt} \text{ if } w = 1,\ 0 \text{ otherwise} \quad (2)$$

Where w_{ijt} is a variable indicating whether or not the household adopt the new technology, taking the value of 1 if the household adopts the technology and 0 otherwise; Y_{ijt} is the observed intensity of adoption measured as the log of area planted with the technology for the households that have adopted the technology; P_{ijt} represents household and community population pressure; R_{ct} is a vector representing the rainfall variables; D_{ct} is the distance to market; and X_{ijt} is a vector of the control variables as explained above. To control for unobserved heterogeneity the means of the time-varying *X* variables, $\bar{X}_{ij}$, are included, which is the Mundlak (1978), and Chamberlain (1982), approach, also known as the Correlated Random Effects (CRE) approach (Wooldridge, 2010). This approach controls for other time-constant unobservable variables in a similar way as household fixed effects do in a linear panel data model. i, j and t are individual household, technology type, and time identifiers, respectively; α and β are the parameters to be estimated for the *n X*-variables, and u_i and μ_i are normally distributed random effects, constant for each household over time; e_{ijt} and ε_{ijt} are error terms assumed to be independent and normally distributed, $e_{ijt} \sim N(0,1)$ and $\varepsilon_{ijt} \sim N(0, \sigma^2)$.

A limitation of the CRE approach is that it takes many degrees of freedom and that may affect significance levels in small samples such as in the second stage of our double-hurdle models. We, therefore, run models without and with this specification as a robustness check. We have also tested for attrition bias, but found no significant effect on our results, and hence report the results without attrition controls.

5. Descriptive analysis

Table 1 presents the mean values of technology adoption rates and intensity of adoption by technology and year in our panel, as well as the key variables of interest for our study. The adoption rates measure the share of households using each crop in the region they are available, while the adoption intensity measures the area the adopters planted with each crop. The areas are measured in *tsimdi*, one *tsimdi* is approximately 0.25 ha. Average farm size in *tsimdi* is also included in the table, for comparison with areas planted with the new crops of interest to our study.

We observe that the adoption rate for the improved wheat increased from 12.9 % in 2006 to 18.4 % in 2010 and decreased to 13.8 % in 2015, indicating an initial increase and then stagnation and decline in adoption. The pattern for adoption intensity shows a similar trend over time. On average across years, adopters of improved wheat had planted about 5 % of their farm area with improved wheat.

Drought-tolerant teff had adoption rates of 6 %, 3.9 %, and 16 % respectively over the three years, indicating a stagnant low rate first but then a substantial increase in the adoption rate. The adoption intensity was stagnant and small from 2006 to 2010 but then more than doubled from 2010 to 2015. On average across years, adopters of drought-tolerant teff had planted about 3 % of their farm area with drought-tolerant teff.

For cash crops, we see an initial increase in adoption rate from 11.5% to 18.4%, and then a weak decline to 16%. On average across years, adopters of cash crops had planted about 3 % of their farm area with cash crops.

Overall, we see low adoption rates and only small shares of the farms of adopters covered by the new crops. Only for drought-tolerant teff do we see a clear trend towards increasing adoption. For the two other technologies we see a stagnation or decline in the adoption rates over time. Hence, we do not find support for our Hypothesis H1 stating, “There is a gradual increase in the adoption and intensity of adoption of the three improved agricultural technologies over the ten-year time period.”

Table 1: Summary statistics of variables used in the analysis by survey year (mean values)

Variables description	2006		2010		2015		Pooled	
	Mean	St. Err.	Mean	St. Err.	Mean	St. Err.	Mean	St. Err.
Three subsamples								
High yield wheat adoption (yes =1)	0.129	0.018	0.184	0.018	0.138	0.016	0.151	0.010
High yield wheat area planted, adopters (*tsimidi*)	0.158	0.029	0.306	0.041	0.199	0.031	0.225	0.020
Drought-tolerant teff adoption (yes=1)	0.060	0.013	0.039	0.009	0.160	0.017	0.091	0.008
Drought-tolerant teff area planted, adopters (*tsimidi*)	0.097	0.026	0.087	0.027	0.233	0.040	0.145	0.019
Cash crops adoption (yes =1)	0.115	0.017	0.184	0.018	0.160	0.017	0.156	0.010
Cash crop area planted, adopters (*tsimidi*)	0.044	0.008	0.190	0.034	0.191	0.037	0.150	0.019
Owned land (*tsimidi*)	4.430	3.261	4.429	3.093	4.542	2.928	4.472	3.077
Full sample								
Farm level population pressure	2.168	0.176	1.778	0.075	2.100	0 .330	2.007	0.136
Mean value of farm level pop. pressure at community level	2.091	0.076	1.987	0.061	1.965	0.058	2.007	0 .037
Distance to market (hours)	1.407	0.048	1.401	0.043	1.394	0.043	1.400	0.025
Mean rainfall of 12 years panel (cm)	47.057	0.953	45.203	0.710	44.948	0.673	45.615	0.441
Rainfall variability (std. dev.) of 12-year panel (cm)	8.566	0.069	8.820	0.054	8.838	0.052	8.757	0.033
One-year lagged positive deviation from long term mean rainfall (cm)	0.000	-	1.287	0.110	15.890	0.650	6.457	0.323
One-year lagged negative deviation from long term mean rainfall (cm)	10.612	0.175	5.199	0.199	0.000	-	4.717	0.145
Two-year lagged positive deviation from long term mean rainfall (cm)	0.000	-	0.991	0.119	2.817	0.133	1.410	0.072
Two-year lagged negative deviation from long term mean rainfall (cm)	14.504	0.363	7.011	0.305	1.335	0.104	6.919	0.211
Sample size								
Improved wheat	187		287		340		814	
Drought-tolerant teff	218		336		441		995	
Cash crops	31		126		141		298	

Source: NMBU and MU household panel.

6. Estimation results

The results of the double-hurdle model for adoption and intensity of adoption are presented in Table 2 for improved wheat, Table 3 for drought-tolerant teff, and Table 4 for cash crops. We discuss one technology at a time in the following three sections. The three technologies are largely adopted in different areas and do to a very small extent compete for the same land. We can, therefore, consider their adoption as independent processes. The adoption for each technology is estimated for the areas that have access to these technologies and where these technologies are suitable.

To verify whether the results are robust we present the results from three different double-hurdle models for each technology. The first is a parsimonious version that includes only the key variables of interest, the second includes additional controls, and the third includes the means of the RHS variables including additional controls (CRE approach). In our interpretation we give most weight to the results that are significant across all three model versions. We focus primarily of the assessment of our four hypotheses in the interpretation of the results.

6.1 Improved wheat adoption

The results for the improved wheat models are presented in Table 2. Our Hypothesis H2 stated, "Improved wheat is more likely to be adopted in areas with high population pressure and by more land-constrained households (high farm level population pressure)". Table 2 shows that farm-level population pressure is strongly and robustly positively correlated with adoption of improved wheat. This result is significant at 1% level in two of three model variants, and significant at 5% level in the third. The intensity of adoption was negatively correlated with community-level population pressure and significant at 1 and 5% levels in two of three models. This means we have support only for the second part of the hypothesis, that more land-constrained households are more likely to adopt improved wheat.

The results further show that improved wheat adoption was more likely in areas with lower average rainfall, higher rainfall variability and two years after a negative rainfall shock. This indicates that improved wheat adoption can be a response to droughts in areas with lower than average and more variable rainfall. These results were also robust to the alternative model specifications. Finally, improved wheat adoption was not significantly affected by distance to markets.

6.2. Drought-tolerant teff adoption

We formulated the following hypothesis H3 that “Drought-tolerant teff is more likely to be adopted in areas with more rainfall variability and in areas exposed to recent rainfall shocks (droughts)”. We see from Table 3 that the standard deviation for rainfall is insignificant in all models. Furthermore, the lagged negative rainfall shock variables were also insignificant while the one year lagged positive rainfall shock variable was highly significant and positive in all three versions of the adoption (first hurdle) models. We, therefore, have to reject our hypothesis H3.

Intensity of adoption of drought-tolerant teff was found to be higher in areas with larger distance to markets. This result was highly significant (1% level) in all three models. The year dummy for 2015 was significant and negative in all three models. This should point in direction of dis-adoption of drought-tolerant teff from 2006 to 2015 but Table 1 indicates that adoption has increased over time. This difference could be due to the unbalanced sample or changes in drivers over time.

6.3. Cash crop production

We have assessed factors associated with cash crop production in areas with access to irrigation in Table 4. We hypothesized (H4) that cash crops are more likely to be adopted in areas with good market access. The distance to market variable is, however, insignificant in all models and we, therefore, must reject hypothesis H4. On the other hand, we see that farm-level population pressure is highly significant and positive in the first hurdle, indicating that cash crops are more likely to be grown on farms with high family size/farm size ratio. This may be because such households have more labor to grow labor-intensive crops. Furthermore, cash crops are more likely to be grown in areas with higher rainfall variability and after a year with good rainfall. This may indicate that food crops are given priority after years with lower rainfall. The negative signs for the year dummy variables are not consistent with the probabilities of growing cash crops across years in Table 1. This difference could be due to the unbalanced sample or changes in drivers over time.

Table 2: Double-hurdle estimation factors affecting adoption of improved wheat (craggit model).

	Without HH controls		With HH controls		HH controls +CRE	
Variables	Hurdle 1	Hurdle 2	Hurdle 1	Hurdle 2	Hurdle 1	Hurdle 2
Mean farm level pop pressure at community level	0.018	-0.163***	0.052	-0.069**	0.049	-0.054
	(0.040)	(0.038)	(0.046)	(0.034)	(0.052)	(80.035
Deviation of farm level pop pressure from community mean	0.013**	-0.003	0.014***	0.000	0.017***	0.000
	(0.005)	(0.003)	(0.005)	(0.001)	(0.006)	(0.001)
Mean rainfall 2003-2014 (cm)	-0.042**	-0.010	-0.052***	-0.006	-0.059***	-0.008
	(0.017)	(0.017)	(0.018)	(0.014)	(0.018)	(0.015)
St. Dev. rainfall 2003-2014 (cm)	0.179**	0.011	0.235**	0.055	0.279***	0.063
	(0.100)	(0.100)	(0.107)	(0.090)	(0.108)	(0.091)
One year lagged positive deviation rainfall (cm)	0.011	0.008	0.013	0.005	0.017	0.007
	(0.012)	(0.010)	(0.012)	(0.009)	(0.012)	(0.010)
One year lagged negative deviation rainfall cm)	-0.018	0.004	-0.021	-0.008	-0.022	-0.004
	(0.018)	(0.014)	(0.018)	(0.014)	(0.018)	(0.014)
Two years lagged positive deviation rainfall (cm)	0.001	0.030	0.005	0.017	0.006	0.016
	(0.023)	(0.019)	(0.024)	(0.018)	(0.024)	(0.019)
Two years lagged negative deviation rainfall (cm)	0.030**	-0.003	0.033***	0.000	0.031**	0.001
	(0.012)	(0.007)	(0.012)	(0.006)	(0.012)	(0.007)
Distance to market(hours)	-0.056	0.072	-0.054	0.048	-0.060	0.056
	(0.073)	(0.044)	(0.075)	(0.038)	(0.075)	(0.037)
Year 2010 dummy	0.174	0.219**	-0.016	0.168	0.072	0.227**
	(0.157)	(0.107)	(0.171)	(0.111)	(0.178)	(0.124)
Year 2015 dummy	-0.055	0.097	-0.217	0.002	-0.304	0.061
	(0.259)	(0.170)	(0.262)	(0.157)	(0.263)	(0.165)
Constant	-0.755*	1.105***	-2.212**	-0.605	-2.354**	-0.624
	(0.451)	(0.324)	(0.928)	(0.555)	(1.136)	(0.653)
Sigma constant		0.427***		0.380***		0.371***
		(0.030)		(0.024)		(0.024)
Chi2	35.04		75.57		84.29	
Log like hood	-514.01		-473.97		-461.78	
Prob>chi2	0.0000		0.0000		0.0000	
N	814	192	814	192	814	192

Hurdle 1: probability of adoption and hurdle 2= Log of area planted upon adoption of the technology. The HH Control + CRE models include the mean and actual value of time-variant household control variables (not reported in this table to save space). Numbers in parenthesis are cluster robust standard errors. ***, **, and * are to 1, 5, and 10 % levels of significance, respectively. Source: NMBU and MU household panel survey.

Table 3 Double-hurdle estimation factors affecting adoption of Drought-tolerant teff (craggit model).

	Without HH controls		With HH controls		HH controls +CRE	
Variables	Hurdle 1	Hurdle 2	Hurdle 1	Hurdle 2	Hurdle 1	Hurdle 2
Mean farm level pop pressure at community level	0.091	-0.179*	0.080	-0.061	0.102	-0.061
	(0.088)	(0.104)	(0.108)	(0.107)	(0.122)	(0.118)
Deviation of farm-level pop pressure from community mean	-0.012	-0.053	0.003	0.033	0.008	0.035
	(0.047)	(0.078)	(0.060)	(0.060)	(0.065)	(0.052)
Mean rainfall 2003-2014 (cm)	-0.001	-0.004	-0.002	-0.004	-0.001	-0.009
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
St. Dev. rainfall 2003-2014 (cm)	0.015	-0.027	0.055	0.042	0.028	0.069
	(0.112)	(0.096)	(0.116)	(0.116)	(0.117)	(0.102)
One year. lagged positive deviation rainfall (cm)	0.029***	0.005	0.031***	0.002	0.030***	0.008*
	(0.007)	(0.006)	(0.007)	(0.005)	(0.007)	(0.005)
One year. lagged negative deviation rainfall (cm)	-0.017	-0.004	-0.021	0.000	-0.016	0.016
	(0.025)	(0.019)	(0.025)	(0.021)	(0.025)	(0.022)
Two years lagged positive deviation rainfall (cm)	0.014	0.007	0.004	-0.008	-0.002	0.018
	(0.030)	(0.034)	(0.031)	(0.026)	(0.033)	(0.027)
Two years lagged negative deviation rainfall (cm)	-0.008	-0.018	-0.008	-0.014	-0.010	-0.018
	(0.014)	(0.011)	(0.015)	(0.010)	(0.015)	(0.011)
Distance to market(hours)	0.052	0.158***	0.045	0.123***	0.060	0.109***
	(0.062)	(0.044)	(0.063)	(0.044)	(0.061)	(0.038)
Year 2010 dummy	-0.616*	-0.157	0.901***	-0.049	-0.680**	0.015
	(0.317)	(0.208)	(0.321)	(0.225)	(0.331)	(0.198)
Year 2015 dummy	-0.701*	-0.373	-0.912**	-0.167	-0.843**	-0.109
	(0.425)	(0.342)	(0.425)	(0.308)	(0.427)	(0.327)
Constant	-1.291*	1.693***	2.810***	-0.169	-2.126*	-1.910
	(0.710)	(0.548)	(1.061)	(1.626)	(1.217)	(1.419)
Sigma constant		0.458***		0.394***		0.359***
		(0.042)		(0.029)		(0.025)
Chi2	57.21		92.38		130.10	
Log-likelihood	-333.77		-309.32		-294.78	
Prob>chi2	0.0000		0.0000		0.0000	
N	995	115	995	115	995	115

Note: Hurdle 1: probability of adoption and hurdle 2= Log of area planted upon adoption of the technology. The HH Control + CRE models include the mean and actual value of time-variant household control variables (not reported in this table to save space). Numbers in parenthesis are cluster robust standard errors. ***, **, and * are to 1, 5, and 10 % levels of significance, respectively. Source: NMBU and MU household panel survey.

Table 4 Double-hurdle models for adoption of Cash crops (craggit models).

	Without HH controls		With HH controls		HH controls +CRE	
Variables	Hurdle 1	Hurdle 2	Hurdle 1	Hurdle 2	Hurdle 1	Hurdle 2
Mean farm level population pressure at community level	0.391***	-0.792**	0.517***	-0.303	0.488***	-0.211
	(0.129)	(0.325)	(0.167)	(0.225)	(0.172)	(0.207)
Deviation of farm level population pressure from community mean	0.067	-0.073	0.138	0.098	0.117	0.094
	(0.066)	(0.094)	(0.089)	(0.100)	(0.093)	(0.083)
Mean rainfall 2003-2014 (cm)	-0.019	-0.018	-0.020	-0.017	-0.026**	-0.017
	(0.013)	(0.017)	(0.013)	(0.014)	(0.014)	(0.014)
St. Dev. rainfall 2003-2014 (cm)	0.273**	0.358*	0.313**	0.386**	0.328**	0.364**
	(0.126)	(0.211)	(0.129)	(0.174)	(0.143)	(0.158)
One year lagged positive deviation rainfall (cm)	0.028**	0.000	0.026**	0.000	0.032**	0.004
	(0.012)	(0.014)	(0.012)	(0.012)	(0.013)	(0.011)
One year lagged negative deviation rainfall (cm)	-0.017	-0.002	-0.024	0.019	-0.044	0.001
	(0.054)	(0.091)	(0.059)	(0.068)	(0.062)	(0.060)
Two years lagged positive deviation rainfall (cm)	0.041	-0.018	0.026	-0.035	0.035	-0.057
	(0.040)	(0.040)	(0.038)	(0.041)	(0.041)	(0.035)
Two years lagged negative deviation rainfall (cm)	-0.037	0.011	-0.039	0.007	-0.033	0.014
	(0.028)	(0.035)	(0.029)	(0.026)	(0.031)	(0.023)
Distance to market (hours)	-0.018	-0.063	-0.016	-0.060	-0.041	-0.059
	(0.109)	(0.101)	(0.112)	(0.091)	(0.111)	(0.090)
Year 2010 dummy	-1.231***	0.020	-1.416***	-0.383	-1.395***	-0.464
	(0.337)	(0.533)	(0.378)	(0.389)	(0.402)	(0.361)
Year 2015 dummy	-1.404***	0.161	-1.597***	0.193	-2.077***	0.140
	(0.477)	(0.776)	(0.513)	(0.560)	(0.586)	(0.511)
Constant	-1.616*	-0.850	-0.537	-1.564	-0.220	0.300
	(0.875)	(1.530)	(1.288)	(1.374)	(1.536)	(1.458)
Sigma constant		0.567***		0.481***		0.444***
		(0.080)		(0.063)		(0.063)
Chi2		39.22		53.16		60.49
Log-likelihood		-174.356		-161.095		-150.56
Prob>chi2		0.0000		0.0000		0.0004
N	298	90	298	90	298	90

Note: Hurdle 1: probability of adoption and hurdle 2= Log of area planted upon adoption of the technology. The HH Control + CRE models include the mean and actual value of time-variant household control variables (not reported in this table to save space). Numbers in parenthesis are cluster robust standard errors. ***, **, and * are to 1, 5, and 10 % levels of significance, respectively. Source: NMBU and MU household panel survey.

7. Discussion

We will here discuss strength and limitations of our study and assess the adoption rates we find in comparison to other studies in Ethiopia, to assess the external validity of our findings.

Our study provides new evidence based on household panel data over a ten-year period for crop varieties and crops that are relevant for adaptation to climate change by smallholder farm households in a semi-arid environment. The strengths of our study include the consistency of data collection methods over time, use of good data on rainfall and rainfall variability over time and space and having data from areas with substantial variation in population pressure, market access and access to irrigation. A limitation of our study is that we do not have detailed data on access to extension services that may have affected the technology diffusion processes. Another limitation is that we have not assessed how these technologies are combined with other yield-enhancing technologies such as fertilizer. We are aware that fertilizer use intensity has increased substantially in our study areas during the same period. We leave these issues for other studies. We know that extension programs to stimulate the adoption of agricultural technologies have been part of the Ethiopian government's policies since the mid-1990s (Wubeneh & Sanders, 2006).

Large farm household surveys in Ethiopia seem to indicate that use of improved seeds of wheat and teff is modest not only in our study areas but in the whole country. Bachewe et al. (2014), based on the Feed the Future survey of 7000 households in 251 kebeles in 84 woredas in 2013, found that only 18% of all households used improved seeds in the main growing season. Those who adopted improved seeds used on average 14 kg/ha of seeds. This implies an average rate of 2 kg/ha for the total sample. This is data for all crops and adoption rates are lower for each crop but this baseline report does not present disaggregated data on improved seed adoption rates by crop and variety type.

We may wonder why we see so limited adoption of improved varieties in Ethiopia compared to some other African countries such as Kenya, Zambia, and Zimbabwe (Ethiopian Agricultural Transformation Agency, 2017). There has been a large increase in the number of new varieties released in Ethiopia in the period 2000-2011 compared to earlier periods according to National Crop Variety Register (Fire et al., 2016). Cereal varieties also dominate with about 200 new varieties released in the period 2000-2011. Of these, 50 varieties are new wheat varieties and 20 are new teff varieties. Very few of these varieties are commercialized and adopted by farmers, however. Seed production is dominated by a few old varieties (Ethiopian Agricultural Transformation Agency, 2017). One of the reasons for limited adoption in semi-arid areas like Tigray may be that only 11% of the cereal varieties released are adopted to low rainfall areas (ibid.). The large agro-ecological heterogeneity, including large local variation in soils, elevation and rainfall makes it very challenging to test and identify the best-suited varieties in each location. Taste preferences may also matter, and local varieties may be well adapted to local conditions. Furthermore, most farmers are used to recycle their own seeds. Spielman and Mekonnen (2012) found that only about 28 % of the wheat and teff producers purchased new seeds of these crops every year.

In contrast to this, we see large increases in fertilizer use also in the semi-arid areas in Tigray over the last couple of decades. This may indicate that traditional varieties are responsive to fertilizer. There exists limited knowledge of how the new varieties would perform compared to the local varieties under varying local conditions although they may have performed well under research station conditions.

Most varieties are developed and distributed by the Ethiopian Government but the private sector is growing in importance. The Agricultural Transformation process may lead to better availability and promotion of improved crop varieties.

Of the various crops for which improved seed was multiplied and disturbed by the seed multiplier agency of Ethiopia, wheat remains the first crop in the last three decades (Dixon et al., 2006). Another benefit of growing improved wheat in the highland of Ethiopia is its rust resistance. About 68 % of Ethiopia, particularly the study region is a semi-arid highland and local wheat is affected by “leaf rust” (*Puccinia striiformis*) and “stem rust” (*P. graminis)* during maturity period (Kotu et al., 2000). This reduces not only productivity but also the quality of the crop. We do not know whether the farmers in our survey are aware of these advantages of improved wheat.

Teff is a typical crop of Ethiopia but it cannot grow anywhere else, and we observe few works similar to our study. According to the study of Belay et al. (2006) demonstrated that farmers select the improved teff variety that exhibited early maturity in Gojam, Ethiopia. A similar study conducted in the semi-arid northern Ethiopia shows that farmers prefer the drought-tolerant teff variety not only from its early maturity and drought tolerancy but also it generates a meaning full yield and by-products difference compared to the local teff (Wale & Chianu, 2015).

Shiferaw et al., (2014), using the International Maize and Wheat Improvement Center (CIMMYT) and Ethiopian Institute of Agricultural Research (EIAR) data collected in 2011, found that that wheat is the most important cereal in the most populated regions of the country (Tigray, Amhara, Oromia and SNNP) in terms of area share, total production, home consumption and market integration. About 70 % of households grew improved wheat varieties and the average area planted with wheat per household for those growing wheat was 2.6 *tsimidi*.

Wale and Chinu (2015) assessed adoption of drought-tolerant teff using a sample of 395 households from South Gondar and North Wollo (Amhara region) in 2006/2007. The found that 64% sampled housheolds accessed drought-tolerant teff and 35% had adopted the technology. A similar study in the Amhara region examined adoption of new teff varieties using a sample of 115 farm households in 2014/15 found that 13 % had adopted such varieties and the average area planted with improved teff by the adopters was about 1.2 *tsimidi* (Cafer et al., 2018).

8. Conclusion

We use household panel data for the period 2006-2015 from the semi-arid Tigray region in northern Ethiopia to assess the adoption of improved wheat, drought-tolerant teff and cash crops among smallholder farmers. In particular, we assess the effects of rainfall and rainfall variability, farm and community level population pressure and market access on the likelihood and intensity of adoption of these technologies. Overall, we find low adoption rates and small areas planted with these crop varieties and crops even among the adopters of the technologies. The adoption of improved wheat and cash crops had stagnated and even declined in the study period while adoption of drought-tolerant teff was on the increase.

Lower rainfall, higher rainfall variability and recent negative rainfall shocks were associated with higher adoption rates for improved wheat and so was higher farm level population pressure. Surprisingly, drought-tolerant teff showed higher adoption rates after positive rainfall shocks and intensity of adoption was higher in areas more distant from markets. Higher rainfall variability and recent positive rainfall shocks were associated with higher adoption rates for cash crop and so was farm-level population pressure. These findings illustrate that interactions between climate variables such as rainfall and rainfall variability and population pressure affect technology adoption in unpredictable and sometimes surprising ways.

Several policy implications can be drawn from our results. First, there may be a need to increase diffusion efforts for improved wheat in less population dense areas suitable for wheat production. Second, the puzzling result for drought-tolerant teff may indicate that this variety which as been developed under better rainfall conditions at the Debre Zeit research station may not necessarily perform as a more drought-tolerant variety than the dominant local varieties in the semi-arid Tigray region. Third, to increase the production of cash crops, one should promote irrigation investments where this is technically feasible and cost-effective.

Given that climate change is likely to affect future weather conditions, our study contributes to the limited literature on climate change adaptation in semi-arid areas in Africa. The complexity and seriousness of the issues imply that much more research is needed within this area.

Endnotes

[1]According to the discussion with the experts of the agricultural research institute of Tigray, they used agro-ecologies (districts) historical rainfall data. Agro-ecologies with a shortfall in rain in the previous production years used as criteria for distribution of the drought-tolerant teff. We compute the mean rainfall variability of the previous three years rainy season of each district and used as the mean value as a benchmark to identify a district with lower than the mean value; it is with low rainfall variability while above the mean value is a district with high rainfall variability (drought exposed district).

[2]These are available online IRI/LDEO Climate Data Library:

http://iridl.ldeo.columbia.edu/SOURCES/.NOAA/.NCEP/.CPC/.FEWS/.Africa/.DAILY/.ARC2/..

[3]1 = refers Improved wheat, 2= Drought-tolerant teff and 3 = Cash crops. We used the same notations throughout the paper.

[4]The distance to market place, distance to farmers' training center and district office were also defined as households live in areas above an hour walking time to reach these palaces refers long distance, whereas below an hour is a short distance.

[5]The benchmark for classification of population density of the study region is 200 persons/km^2. Above this number noted as high population density area, while below this number refers to low-density population area.

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Table A1: Population density (pers/Km2) by tabia and survey period.

	Survey period			
Name of tabia	2006	2010	2015	Average
Samire town	1619	1715	1938	1785
Addis Alem	210	230	260	241
May Alem	120	151	169	146
M/genet	155	408	461	349
Seret	379	408	458	413
Kihen	119	92	144	119
Genfel	516	555	628	563
E/mezbule	112	194	185	160
E/Asmena	95.4	194	174	153
H/Selam	629	1715	1938	1446
Mai_Keyahit	307	330	363	333
La/M/Tsemir	307	319	373	334
Adi selma	94.4	101	147	114
Hadegit	94.	126	120	112.
T/Ambora	104	151	134	129
Mai Adrasha	162	177	197	178
Adi Menabir	145	175	176	164
K/Adishabo	-	120	130	153