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Adoption of Drought Tolerant Maize Varieties under Rainfall Stress in Malawi

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Abstract

This paper examines adoption of drought tolerant (DT) maize varieties under rainfall stress in Malawi using a Mundlak-Chamberlain panel Probit model with a Control Function approach. DT maize varieties is a promising technology that has the capacity to help smallholder farmers adapt to drought risks. Using a four-round panel data spanning nine years from six districts, results show an increase in adoption from 2% in 2006 to 41% in 2015. The paper finds a positive impact of one year and two years lag of longest early dry spells and two years lag of late dry spells on the likelihood of adoption but a negative impact of one year lag of late dry spell. The positive findings imply that farmers learn from previous exposure to drought and respond by adopting weather risk-reducing technologies such as DT maize. Furthermore, the impact of lagged early droughts suggests that farmers show a high preference for early maturing DT maize. However, the conflicting results of late dry spells with one year lag reporting negative and two years lag positive suggest that farmers do not immediately respond to late drought shock by adopting DT maize but rather take time to appreciate the significance of the varieties as a technology that survive better under drought during maize flowering phase. These findings could imply that there is still limited awareness among smallholder farmers in Malawi on the benefits of DT maize. There is a need therefore to improve on good extension messages to allow farmers make better-informed decisions.

Key words: Drought tolerant (DT) maize, drought exposure, early and late droughts, Farm Input Subsidy Program (FISP), Mundlak-Chamberlain, Malawi

JEL codes: Q12, Q18.

Introduction

Weather shocks such as droughts and floods undermine crop yields and aggregate production thereby reducing food availability and agricultural incomes especially among smallholder farmers in developing countries (Kassie et al., 2009, Davies et al., 2009, Pauw et al., 2011). Failure by farm households to adapt worsens negative effects and inhibits further investment and economic growth (Kato et al., 2011, Nangoma, 2007, Kassie et al., 2014). The weather shocks kick start a knock-on effect that start from low production to food insecurity and local and national economic shock (Devereux, 2007). Malawi is one of many countries in the developing world greatly affected by negative impacts of weather extremes. In the past two decades, the country has experienced several adverse climatic hazards that have led to severe crop losses, infrastructure damages and occasional displacement of people (Nangoma, 2007, Pauw et al., 2010). The most recent shocks include droughts of 2004/05 and 2011/12 (Holden and Fischer, 2015, Holden and Mangisoni, 2013) and the 2014/15 flash floods early in the growing season and droughts thereafter.

Investing in agricultural production methods that boost farmers' resilience against weather shocks through climate change adaptation and disaster risk reduction approaches is a key strategy to reduce negative impacts (Davies et al., 2009, Pangapanga et al., 2012). In a country with poor or missing markets for insurance and credit and little off-farm activities, adoption of agricultural management strategies that reduce production risks is the only realistic option for smallholder farmers (Kassie et al., 2014). Drought tolerant (DT) maize variety is one potential technology that has the capacity to help smallholder farmers adapt to drought risks. It is estimated that DT maize can produce up to 30% of their potential yield after six weeks of water stress, before and during flowering and grain-formation (Magorokosho et al., 2009). The seed is being promoted in Malawi and other countries in Sub-Saharan Africa (SSA) by the International Maize and Wheat Improvement Centre (CIMMYT) under Drought Tolerant Maize for Africa (DTMA) project.

The government of Malawi has consequently taken a leading role in promoting and disseminating DT maize varieties through the Farm Input Subsidy Program (FISP) and the Agricultural Sector Wide Approach program (ASWAp). Under the FISP, the government includes the DT maize seed in the package effectively making the seed available and affordable on the market. FISP has consequently been reported as a major driver of DT maize adoption (Holden and Fisher, 2015) as it has eased the problem of seed unavailability and high seed prices which Fisher et al. (2015) reported as major barriers to adoption. The government's long-term objective is to promote sustainable and climate-smart agriculture development (Asfaw et al., 2014) and shift from drought and flood prone farming systems to methods that improve farmers' adaptive capacity, enhance resilience and resource use efficiency, increase crop yield and reduce yield variability in the face of weather extremes (Garrity et al., 2010, Lipper et al., 2014).

Adoption of DT maize varieties has been previously studied in Malawi by Fisher et al. (2015), Holden and Fisher (2015) and Holden and Quiggin (2016). Fisher et al. (2015) used cross sectional data from six countries in Africa where DTMA project is promoting dissemination of drought tolerant maize varieties including Malawi. The paper reported unavailability of improved seed, inadequate information, lack of resources, and high seed price as major barriers to adoption. On the other hand, Holden and Fisher (2015) used three year panel data (2006, 2009 and 2012) and reported Farm Input Subsidy Program, recent droughts and farmer risk aversion as major drivers of adoption. Building on that, Holden and Quiggin (2016) combined a 2012 farm household survey and field experiments to estimate a state-contingent production model. The paper noted that households that are more risk-averse are more likely to adopt DT maize varieties. DT maize adoption was also found to be stimulated by exposure to past drought shocks.

This paper builds on these three studies using a four-round panel data to examine adoption of DT maize under rainfall stress conditions. While Holden and Quiggin (2016) used a subjective variable of drought exposure which was based on farmer recall on whether they have been affected by a drought shock for the past four years, we construct a more objective drought variable from daily rainfall data provided by the Department of Climate Change and Meteorological Services. According to Charles L. Vanya (Principal Meteorologist) (personal communication, February 18, 2016), a dry spell is defined as a period of 5 – 15 days with a total rainfall of less than 20 mm following a rainy day of at least 20 mm. Following this definition, we identified how long a longest dry spell lasted in each of the survey years and the previous two seasons.

The hypothesis of interest is that the length of dry spells, which signify more exposure to droughts, should have a positive effect on adoption of DT maize in later years (assuming that farmers have learnt that DT maize performed better than other maize varieties). This requires that they were able to observe the performance of alternative varieties under those growth conditions. On the other hand, an average rainfall, a proxy for good rains should be associated with a less likelihood of adopting DT maize varieties. This may be because areas with higher average rainfall are less likely to have droughts or have longer growing seasons and this may reduce the probability that households plant early-maturing DT maize varieties.

We also note that the results of Holden and Quiggin (2016) are based on 2012 cross sectional data, a year which was characterized by early drought, combined with information from farmers on droughts in the previous years. This paper uses a four-round panel data covering three important weather variations namely good rains in 2006 and 2009, early droughts in 2012 and a combination of floods and late droughts in 2015. The importance of our paper is that while farmers in 2012 may have adopted early maturing DT maize varieties in response to early drought of 2012, adoption in our paper would be due to farmers' further exposure to droughts for a number of years. DT maize did not outperform other maize varieties in the 2012 season with early drought (Holden and Fisher, 2015). This could be because the comparative advantage of DT maize over other hybrids primarily relates to its better performance under late droughts. This 2012 experience may therefore have discouraged farmers from further adoption of DT maize over other high-yielding varieties. This may negatively have affected adoption rates from 2012 to 2015, our last survey round.

Our paper adds value to the body of literature by assessing how early and late droughts affect adoption. We use detailed rainfall data to construct one and two years lagged variables for early and late longest dry spells for all the four survey years. The early dry spells cover a period between December and early January which coincides planting time while late dry spells occur in the period between February and early March which coincides with maize grain formation. We use one and two years lagged variables. Our hypothesis is that since DT maize has yield advantage over other maize varieties during late droughts when maize is forming grains (Magorokosho et al., 2009), exposure to late droughts should have a significant effect on adoption of DT maize among farmers that have observed this through exposure to such droughts in earlier years. Such exposure has been enhanced by the FISP, which distributed free seeds of DT maize varieties. Finding of these effects relies on sufficient exposure to the combined access to DT maize and late droughts.

Theoretical Framework, Model Specification and Estimation Strategy

Theoretical Framework

Smallholder farmers in most parts of Malawi experience frequent dry spells and flood shocks that result in low and uncertain crop production. Such shocks create fear and worry amongst people, and hence increase the degree of risk aversion (Van Den Berg et al., 2009, Balgah and Buchenrieder, 2011) which then affects technology adoption decisions (Liu, 2013). Production under uncertainty can be presented as a stochastic production function. This model is however inflexible and in most cases unrealistic hence Chambers and Quiggin (2000) and Quiggin and Chambers (2006) proposed an alternative model based on the state-contingent production concept. The state-contingent model assumes y distinct outputs, x distinct inputs and s possible states of nature. A farm household allocates input $x \in \Re_+^X$ and chooses state contingent output $y \in \Re_+^{S*Y}$ before the state of nature is revealed (ex ante). Inputs are then fixed and output produced ex post (Quiggin and Chambers, 2006). If the household chooses output y and state of nature s is realized then the observed output is y_s. The technology can then be summarized as:

$$T = \{(x, y): x\ can\ produce\ y\} \qquad 1$$

Given p_y as output price and p_x as price of inputs, we can express the technology as a cost function

$$C(p_{x,}y) = min\{p_x x: (x, y) is\ in\ T\} \qquad 2$$

or as demand function

$$x(p_{x,}y) = argmin\{p_x x: (x, y) is\ in\ T\} \qquad 3$$

Assuming a simple case of two states of nature, one of which is unfavorable, the farmer's interest is to maximize output (y). The producer's problem is choice under uncertainty whereby state one is unfavorable if and only if output $y_1 < y_2$. We may distinguish between inputs that are risk-complementary or risk-substituting in this kind of setting. An increase in probability of less favorable state will lead to an increased share of risk-substituting inputs in the input mix for a given expected output. In the context of this paper, we may observe that adaptation to adverse climate change will increase the likelihood of adoption of risk-substituting crop varieties. If a shift from a state-contingent output vector y to a riskier output y' leads to an increase in demand for an input x_j that is $x_j(p_x, y) < x_j(p_x, y')$, then input x_j is a risk-complementary otherwise it is a risk-substitute if $x_j(p_x, y) > x_j(p_x, y')$ (Holden and Quiggin, 2016).

Given that the farmer's objective is to maximize expected utility [EU(.)] from output y under the expected utility theory, the adoption decision of alternative inputs can be modelled as an optimal land allocation problem (Ding et al., 2009). Given that smallholder farmers are price takers, and that prices are assumed non-random, the only source of uncertainty is climatic risks. An individual farmer will allocate a mix of inputs so that s/he maximizes expected utility from output (y). The farmers' optimal land allocation problem can therefore be specified as:

$$\underset{X}{Max}\ E[U(\pi)] = Max\ EU[p_y y - p_X(X)] \qquad 4$$

Producers who are less risk-averse will choose more risky state-contingent output plan than more risk-averse producers. This implies that for a given expected output, the more risk-averse producer will use more of a risk-substituting input and less of risk-complementary inputs (Holden and Quiggin, 2015, Chambers and Quiggin, 2000). The analysis can be extended beyond the expected utility theory to consider the prospect theory (Holden and Quiggin (2016)). This may require taking loss aversion and subjective probability weighting into account. We only have access to such data for one year in our panel. We resort to assuming that these prospect theory parameters are stable over time for individual respondents and that we therefore can control for them with household fixed effects. We cannot rule out, however, that some of the effects of past shock exposures on technology adoption come through preference changes but we leave this issue for future research.

Model Specification and Estimation Strategy

The farmers' decision to adopt DT maize variety technology can be modelled using latent variable approach (Wooldridge, 2014). Farmers choose a certain agricultural technology before planting, and we assume that their choice is based on the technology's characteristics and weather expectations in that season (Ding et al., 2009). Farmers expect to maximize utility from their state-contingent returns under alternative technologies including DT maize. This implies that we allow for partial adoption and farmers choosing a portfolio of technologies. Market imperfections cause production and consumption decisions to be inseparable, the technology demand functions therefore are based on both wealth (consumption) and production characteristics in a time-recursive context. We therefore model the adoption decision of DT maize as follows:

$$DT_{ipt} = \alpha_0 + \alpha_1 R_{dt} + \alpha_2 S_{ipt} + \alpha_3 H_{it} + \alpha_4 P_{ipt} + \alpha_5 Ds_{it} + \alpha_i + \varepsilon_{ipt} \qquad 5$$

where DT_{ipt} is the dependent variable and is a dummy on whether household *i* grew DT maize on plot *p* in year *t* or not. The explanatory variables captured as X_{ipt} are defined as follows: R_{dt} is a vector of variables capturing rainfall stress (length of longest early and late dry spells) in the farmer' district *d* in year *t*. S_{ipt} is a dummy for access to subsidized inputs, H_{it} denotes household characteristics while P_{ipt} controls for observable farm plot characteristics such as soil type, slope, fertility status, and plot size. Ds_{it} controls for location variables (survey districts). α_i captures unobservable time-invariant characteristics of households and farms such as time-invariant observable and unobservable preferences, managerial ability and land quality. ε_{ipt} is normally distributed error term and we assume is independent of X_{ipt}.

Parameters in equation (5) can be estimated using several models such as Linear Probability (HHFE and HHRE), Probit (HHRE), and Mundlak-Chamberlain Probit models with a Control Function Approach (CFA). The HHFE method removes the unobserved effect (α_i) by time demeaning the data. Thus, taking time averages in equation (5) we come up with equation 6 as:

$$\overline{DT}^*_{ipt} = \beta \bar{X}_{ipt} + \bar{\varepsilon}_{it} + \alpha_i, t = 1, 2, \ldots, T, \& \ i = 1, \ldots, n \qquad 6$$

where $\overline{DT}^*_{it} = T^{-1} \sum_{t=1}^{T} DT^*_{it}$ and so on. Subtracting (6) from (5) we get

$$\ddot{DT}^*_{it} = \beta \ddot{X}_{it} + \ddot{\varepsilon}_{it}, t = 1, 2, \ldots, T, \& \ i = 1, \ldots, n \qquad 7$$

$where\ \ddot{DT}^*_{it} = DT^*_{it} - \overline{DT}^*_{it}, same\ as\ \ddot{X}_{it}\ and\ \ddot{\varepsilon}_{it}.$

Equation (11) can then be estimated as fixed effects estimator expressed as:

$$P(\ddot{DT}_{it} = 1 \left| \ddot{X}_{it} \right) = \emptyset\left(\beta \ddot{X}_{it}\right), t = 1, 2, \ldots, T, \& \ i = 1, \ldots, n \qquad 8$$

However, using the fixed effects regression to estimate the parameters of interest sweeps away all explanatory variables that are constant over time (Wooldridge, 2014). Again fixed effects estimation may cause incidental parameters problem especially when unobserved effects (α_i) are taken as parameters to be estimated (Wooldridge, 2009). The alternative method is the random effects estimator. The traditional RE Probit model assumes that unobserved effects (α_i) and explanatory variables (X_i) are independent, i.e.

$$Cov(X_{it}, \alpha_{it}) = 0, t = 1, 2, \dots, T, \& \ i = 1, \dots, n \qquad 9$$

and that α_i is normally distributed, i.e.:

$$\alpha_i | X_i \sim N(0, \sigma_\alpha^2) \qquad 10$$

The validity of this unconditional normality depends on some restrictive assumptions but becomes more reasonable as T gets large (Wooldridge, 2009). Thus, Arslan et al. (2014) proposes testing the unconditional normality within conditional maximum likelihood (CMLE) framework. The CMLE approach allows α_i and X_i to be correlated (Chamberlain, 1980, Wooldridge, 2010) assuming that

$$\alpha_i | X_i \sim N(\varphi + \delta \bar{X}_i, \sigma_\alpha^2) \qquad 11$$

where σ_α^2 is the variance of $\alpha_i$in the equation $\alpha_i = |(\varphi + \delta \bar{X}_\imath + \alpha_i)$

and $\bar{X}_i \equiv T^{-1} \sum_{t=1}^{T} X_{it}$ is the 1 × K vector of time averages.

This approach enables the paper to estimate partial effects of X_i on response probability at the average value of α_i (α_i= 0). The approach also avoids incidental parameters problem.

Although the equations above assume that ε_{ipt} is independent of X_{ipt}, we notice from equation 5, that S_{ipt}which is a dummy for access to FISP (maize seed in our case), is potentially endogenous due to non-random targeting of beneficiaries. The first approach to solve this endogeneity problem is to use instrumental variable (IV) method. Alternatively, a stepwise error correction method is used especially in the absence of suitable instruments. This approach uses predicted values or residuals of the potentially endogenous variable as instruments in an estimation of a true endogenous variable. The outcome equation eliminates potential endogeneity bias in addition to estimating direct and indirect effects of exogenous variables (Kabubo-Mariara and Linderhof, 2011, Petrin and Train, 2010). Our paper uses this approach.

In the first step, S_{ipt} variable is written as a function of all exogenous variables entering the adoption model and the instruments that do not enter the adoption equation.

$$S_{it} = \alpha_0 + \alpha_i X_{ipt} + \beta_i Z_{ipt} + \varepsilon_{ipt} \qquad 12$$

where Z_{ipt} are instrumental variables that can affect access to FISP but have no direct impact on adoption. Such variables include Tropical Livestock Unit (TLU), farm size and sex of household head. The selection of these variables is based on the targeting criteria of FISP. The program has been targeting resource poor households, those that own a piece of land, resident of the village and vulnerable groups such as child, female or orphan headed households (Holden and Lunduka, 2013). We estimate equation 12 as a first step in this procedure and observe the significance of the instruments. If the instruments are significant and hence relevant we then predict the error term that is used to create a control function $\bar{\mu}_{ipt}$. In the second stage, we use the control function in the adoption equation to explain the adoption decision of DT maize. At this second stage, we also test for the validity of the instruments by including them in one of the adoption equations and ensure that they do affect the adoption decision. The adoption equation is thus, estimated as:

$$DT_{ipt} = \alpha_0 + \alpha_1 R_{dt} + \alpha_2 S_{ipt} + \alpha_3 H_{it} + \alpha_4 P_{ipt} + \alpha_5 Ds_{it} + \alpha_6 \bar{\mu}_{ipt} + \alpha_i + \varepsilon_{ipt} \qquad 13$$

Data and Descriptive Statistics of Dependent and Explanatory Variables

Data

The paper uses four-round panel data from six districts in Malawi namely Lilongwe, Kasungu, Chiradzulu, Machinga, Thyolo and Zomba. The data is based on an original sample of 463 households surveyed in 2006 and 376 in 2009, 350 in 2012 and 2015 (Table 1). The initial sample was randomly selected following the 2004 Integrated Household Survey Two (IHS 2). Data collection involves detailed farm plot level information measured with GPS on plot sizes of which a total of 854, 648, 620 and 657 plots are reported in 2006, 2009, 2012 and 2015, respectively.

Table 1: Study areas

District	2006		2009		2012		2015		Total	
	HHs	Plots	HHs	Plots	HHs	Plots	HHs	Plots	HHs	Plots
Thyolo	64	109	50	104	47	99	47	96	208	408
Zomba	91	191	41	156	76	142	79	172	287	661
Chiradzulu	53	119	79	85	37	93	34	83	203	380
Machinga	55	82	45	75	47	58	45	57	192	272
Kasungu	103	178	90	128	82	137	80	136	355	579
Lilongwe	97	175	71	100	61	91	65	113	294	479

Total	463	854	376	648	350	620	350	657	1,539	2,779

Descriptive Statistics of dependent and explanatory variables

Presented in Table 2 are descriptive statistics for the variables. Adoption is measured by whether an individual farm household planted DT maize variety in at least one of the plots or otherwise. Our results show 2% adoption of DT maize in 2006, 21% in 2009, 45% in 2012 and 41% in 2015. The results show an increase in adoption from 2006 to 2012 but a decrease in 2015. The question is whether the increase is due to farmers' response to drought or other factors. Holden and Fisher (2015) reported that the increase in adoption is mainly due to Farm Input Subsidy Program, which has over the years disseminated DT maize varieties. This could be the main reason why there is a decrease in adoption in 2015 compared to 2012 as there is a scaling down of FISP beneficiaries by the Government of Malawi.

The choice of explanatory variables is based on our hypotheses, previous studies and available data. Such variables include (1) rainfall stress; (2) access to seeds from the Farm Input Subsidy Program (FISP) (3) plot-level factors (e.g. perceived soil fertility, slope, soil type and farm size; and (4) household level factors (e.g. sex of household head, household size, household labor, hired labor and tropical livestock unit). The rainfall stress variables are defined in this study as those capturing dry spells. We assess the extent to which the sampled households were exposed to dry spells in each of the survey years as well as the lagged variables. Drought stress variables were constructed using daily rainfall data from the Department of Climate Change and Meteorological Services. On average, farmers were exposed to the longest early dry spells in 2005, 2010 and 2012 while longest late dry spells were observed in the following years 2005, 2008 and 2011. We did not include 2015 as late drought of 2015 would not affect adoption in same year.

Farm Input Subsidy Program (FISP) is another key variable considered in this analysis. FISP has been implemented in Malawi since 2005/06 season and the current package include maize and legume seed, and fertilizer. The program enhances availability and affordability of improved maize seed, which includes drought tolerant maize varieties. We note that the share of households receiving maize seed subsidy increased from 35% in 2006 to 68% in 2015. The implication of this observation is that adoption of DT maize seed may increase with the increase in access to FISP. On household level factors, which control for household heterogeneity the paper, includes sex of household head, family size, family and hired labor and Tropical Livestock Unit (TLU). These variables may influence adoption decisions in countries such as Malawi which have high market imperfections and institutional failures (Kassie et al., 2015). About 73% of the sample households are male-headed while the family size is on average composed of five persons.

Table 2: Definitions and summary statistics of variables by year

Variables	2006	2009	2012	2015	Total
Adoption of DT maize, dummy	0.024	0.207	0.449	0.410	0.249
December rainfall in mm	6.712	7.718	7.807	7.668	7.409
6 year average rainfall in mm	5.570	6.165	5.943	5.943	5.878
1 year Lag longest early dry spell, days	10.336	6.080	9.948	4.724	7.888
2 years Lag longest early dry spell, days	10.005	9.002	10.798	7.594	9.346
1 year Lag longest late dry spell, days	14.867	10.557	17.086	6.166	12.195
2 years Lag longest late dry spell, days	9.720	6.336	8.205	10.454	8.790
Maize seed subsidy, dummy	0.350	0.597	0.602	0.678	0.540
Sandy soil, dummy	0.315	0.279	0.189	0.242	0.263
Loam soil, dummy	0.482	0.476	0.575	0.663	0.544
Clay soil, dummy	0.152	0.240	0.236	0.086	0.174
Flats slope, dummy	0.579	0.589	0.616	0.485	0.566
Moderate slope, dummy	0.310	0.350	0.306	0.414	0.344
Steep slope, dummy	0.055	0.056	0.074	0.095	0.069
High soil fertility, dummy	0.180	0.132	0.180	0.051	0.137
Medium soil fertility, dummy	0.477	0.607	0.726	0.683	0.609
Low soil fertility, dummy	0.314	0.256	0.090	0.256	0.240
Land tenure, dummy	1.000	1.000	1.000	0.934	0.984
Ganyu labor, (no of adults)	0.152	0.232	0.375	0.241	0.239
Family labor, (no of adults)	2.953	3.126	3.312	2.668	2.998
Male labor force (# of adults/ha)	4.023	1.738	1.826	1.812	2.443
Sex of household head, dummy (1=male)	0.755	0.760	0.736	0.658	0.729
Household size	5.374	5.412	5.453	5.635	5.470
Household lives in wife's village (1=yes)	0.356	0.398	0.578	0.337	0.407
Farm size (ha)	0.414	0.357	0.361	0.355	0.373

Tropical livestock units	1.116	1.690	1.074	0.535	1.082

Results and Discussion

The paper examines whether exposure to drought shocks enhances adoption of drought tolerant maize varieties using Mundlak-Chamberlain panel Probit model with a Control Function Approach (CFA). The results are presented in Table 3. We have used a stepwise error correction method in a Control Function Approach to control for potential endogeneity that may arise due to the inclusion of a potentially endogenous FISP variable (maize seed subsidy). FISP is potentially endogenous because of non-random targeting of beneficiaries. We use TLU, male labor force and sex of household head as instruments in this approach with an assumption that these can influence access to input subsidies because of the program's targeting criteria, but may not have a direct impact on adoption of DT maize. The Farm Input Subsidy Program in Malawi has been targeting resource poor farmers (Bezu et al., 2014), those that own a piece of land, resident of the village and vulnerable groups such as female headed households (Holden and Lunduka, 2013).

The first stage IV regression shows that the instruments are significant in explaining accessibility to FISP. The instruments are however not significant in the adoption equation as shown in CFA1. However, the error term from the FISP equation is significant in CFA2, which signifies that there is indeed endogeneity in the model and the use of the CFA method is appropriate. The results show that droughts significantly increase the likelihood of adopting drought tolerant maize varieties. We note a positive and significant impact of one year and two years lag of longest early dry spells and the two years lag of longest late dry spell but a negative and significant impact of one year lag of longest late dry spell. The positive impact suggests that the more severe (more days) the dry spells, the more the farmers become aware of the risks associated and hence a need to adopt more of climate-smart agriculture technologies that have a potential to minimize the negative impact of such weather shocks. Thus, exposure to previous droughts makes farmers respond to likely reoccurrence of the dry spell in the subsequent years. The use of lagged dry spell variables ensures that farmers indeed learn from previous exposure to weather shocks.

The significant impact of early drought can be explained by the fact that early drought acts as early warning to farmers such that farmers are more likely to buy and plant maize varieties which are drought tolerant. The previous exposure of the same implies that the following season, farmers being rational and risk averse will respond in a similar manner and hence increase adoption. Another possible explanation is that early drought affects germination rate of maize forcing farmers to replant. Replanting involves farmers buying more of early maturing varieties to fit into the growing season as Malawi has a unimodal type of rainy season that ends by March. Although other hybrids are also early maturing, the 2012 experience shows that most farmers opt for DT early maturing maize varieties (Holden and Fisher, 2015) such as SC403 (*Kanyani*) which matures within 90 days after planting. Such varieties are not just drought tolerant but also suitable for replanting after an early drought.

An adoption of DT maize in response to lagged late dry spells means that previous season's experience shows farmers the importance of drought tolerant maize varieties under rainfall stress. The most important advantage of DT maize is its performance over other maize varieties under rainfall stress before and during the flowering period for maize, as reported by Magorokosho et al. (2009). If farmers' experience is in line with this, then more adoption will follow in years after such droughts where DT and other maize varieties were planted and their relative performance could be assessed. However, there are conflicting results in our analysis on the impact of late droughts. The one year lag of longest late dry spells is negative while the two years lag is positive (and with a significantly larger coefficient). The negative result of the one year lag may suggest that farmers do not immediately respond to late drought shock by adopting DT maize while the positive two years lag implies that farmers take more time to appreciate the significance of adopting DT maize in reducing late drought risks. Alternatively, the farmers in our sample may not yet have had sufficient exposure to late droughts to fully realize the potential of DT maize in such cases[1]. These findings could imply that there is still limited awareness on the benefits of the varieties as varieties with the potential to withstand late season droughts.

The results in this paper overall are consistent with our expectations and the findings of Holden and Fisher (2015) and Holden and Quiggin (2016) that farmers who previously were exposed to drought are more likely to adopt DT maize as an adaptive mechanism. Ding et al. (2009) also

[1] Recall that 2012 was a year with early drought while 2015 was a year with early flood and late drought and it is too early to assess the impact from this last late drought on adoption in our data.

reported that farmers' experience with drought increases their likelihood of adopting risk reducing agricultural systems such as conservation tillage. In a country facing persistent weather shocks, mainly droughts and floods coupled with missing or poor markets for weather insurance and credit, these findings are of great importance to enhance agricultural productivity. Farmers' adoption of drought tolerant maize, a drought risk reducing technology is an indication that farmers in Malawi are more willing to adopt any technology that minimizes the impact of weather shocks.

The paper also tests the impact of access to Farm Input Subsidy Program on adoption of DT maize varieties. Access to FISP increases the probability of adoption of the DT maize varieties. The results are in agreement with Holden and Fisher (2015) who reported FISP as a strongest driver of adoption. The main reason for this observation is that FISP increases availability and affordability of the seed. Fisher et al. (2015) observed that unavailability and high prices of maize seed has been limiting adoption of improved maize varieties in Southern and Eastern Africa. Thus, inclusion of drought tolerant maize varieties in the FISP package has enhanced access by the beneficiaries hence increased adoption. The availability of the affordable DT improved maize seed has also offered an opportunity for farmers to experiment with the new technology and observe the benefits on their own farms. Even though the sustainability of the FISP is in question, the experience gained by the farmers in experimenting with the DT varieties offers a very good platform for sustained adoption in the face of adverse effects of the frequent drought spells and climate change.

Table 3: Results of Mundlak-Chamberlain Model with a Control Function Approach

Variables	M-C[a]	1st Stage IV	CFA1	CFA2
1 year lag longest early dry spell, days	0.017**	0.006	0.020**	0.023***
	(0.008)	*(0.008)*	*(0.008)*	*(0.009)*
2 years lag longest early dry spell, days	0.025	0.025	0.034*	0.047**
	(0.017)	*(0.015)*	*(0.019)*	*(0.020)*
1 year lag longest late dry spell, days	-0.009	-0.021***	-0.011	-0.029***
	(0.008)	*(0.007)*	*(0.009)*	*(0.010)*
2 years Lag longest late dry spell, days	0.047**	0.055***	0.051**	0.081***
	(0.022)	*(0.019)*	*(0.024)*	*(0.029)*
December rainfall in mm	-0.097	0.007	-0.089	-0.084
	(0.077)	*(0.045)*	*(0.083)*	*(0.083)*
6 year average rainfall in mm	-0.851**	-0.600**	-0.839**	-1.158***
	(0.354)	*(0.244)*	*(0.377)*	*(0.396)*
Household lives in wife's village (1=yes)		0.175**	-0.300****	-0.200*
		(0.078)	*(0.086)*	*(0.105)*
Tropical livestock unit[b]		-0.036**	0.028	
		(0.017)	*(0.018)*	
Sex of household head (1=male) [b]		-0.180**	0.051	
		(0.092)	*(0.098)*	
Male labor force (# of adults/ha) [b]		-0.023*	0.014	
		(0.014)	*(0.020)*	
Ganyu labor (# of adults)		0.115	0.081	0.151
		(0.113)	*(0.115)*	*(0.119)*
Household size		0.02	0.069***	0.067***
		(0.022)	*(0.023)*	*(0.023)*
Farm size (ha)		0.085	0.067	0.117
		(0.097)	*(0.114)*	*(0.115)*
Error term for accessing FISP				-0.557*
				(0.335)
Access to maize seed subsidy (1=yes)	0.445****		0.460****	0.462****
	(0.083)		*(0.091)*	*(0.091)*
Year dummies	Yes	Yes	Yes	Yes
Soil characteristics	Yes	Yes	Yes	Yes
District dummies	Yes	Yes	Yes	Yes
Constant	1.526	3.229**	3.473	3.280
	(2.297)	*(1.570)*	*(3.444)*	*(2.500)*
Wald chi	301.01	192.00	258.03	257.37
Prob > chi2	0.000	0.000	0.000	0.000
Rho	0.252	0.31	0.281	0.283
No of Observations	2215	1903	1903	1903

*, **, ***, **** indicate that coefficients are significant at 10, 5, 1 and 0.1 percent levels, respectively

[a] The mean & differences of time varying variables are included as regressors, but are not reported here to save space.

[b] Instrumental variables.

Conclusions and policy implications

Weather extremes especially recurrent droughts threaten agricultural productivity and food security in Malawi whose population largely depends on maize for food. Drought tolerant maize is one promising technology to minimize the grinding impact of drought. In recent times, several drought tolerant maize varieties have been developed by national research institutions in collaboration with CIMMYT and have been disseminated across the country. Examining determinants of adoption of this promising technology is increasingly becoming important. Following the work of Holden and Fisher (2015), Fisher et al. (2015) and Holden and Quiggin (2016) this paper has used a Mundlak-Chamberlain panel Probit model with a Control Function Approach to understand adoption of DT maize in Malawi under rainfall stress.

The data is from farm households in six districts collected in 2006, 2009, 2012 and 2015 using a sample size of 463 households in 2006, 376 in 2009 and 350 for 2012 and 2015. What is new in this study is that we include lagged early and late drought variables in the panel data analysis to assess how adoption is affected by such drought exposure experiences. DT maize is by scientists known to perform better than other maize varieties under late drought conditions but not under early drought conditions except that DT maize varieties are early maturing.

Holden and Fisher (2015) reported a substantial increase in adoption of DT maize from 2006 to 2012. This study also finds a significant increase from 2% in 2006 to 41% in 2015, although with a decrease after 2012, a year with severe early drought. Utilizing one and two years lagged longest dry spell variables, the paper has found strong evidence of the impacts of earlier droughts on adoption. This implies that farmers learn from previous exposure to droughts and respond by adopting risk-reducing technologies such as DT maize varieties. There are, however, conflicting results on the impact of late droughts with one year lag of longest dry spell giving a negative and significant coefficient while the two years lag gave a significant positive and larger coefficient. These results suggest that farmers do not immediately respond to late drought shock by adopting DT. Thus, farmers take more time to appreciate the significance of adopting DT maize as a technology that reduces late drought risks. These findings could imply that there is still limited awareness among smallholder farmers in Malawi on the benefits of DT maize varieties as varieties with the potential to withstand late season droughts. Another important driver of adoption also reported by Holden and Fisher (2015) is the Farm Input Subsidy Program (FISP). The distribution of free DT maize seeds through the program has facilitated farmers' experience with the DT maize varieties under varying rainfall conditions.

The understanding that farmers respond to exposure to weather shocks is an important observation for Malawi for the promotion of climate risk reducing technologies. Promotion of technologies that are perceived by farmers themselves as climate-smart based on their experience are more likely to receive high adoption rates and make an impact on general household livelihood conditions. In Malawi with FISP contributing significantly to the adoption, extension and promotion messages should be intensified with empirical evidence to enhance awareness so that farmers can continue using the DT seed even outside FISP. The government should find ways of ensuring that the seed continues being available and affordable.

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