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Climate risk and state-contingent technology adoption: The role of risk preferences and probability weighting[1]

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Abstract

Climate risk represents an increasing threat to poor and vulnerable farmers in drought-prone areas of Africa. This study assesses the maize and fertilizer adoption responses of food insecure farmers in Malawi, where Drought Tolerant (DT) maize was recently introduced. A field

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experiment, eliciting relative risk aversion, loss aversion and subjective probability weighting parameters of farmers, is combined with a detailed farm household survey. A state-contingent production model with cumulative prospect theory preferences is estimated. More risk averse households were more likely to have adopted DT maize, less likely to have adopted other improved maize varieties and less likely to have dis-adopted traditional local maize. Exposure to past drought shocks stimulated adoption of DT maize and dis-adoption of local maize. Over-weighting of small probabilities was associated with less use of fertilizer on all maize types.

Key words: Climate risk, state-contingent production, subjective probability weighting, loss aversion, technology adoption, adaptation, maize, Drought Tolerant maize, fertilizer use.

JEL codes: Q12, Q18, O33, C93, D03.

Introduction

Climate risk and shocks are expected to increase with climate change (IPCC 2014; Li et al. 2009), a trend that may especially threaten poor and vulnerable populations in Sub-Saharan Africa that are still highly dependent on agriculture for their livelihoods. Cereal crops, notably maize (the most important food crop in many African countries), are sensitive to climatic variability and to droughts in particular. One research and policy response to this threat has been to develop and disseminate more drought-tolerant (DT) maize varieties[2] (Burke and Lobell 2010; CIMMYT 2013; Magorokosho et al. 2010).

Adaptation is the response to shocks and adoption of new technologies is part of such adaptation to climatic risk and change. Adaptation processes may be modelled as a change in the state-contingent production technology (Chambers and Quiggin 2000).

This study investigates how exposure to shocks, household risk preferences and risk judgments affect the adoption of DT maize and other maize varieties as an adaptation strategy of farmers. The study tests the importance of Expected Utility Theory (EUT) or Cumulative Prospect Theory (CPT) (Tversky and Kahneman 1992) parameters in predicting household technology adoption responses, including the intensity of adoption of different types of maize, maize being the main

[2] The Drought Tolerant Maize for Africa (DTMA) project has developed more than 160 drought tolerant maize varieties since 2007. Input requirements are the same as for non-DT commercial varieties. They perform as well as non-DT maize varieties under good rainfall conditions and produce yields that are 20-30% higher under moderate drought conditions (CIMMYT 2013).

staple food, and the intensity of fertilizer use on each of these types of maize. A field experiment is combined with a detailed household farm plot survey in Malawi in 2012, conducted just after the country experienced a severe dry spell during the growing season.

Risk aversion has been found to hinder or delay adoption of new technologies, as uncertainty regarding new technologies can compel extra caution among more risk averse respondents in the adoption of less well-known technologies (Feder 1980; Liu 2013). This may even be the case if optimal exploitation of the new technology permits the use of a state-contingent production plan that is objectively less risky than that associated with traditional technologies; that is, in the terminology of Chambers and Quiggin (2000), if the new technology is risk-substituting.

However, very few technology adoption studies have utilized good measures of risk preference. An exception is Liu (2013), the study that most closely resembles the present study. Her study is an *ex post* study of BT cotton in China after 100% adoption had been reached, and EUT and CPT parameters identified *ex post* are used to explain the timing of BT cotton adoption. Our study is conducted at an earlier stage of the adoption process[3] of DT maize in Malawi, and we study adoption/dis-adoption as well as the intensity of adoption of different maize types.

The objective of the present study is to assess how shock exposure, risk preferences and subjective probability weighting bias are associated with the adoption of drought tolerant (DT) and other improved (OIMP) maize, with possible dis-adoption of local (homegrown) maize varieties, and with adoption intensity of fertilizer use on each of these different types of maize (DT, OIMP and local maize). Adoption[4] is measured by whether the type of maize is grown by individual households and the intensity of adoption by the area planted (measured by GPS) by a given type of maize at the farm level. Fertilizer use intensity is measured as kg of fertilizer applied to the areas planted with each type of maize. Shock exposure recall data were collected through the household survey and include drought shocks and other shocks (such as deaths and serious sickness in a family in the four years preceding the survey).

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[3] Adoption of DT maize had reached 45% of our sample households at the time of our survey in 2012 after being only 2% in 2006. The fairly rapid adoption of DT maize in Malawi indicates that maize farmers' adjustment costs are fairly low, as the technology is highly divisible (Quiggin and Horowitz 2003).

[4] In a stochastic environment with imperfect markets adoption is not a one-point-in-time decision but can depend on market access, relative prices, cash constraints, and available information.

Risk preferences were measured using a combination of framed and artifactual field experiments that combine Expected Utility Theory (EUT) and Cumulative Prospect Theory (CPT). The constant relative risk aversion (CRRA) parameter was estimated based on EUT and a series of Holt and Laury (2002) Multiple Price List type experiments. Loss aversion (the lambda parameter) and subjective probability weights (the alpha parameter) were estimated based on the approach of Tanaka et al. (2010).

Adoption decisions may have to be made before the state of nature is revealed[5]. Our study was carried out in six districts in Central and Southern Malawi in 2012, a year in which a large part of the study area was exposed to a severe dry spell during the early rainy season when most households had planted their maize and applied basal fertilizer to their crops. Holden and Fisher (2015) found that DT maize expanded substantially in Malawi in the 2006-2012 period and that the input subsidy program (FISP), which provides subsidized fertilizer and seeds, had been a major driver of this adoption process. They found that exposure to earlier shocks and risk aversion were positively associated with adoption of DT maize.

The present study expands on this work in three ways. First, we do not study only whether DT maize is adopted or not but also the intensity of adoption. Additionally, we compare DT maize with OIMP maize and local maize. Second, not only is relative risk aversion used to capture household preferences but also the CPT parameters of loss aversion and subjective probability weighting. Third, we assess how the intensity of fertilizer use (fertilizer itself being a risky input) differs for DT, OIMP and local maize and is correlated with exposure to shocks and the EUT and CPT parameters.

We hypothesize that risk aversion (CRRA and loss aversion) are positively associated with DT maize adoption, including adoption intensity, and negatively correlated with OIMP adoption, including intensity of adoption. We also hypothesize that overvaluation of low probability extreme events (CPT alpha parameter below one) is associated with higher probability of DT maize adoption, with lower probability and intensity of OIMP adoption and with lower intensity of fertilizer use on OIMP and local maize.

[5] Where droughts in the form of dry spells occur during the rainy season.

The hypotheses build on the assumption that people perceive that DT maize produces higher yields in drought years[6]. Risk averse and loss averse persons should therefore favor DT maize. Subjective over-weighting of low probability extreme events should also favor DT maize adoption relative to other more risky maize varieties, including local maize, because more weight is given to the bad low-probability state of nature. The results have significant policy implications for Malawi and other drought prone areas throughout the world, as technological change will be an essential part of adaptation to climate change.

2. Risk preferences and technology adoption: A brief literature review

A large body of literature on risk preference characteristics, including studies in developing countries, has been developed. As survey based data have been found unsuitable for our purpose, we focus on field experimental approaches that started with the seminal work of Hans Binswanger (1980; 1981) in India, studies that were replicated in several other developing countries (Binswanger and Sillers 1983; Miyata 2003; Wik et al. 2004). These studies reveal that the large majority of rural dwellers in developing countries are risk averse and that they became more risk averse when stakes increased and when losses were introduced in the experiments. Risk aversion was less highly correlated with total wealth of the respondents.

While this early work was founded on EUT, more recent work has expanded into Rank Dependent Utility (RDU) (Quiggin 1993) and Cumulative Prospect Theory (CPT) (Kahneman and Tversky 1979), with these approaches opening the way for subjective probability weighing and the latter also opening the way for differing valuations of gains and losses. The early studies of Binswanger (1980) and Wik et al. (2004) also revealed that losses were given more weight than gains in such experiments, as games with losses revealed significantly higher levels of risk aversion than games with gains only.

Tanaka et al. (2010) and Liu (2013) build on CPT and are, to our knowledge, the first to comprehensively test the relevance of CPT versus EUT among poor people in developing countries by considering both subjective probability weighting and loss aversion in addition to the curvature of the utility function in their studies in Vietnam and China.

[6] It is possible that such experience and knowledge had not reached all households at the time of the study.

Fewer experimental studies in developing countries have assessed how risk preferences affect technology adoption, and many of those that exist have relied on less comprehensive experimental designs that did not allow for testing of alternative theories, such as the relative importance of EUT and CPT, to explain technology adoption. Knight et al. (2003) studied farmer technology adoption in Ethiopia by dividing farmers into risk-averse and risk-neutral groups, based on a hypothetical question. They found that risk aversion is associated with a lower probability of technology adoption. Engle-Warnick et al. (2006) studied farmers' technology adoption in Peru, distinguishing between ambiguity aversion and risk aversion, but did not find that any of these measures affected technology adoption in a probit model of adoption of a new technology. Hill (2009) used stated preference methods to assess the effects of risk aversion on technology adoption by coffee growers in Uganda. She found that higher risk aversion is correlated with less use of labor on the risky perennial crop. De Braun and Eozenou (2014) assessed the risk preferences of farmers in a hypothetical field experiment in Mozambique and examined whether such risk preferences were related to the adoption of new sweet potato varieties. However, they found no significant relationship.

Liu (2013) and Liu and Huang (2013) are the only studies we have found that comprehensively assesses the relevance of EUT and CPT to the adoption of specific technologies. In a study of adoption of BT cotton in China, Liu (2013) found that more risk averse and more loss averse farmers adopted BT cotton later, while farmers who overweight small probabilities adopted BT cotton earlier.

The first results are consistent with a variety of interpretations. One is that, at the time of adoption, farmers initially have mistaken beliefs about the BT production technology, leading them to perceive the state-contingent production plans chosen by BT adopters as more risky than traditional plans. With experience, however, farmers learn that that state-contingent production plans based on BT cotton are less risky. A second is that the production plans initially adopted for BT are objectively riskier than traditional plans, but that farmers learn to manage risk more effectively over time, obtaining both higher returns and lower risks. Either is consistent with the observed outcome of 100% adoption being reached at the time of the study.

In a related study, Liu and Huang (2013) found that more risk averse farmers use more pesticide on cotton, while more loss averse farmers use less pesticide on cotton. Their finding is consistent with farmers placing more emphasis on loss aversion in the health domain than in the profit domain. This is the only study that we are aware of before our own study to combine a comprehensive field experiment, to reveal EUT, and CPT parameters, to assess how these are related to the intensity of adoption of a technology.

Our study is, to our knowledge, the first to comprehensively assess how EUT and CPT parameters affect the adoption and intensity of adoption of agricultural technologies in Africa. Our study also assesses how drought shocks affect technology adoption and dis-adoption (adaptation). We are not aware of any earlier studies that have assessed how farmers' EUT and CPT parameters affect their adaptation to climate risk through technology adoption.

3. Factors conditioning technology adoption

Our context, in a nutshell, is food insecure and vulnerable smallholder farmers in Malawi who, to a large extent, rely on rain-fed agriculture as their main source of livelihood. The majority of these farmers are deficit producers of maize, which is their main staple food crop even after a large-scale input subsidy program was introduced in 2005 (Dorward and Chirwa 2011; Holden and Lunduka 2013; 2014). A closer examination of factors that may condition maize technology adoption in our context reveals that the different types of risks and uncertainty they face are related not only to weather but also to pests and disease, health risks and shocks, market risks (including access and price risk), and access to subsidized inputs.

3.1. Weather risks and shocks

The most relevant weather-related risks to crop production in Africa include rainfall risk (too much and too little rain) in the crucial stages of the crop cycle from before planting until after the harvest. The distribution of rainfall is particularly important, and stochastic events such as no rain or too much rain can cause severe damage. In this study, we focus particularly on the effects of too little rain arriving during the crucial growth stages of the maize crop.

Widespread occurrence of such dry spells varies across years and locations. There can also be local variation in the occurrence of dry spells, as rainfall can be highly localized. We therefore depend on information from the farmers themselves regarding the occurrence of such dry spells. Such events are highly salient for farmers, and we have asked them to recall whether they experienced dry spells that affected their crops in each of the last three years. The farmers had no difficulties recalling such events, and their answers are consistent across farms in given neighborhoods. Lagged drought dummy variables, therefore, are good indicators of recent drought experiences[7].

Data from the nearest weather stations do not provide accurate information on local spatial variability. We utilize average rainfall from the weather stations as an indicator of expected rainfall in the area, which may also influence maize adoption decisions of farmers in the area.

3.2. Market access risk and shocks

Small farmers can face difficulties in accessing farm inputs such as maize seeds and fertilizers for several reasons, including poor market access (long distance and poor infrastructure), erratic and limited supply in thin and poorly developed markets, and policy interventions that affect access and prices, such as the distribution of targeted subsidized inputs in Malawi.

Heterogeneity of input access is captured as follows. Dummy variables for the receipt of vouchers for subsidized fertilizer and maize seeds in the 2011/12 production season are included. The farmers can use these vouchers to obtain fertilizer and maize seeds at the nearest depot. While such access is partly random, it is also partly non-random, as such subsidies are targeted partly on the basis of unclear criteria and may be influenced by social networks in which the well-connected are likely to be more successful in obtaining subsidized inputs (Holden and Lunduka 2013; 2014; Ricker-Gilbert et al. 2011). The endogeneity of these variables has econometric implications that are discussed in relation to the estimation strategy.

Whether households can obtain the preferred inputs at commercial outlets is another issue. A substantial share of farmers (33.7%) stated that they were unable to find their preferred maize varieties and therefore had to resort to second-best options. Such access constraints may distort observed adoption. A dummy variable was included to control for this based on the assumption that this is a random shock variable.

The affordability of input purchase depends on the availability of cash in the household. Farmers were asked how much money they had saved for purchases of fertilizer (the most expensive input). Having a non-agricultural business and access to formal employment may also improve cash availability in households, and dummy variables were included to capture such access/activity.

[7] While the severity of such dry spells can vary from place to place and year to year, farmers' notions of droughts of this nature appeared to be quite accurate and related to the drought having a significant negative impact on their crop yields.

These variables also fall into the category of potentially endogenous variables, which require careful treatment if they are to be included as controls (see the estimation strategy).

The implication of this uncertainty regarding access to maize technologies is that technology adoption itself becomes stochastic. This stochastic variation in technology adoption includes the outcome of the decision to adopt or not adopt and the degree of adoption.

3.3. Exposure to shocks

Households may have been exposed to several types of shocks in the recent past, and this may affect their production decisions, as there may be some learning from these shocks. The main types of shocks are droughts, and households may have gained insights into the performance of different maize varieties after such shocks. Shocks may also have affected farmers' liquidity, their endowments, and the needs of households, and thus, they may have indirectly affected input decisions and technology choices.

We asked households about their shock experiences during the last four years (2009-2012) and include a measure of the number of shocks households experienced in this period. It is possible that households have learned from the shocks and become more willing to adopt new technologies that make them better able to handle the types of uncertainties they face. It is also possible that the shocks have locked households into the use of inferior technologies that render their production more inefficient and may have made them more vulnerable.

3.4. Risk preferences and maize variety preferences

While it is usually thought that risk aversion makes households more hesitant to adopt new technologies, what if new technologies allow reductions in risk? We assess the perceptions of households regarding the riskiness and other properties of different maize varieties. If DT maize is both higher yielding and more drought tolerant, why should farmers still prefer to grow traditional varieties?

We find that preferences for local maize are related to its superior post-harvest pest resistance. This creates a trade-off between yield and pest resistance in the choice of varieties. We do not have quantitative data on the extent of post-harvest losses and their variability/risk but also assess the degree of adoption of local maize and intensity of fertilizer use on local maize. Post-harvest loss expectations may compel more risk averse households to prefer local maize, but this may be countered by the higher yield risk of local maize (trade-off between two types of risk).

4. Theoretical framework: A state-contingent approach to technology adoption

Analysis of decisions under risk and uncertainty has been a central focus of economics since von Neuman and Morgenstern (1944) introduced expected utility theory, with important contributions from Savage (1954), Arrow (1953), Debreu (1952), Pratt (1964), and Arrow (1965). Arrow (1953) and Debreu (1952) handled uncertainty by treating commodities produced in different states of nature as distinct.

This approach was applied to the problem of production under uncertainty by Chambers and Quiggin (2000). The state-contingent model of production analyzed by Chambers and Quiggin includes, as a special case, the stochastic production function model of Just and Pope (1978) and Feder (1980).

Let the set of states of nature be denoted *S*. The probability of state *s* in *S* is denoted by π_s

.A state contingent output vector is denoted by *z* in R^S. Here z_s denotes the output realised if the producer chooses *z* and state *s* is realised.

Input use is decided before the state of nature is revealed. The non-stochastic vector of inputs is denoted by *x*. The technology is summarized by a set

$T=\{(x,z): x \text{ can produce } z\}$

Note that, except in the special case of a Leontief or 'output-cubical' technology, the choice of inputs *x* does not determine the state-contingent output *z*. As is emphasized by Chambers and Quiggin (2000), inputs may be allocated to increase output in some states of nature, at the cost of lower outputs in other states.

For given input prices *w*, the technology may be summarized by a cost function

$C(w,z) = \min\{wx: (x,z) \text{ is in } T\}$

Conversely can derive the input demand function

$x(w,z) = \operatorname{argmin}\{wx: (x,z) \text{ is in } T\}$

A particularly simple case, for which Chambers and Quiggin (2000) present a graphical analysis is that of two states of nature, one of which is unfavorable in a sense that will be made precise. Chambers and Quiggin use the example, appropriate for the present paper, where the bad state is represented by a drought.

The producer is concerned with net income

$y = pz - wx$

$= pz - C(w,z)$

assuming cost minimization. Under the stated conditions, y is a stochastic variable taking values in R^S. The producer's problem is therefore one of choice under uncertainty.

We will not, initially at least, impose a specific assumption about the producer's preferences under uncertainty, such as maximization of expected value or expected utility, but will assume that preferences can be represented by a continuous functional V mapping R^S to R such that V(y) is increasing in y.

We now define the unfavorable state by considering the problem of achieving a given expected output $\underline{z}$ at minimum cost, that is

$z^* = \text{Min } \{C(w,z): \pi_1 z_1 + \pi_2 z_2 = \underline{z}\}$.

Definition: State 1 is unfavorable if in the solution to the problem above, we have

$z_1 < z_2$

That is, while it would be technically feasible to produce more in the drought state than in the normal state, for example, by heavy use of irrigation, a cost-minimizing producer, seeking to achieve a given expected output, would never choose to do this. For the remainder of the paper, we will order the states so that $z_1 < z_2$.

State-contingent output vectors with the same mean may be ordered in terms of riskiness in various ways (Chateauneuf et al. 2004, Quiggin 1991a, Rothschild and Stiglitz 1970, Sandmo 1971). For the case of two-states of nature, these all coincide. For z, z' such that $E[z] = E[z']$, we say that z' is riskier than z if and only if

$$z_1' < z_1 < z_2 < z_2'$$

Chambers and Quiggin define an input x_j as risk-complementary if a shift from a state-contingent output vector z to a riskier z' leads to an increase in demand for x_j that is if

$x_j(w,z) < x_j(w,z')$

and as a risk-substitute if

$x_j(w,z) > x_j(w,z')$.

The state-contingent technology framework, with the standard assumption of convex production sets, allows for mixtures of technology, such as those arising from partial adoption of a new technology. Partial adoption may yield benefits from diversification. Alternatively, it may reflect constraints to adoption, such as access constraints in the input markets, lumpiness or a high cost of the new technology, or heterogeneous farming conditions that make technology choice and performance more complex. Uncertainty about future states of nature may be another reason for partial adoption and heterogeneity in adoption (a portfolio approach to technology adoption) [8].

Under expected utility we may write a market producer's problem as

$\mathrm{Max}_{iz}\ E[u(pz - C(w,z)]$

with first-order condition

$E[u'(pz - C(w,z)(p-C(w,z)] = 0$

This analysis may be extended to allow for subsistence production. The simplest approach is to require output to meet a subsistence demand z0, with the residual z-z0 being marketed. The objective function then becomes

$\mathrm{Max}_{iz}\ E[u(p(z-z0) - C(w,z)]$

As is shown by Chambers and Quiggin (2000), a less risk-averse producer will choose a less risky state-contingent output plan than a more risk-averse producer. Hence, for a given expected output, the less risk-averse producer will use more risk-substituting inputs, and less risk-complementary inputs.

[8] Also allowing for subjective beliefs about technology performance to deviate from real performance of the technologies.

Using the ‘correspondence condition’ proposed by Quiggin (1991b), the analysis may be extended to the case of non-EU preferences represented by a rank-dependent or prospect theory model (these coincide for the case where there are two states and returns are strictly positive). If the producer is uncertain about the probability of a bad state of nature and therefore has a subjective probability rather than an objective probability (Savage 1954), the subjective probability may replace the objective probability.

People are commonly observed to overweight low probabilities and underweight high probabilities (Kahnemann and Tversky 1979; Wu and Gonzales 1999; Gonzales and Wu 1999). Moreover, provided probability weighting leads to a greater weight on the less favorable state, an RDU or CPT maximizer will use more risk-substituting inputs and less risk-complementary inputs. The same is true of a CPT maximizer displaying loss aversion. Both probability weighting and the reference point feature of CPT raise the possibility that risk attitudes may evolve endogenously as a result of exposure to shocks.

The questions of how exposure to shocks affects technology adoption and whether such shocks make poor people less risk averse, as predicted by CPT[9], have received little attention in the literature. The empirical evidence on the curvature of the value function in the loss domain is less clear than in the gain domain (Abdellaoui 2000; Fennema and van Assen 1999; Abdellaoui and Weber 2003).

While we indicated above that extreme loss aversion could lead to a maximin strategy, uncertainty about how exposure to shocks affects the value function makes us less confident to predict how loss aversion is associated with technology choice and intensity of use. We have elicited loss aversion and assess its correlation with technology adoption and nevertheless propose a thesis regarding its impact on technology choice or intensity of adoption.

The main hypotheses we want to test are therefore the following:

H1) Relative risk aversion is associated with a higher probability and a higher intensity of adoption of DT and LM maize (assuming these are risk substitutes) and the opposite for OIMP maize (assuming it is risk complementary).

[9] If such a shock is perceived as a loss that places them below the reference point.

H2) Loss aversion is associated with a higher probability of DT maize adoption and a lower probability of OIMP maize adoption.

H3) Subjective overweighting of low probability extreme events is associated with less adoption of OIMP maize and of fertilizer on OIMP and local maize (assuming fertilizer is risk complementary).

H4) Shock exposure in the form of droughts in previous years is associated with increased adoption of DT maize and dis-adoption of LM maize[10].

H5) Access to subsidized inputs enhances adoption of DT maize and intensity of fertilizer use for all types of maize.

This study focuses on the input decisions that were mostly made before the state of nature was revealed. However, the drought in the 2011/12 season came so early in the rainy season that it also affected the planting of maize and fertilizer use.

5. Estimation strategy

This study focuses on the input decisions that were mostly made before the state of nature was revealed. However, the drought in the 2011/12 season came so early in the rainy season that it also affected the planting of maize and fertilizer use.

We focus primarily on *ex ante* technology choice and intensity decisions and assume that a non-separable farm household model is an appropriate framework for input use decisions at the household level, as input markets are imperfect (Ricker-Gilbert et al. 2011). Input demands for maize seeds and fertilizer are therefore captured by the two sets (system) of equations below;

1) $M_i^M = M_i^M(P_i^{Me}, P_c^M, P_s^M, S_i^M, S_i^F, R_v, C_i, \circledR_i, \alpha_i, \lambda_i, X_i, A_i, \sigma_v)$
2) $F_i^M = F_i^M(P_i^{Me}, P_c^M, P_s^M, S_i^M, S_i^F, R_v, C_i, \circledR_i, \alpha_i, \lambda_i, X_i, A_i, \sigma_v)$

where M_i^M represents the input investment by maize type, with the superscript M representing type of maize (three types: DT (drought tolerant), OIMP (other improved variety), LM (local maize)) for farmer *i*. P_i^{Me} is the unobserved expected price of maize for farmer *i*. P_c^M is the commercial price of maize seed by maize type, and P_s^M is the subsidized price of maize seed. S_i^M is a dummy indicating whether the farmer has access to subsidized seed in the form of a maize seed voucher,

[10] Shock exposure may have provided relevant experience regarding the performance of alternative maize technologies and may therefore stimulate adoption of DT maize, if it performed better than other maize types. This implies reduced uncertainty about the performance of DT maize.

S_i^F is a dummy indicating whether the farmer has access to subsidized fertilizer in the form of a fertilizer and seed voucher(s), R_v is average rainfall in the area as an indicator of agronomic suitability to maize production. C_i is a vector of shock and risk variables, including contemporary and lagged exposure to drought shocks, access to preferred maize varieties and the number of shocks that a farm household has been exposed to over the last three years. ®$_i$ represents the relative risk aversion coefficient, α_i is the subjective probability weighting parameter, and λ_i is the loss aversion parameter for farmer *i*. X_i represents other household characteristics, A_i represents farm characteristics, and σ_v is a vector of village dummies. Similarly, fertilizer use intensity for each type of maize is a function of the same set of variables.

5.1. Maize type adoption

The focus is on the adoption (at the farm level) and the intensity of adoption of DT maize, OIMP maize and local maize and on fertilizer use intensity for different types of maize[11]. It is first necessary to say something about the structure of these input demand equations. The input demands are non-negative but can be zero for each maize type and fertilizer use on each maize type at the household level. Households may choose to grow more than one type of maize and choose to use fertilizer on more than one type of maize[12]. This is therefore an inter-related set of demand equations, where fertilizer demands for each maize type are conditional on households growing a given type of maize[13].

The specific model for adoption by maize type is as follows[14]:

$$3)\quad M_i^M = \beta_0^M + \beta_1^M crra_i + \beta_2^M \alpha_i + \beta_3^M \lambda_i + \beta_{41}^M D_i^{2012} + \beta_{42}^M D_i^{2011} + \beta_{43}^M D_i^{2010} + \beta_{44}^M NS_i + \beta_5^M FG_i + \beta_6^M R_v + \beta_7^M EX_i + \left(\beta_8^M EN_i + \beta_9^M S_i^S + \beta_{10}^M S_i^F + \beta_{11}^M M_i^{\neq M}\right) + \alpha_9^M D_v + v_i^{LM}; ipw_i$$

M_i^M is either a dummy variable indicating whether the type of maize is grown by the household or

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[11] Holden and Fisher (2015) analyzed determinants of farm plot level adoption of DT maize by assessing variables that were related to whether DT maize was planted on the plot. They did not assess the intensity of adoption.
[12] In Malawi, almost all households grow at least one type of maize, as maize is such a dominant crop and the preferred staple food in the country as a whole.
[13] The limited dependent variable nature of the data was not conducive to system estimation.
[14] Because we only use cross-sectional data, there is little price variation in the data, except the price differences between subsidized and commercially demanded inputs. We also lack a measure of farmers' future expected maize price. This unobserved heterogeneity is controlled for with the input subsidy access dummies and village fixed effects. We attempt to control for differences in shadow wages (opportunity cost of time) by including formal employment and non-agricultural business dummies. Actual *ex ante* labor input in production is included as a control for labor supply (complementary input).

a measure of the intensity of adoption of that type of maize. The intensity of adoption is measured as the area planted with that type of maize[15]. We tested censored tobit models versus double hurdle models and found double hurdle models to be appropriate in this case[16]. Models with log-transformed input quantity variables are used as untransformed variables created more convergence problems. The variable $crra_i$ is the relative risk aversion coefficient, estimated using a structural model using Holt and Laury's (2002) type of Multiple Price List data[17]. Subjective probability weights (α_i) and loss aversion (λ_i) were elicited using the approach of Tanaka et al. (2010)[18].

The next variables are the shock variables (drought shock dummies, number of shocks in last four years (NS_i) and a dummy for farmers who failed to obtain their preferred maize variety (FG_i)). The number of shocks includes shocks other than droughts, such as deaths or serious sickness in the family. Such shocks may affect both the ability and the willingness to adopt. R_{vt} is average annual rainfall. EX_i are exogenous[19] household characteristics such as (owned) farm size and sex of household head. Farm size may limit the intensity of adoption, as farm sizes are small due to high population density in the study areas. The following parenthesis in equation 5) contains variables that are more endogenous in character, and models are run both without and with them to assess the stability of the results and the potential importance of these endogenous variables. We were unable to find an IV strategy that would help identify these potential endogenous variables[20]. The

[15] Planted areas were measured with GPS during the survey and are therefore a reliable measure of the intensity of adoption.
[16] The results of the double hurdle models clearly demonstrate that different factors were important in the decision to adopt than in the intensity of adoption decision.
[17] Holt and Laury (2002) type hypothetical and monetary experiments were used. See the Appendix for the format of the field experiments and a structural model with a constant relative risk aversion coefficient utility function; $U = \left(1 - crra\right)^{-1}\left(Y^{1-crra} - 1\right)$ was used, combining the hypothetical and monetary experiments. See Holden (2014) for elaboration of the risk preference experiments.
[18] Three choice series were used to elicit three parameters: one for the curvature of the value function (sigma), one for the subjective probability weighting (alpha), and one for loss aversion (lambda), with sigma representing the curvature of the convex function below the reference point and the curvature of the concave value function above the reference point.
[19] Exogenous in the sense that they cannot easily be changed in the short run.
[20] While, e.g., Ricker-Gilbert et al. (2011) used age of household head as an instrument to access subsidized inputs (older persons may be better connected and therefore have superior access), this instrument did not work in our data. Additionally, we believe that age itself is likely to affect technology adoption, including intensity of adoption (and the results confirm this).

key findings we present were very robust to alternative model specifications[21], giving us confidence in our conclusions, which also fit well with theoretical expectations.

EN_i includes household saving for purchases of fertilizer and dummies that indicate non-agricultural business activity and off-farm formal employment. These variables may capture the liquidity situations of households, their opportunity cost of time, and their ability. It also includes *ex ante* labor allocation[22] to this type of maize production. Labor is assumed to be a complementary input that is essential to the intensity of adoption (land preparation, planting and fertilization). S_i^F is a dummy indicating whether the household received subsidized fertilizer (received at least one fertilizer voucher alone or to share with another household). S_i^S is a dummy indicating whether the household received a maize seed voucher under the subsidy program that can be used to obtain a free seed package. It is assumed that access to subsidies stimulates use of these inputs, due to market imperfections (Ricker-Gilbert et al. 2011). $M_i^{\neq M}$ represents the intensity of adoption of other maize types.

We assume that maize types are substitutes and therefore expect negative correlations in the intensity of adoption of alternative maize types, due to constrained access to land, labor and liquidity for input purchase. ipw_i is the inverse probability weight, included to control for attrition in the sample[23]. Village fixed effects were also used to control for cross village differences in market access, prices and the distribution of improved maize seeds through and outside the subsidy program. Average partial effects (APEs) were obtained for each of the hurdles of the double hurdle models for the key variables of interest, based on Burke (2009), and standard errors were derived using bootstrapping with 400 replications for key variables for one APE at the time[24].

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[21] These alternative specifications include varying the number of potentially endogenous variables. Here we only present the results without endogenous variables and with the full set of endogenous variables. Alternative specifications also include models with untransformed and log transformed variables, but models with log transformed models were preferred, due to their better distributional properties. The key results also remained robust across the alternative functional form specifications. The results are available upon request.

[22] By *ex ante* labor allocation, we mean labor allocated before the state of nature (in the form of drought in this case) is revealed.

[23] It is constructed from the baseline household data, including all households in the initial survey in 2006. The baseline survey contained 450 households, of which only 350 were found and re-interviewed in 2012. From these, we were able to obtain high quality data from field experiments and the survey, including measurement of maize plots for 282 households after removal of outlier observations.

[24] The *margins* command in Stata 13 does not work for *craggit* models. Obtaining the bootstrapped standard errors was a time-consuming process.

5.2. Intensity of fertilizer use by maize type

Household level intensity of fertilizer use in kg of fertilizer by maize type was estimated for the three maize types. Some households had only one maize type, others had two, while hardly any had all three types[25]. To handle possible attrition bias and possible bias related to selection into maize type, inverse probability weights (IPWs) were generated for households having a given maize type, using probit models with baseline household characteristics. The fertilizer intensity models were then weighted with these IPWs. Fertilizer intensity models were estimated for each maize type as censored tobit models[26].

$$4)\ F_i^M = \gamma_0^M + \gamma_1^M crra_i + \gamma_2^M \alpha_i + \gamma_3^M \lambda_i + \gamma_{41}^M D_i^{2012} + \gamma_{42}^M D_i^{2011} + \gamma_{43}^M D_i^{2010} + \gamma_{44}^M NS_i + \gamma_5^M FG_i + \gamma_6^M R_v + \gamma_7^M EX_i + \left(\gamma_8^M EN_i + \gamma_9^M S_i^S + \gamma_{10}^M S_i^F + \gamma_{11}^M M_i^{\neq M} + \gamma_{12}^M F_i^{\neq M}\right) + \gamma_{13}^M D_v + v_i^{LM}; ipw_i^M$$

The dependent variables are in log-form and are left censored[27]. Variables are otherwise specified as in equation 5), with two exceptions. With the recursive nature of input use in the study area, planting of seeds takes place before application of fertilizers, which therefore is conditional on the choice of maize type. Selection into maize type is therefore controlled for by jointly controlling for attrition and sample selection by constructing joint inverse probability weights, ipw_i^M. Average marginal effects for this model were calculated using the delta method with the margins command in Stata 13 (presented in Table 5).

6. Descriptive statistics

The survey contained separate questions on preferences for improved versus local maize in situations without and with access to fertilizer. Local maize was preferred by 16.5% of the respondents in the case of good fertilizer access and by 47.9% in the case of poor or no fertilizer access. The most common reason given for the preference for local maize was that local maize was considered to be less prone to pest attack after harvest, while other post-harvest properties such as poundability, “flour lasts long” and good taste were also mentioned. Pest resistance was cited by 41.4% of respondents stated as the most important reason for preference for local maize. Low yield, noted by 56.5% of the farmers, was the most important reason farmers did not prefer

[25] See Holden and Fisher (2015) for the details on the classification of maize varieties into these three maize types.
[26] Double hurdle models were also tested but failed to converge.
[27] To enable us to take logs for observations with no fertilizer use, we added one to the fertilizer quantities (measured in kg by maize type).

local maize. High yield (71.7%) and early maturity/drought tolerance (26.3%) were cited as the most important characteristics of improved maize varieties[28].

Exposure to shocks may affect technology adoption. We asked the farm households whether they have been affected by any shocks in each of the last four years, i.e., from 2009 to 2012, and to rank shocks by severity. Table 1 shows the distribution of the most severe shocks they perceived they had been affected by in 2011-12. We observe that the drought shock dominated (reported as the most severe shock by 51% of the respondents experiencing a shock), followed by livestock death/theft, large rises in food prices, crop disease/pests, and deaths/illness of family members. We constructed a simple measure of shock exposure in the form of a count of the number of shocks the households had been exposed to in the 2009-2012 period and tested how this may affect their technology adoption in terms of maize type and fertilizer use.

Table 1. Most severe shock in 2011/12, type of shock, for those experiencing shocks in this year

Shock type, shock 1, 2012	Freq.	Percent	Cum.
Lower yields due to drought/flood	123	50.62	50.62
Crop disease/pests	14	5.76	56.38
Livestock death/theft	35	14.40	70.78
Household business failure	2	0.82	71.60
Loss of paid employment	1	0.41	72.02
Non-payment of salary	2	0.82	72.84
Large rise in price of food	19	7.82	80.66
Death of head	2	0.82	81.48
Death of working hh members	1	0.41	81.89
Illness/accident of hh member	11	4.53	86.42
Death of other family member	10	4.12	90.53
Dwelling damaged/destroyed	8	3.29	93.83
Theft	6	2.47	96.30
Other	9	3.70	100.00
Total	243	100.00	

Note: Based on the sample of 282 households with good quality data.

Artifactual field experiments that combined the approaches of Holt and Laury (2002) (with a hypothetical and monetary part) and the Tanaka et al. (2010) approach were used to elicit Prospect Theory parameters. The Holt and Laury approach contained four hypothetical series with high

[28] We did not have questions that specifically asked farmers to compare DT and OIMP maize varieties.

stakes choices between risk complementary and risk substituting varieties (framed in line with the technology adoption issues we are interested in). These were introduced to the respondents first, followed by four incentivized lower stake monetary series; see the Appendix for details.

A structural model with constant relative risk aversion was used to predict the relative risk aversion parameter (CRRA) for each respondent, based on the four hypothetical and four monetary series[29]. The Tanaka et al. approach requires three choice series to elicit three parameters, one for the subjective probability weighting (alpha parameter) based on the formula $w(p) = 1/\exp(\ln(1/p))^{\alpha}$, one for loss aversion (lambda parameter) and one for the curvature of the value function (sigma parameter) based on the following function: $v(x) = x^{\sigma}$ for gains and $v(x) = -\lambda(-x)^{\sigma}$ for losses. We use only the first two of these in combination with the CRRA parameter in this study[30]. The distributions of the three preference parameters are presented in Figure 1 a), b) and c). Most respondents have a CRRA parameter between one and two. A substantial share have an alpha parameter below one, indicating that they overweight low probability extreme events. The loss aversion parameter indicates high levels of loss aversion compared with findings of other studies (Tanaka et al. 2010 in Vietnam; Liu (2013) in China). Summary statistics for the key variables are presented in Table 2.

[29] Separate estimation of the hypothetical and monetary series resulted in substantially higher CRRA in the high stakes hypothetical series than in the lower-stake monetary series. The payments in the monetary series were substantial and equivalent to the average input expenditure of a household in a year. The potential payout in the monetary series varied from 0.3 to 12.6 daily wage rates (DWR) in the case of bad and good outcomes for the riskier option and from 3.2 to 6.3 DWR for the less risky option. This compares to the hypothetical series, where the riskier option had hypothetical payouts of 13.3 to 732 DWR, and the less risky option had a hypothetical payout of 183 to 366 DWR (Holden 2014). All respondents received a payout in the monetary experiments but did not know from which series. This was determined randomly, after all series had been played. The CRRA parameter used in the following analysis was derived by combining the hypothetical and monetary series.

[30] We consider the CRRA parameter to be more accurate, as it is derived from eight series. The alpha and sigma parameters are elicited jointly, which can potentially lead to correlated measurement errors that are likely to be less problematic under our approach.

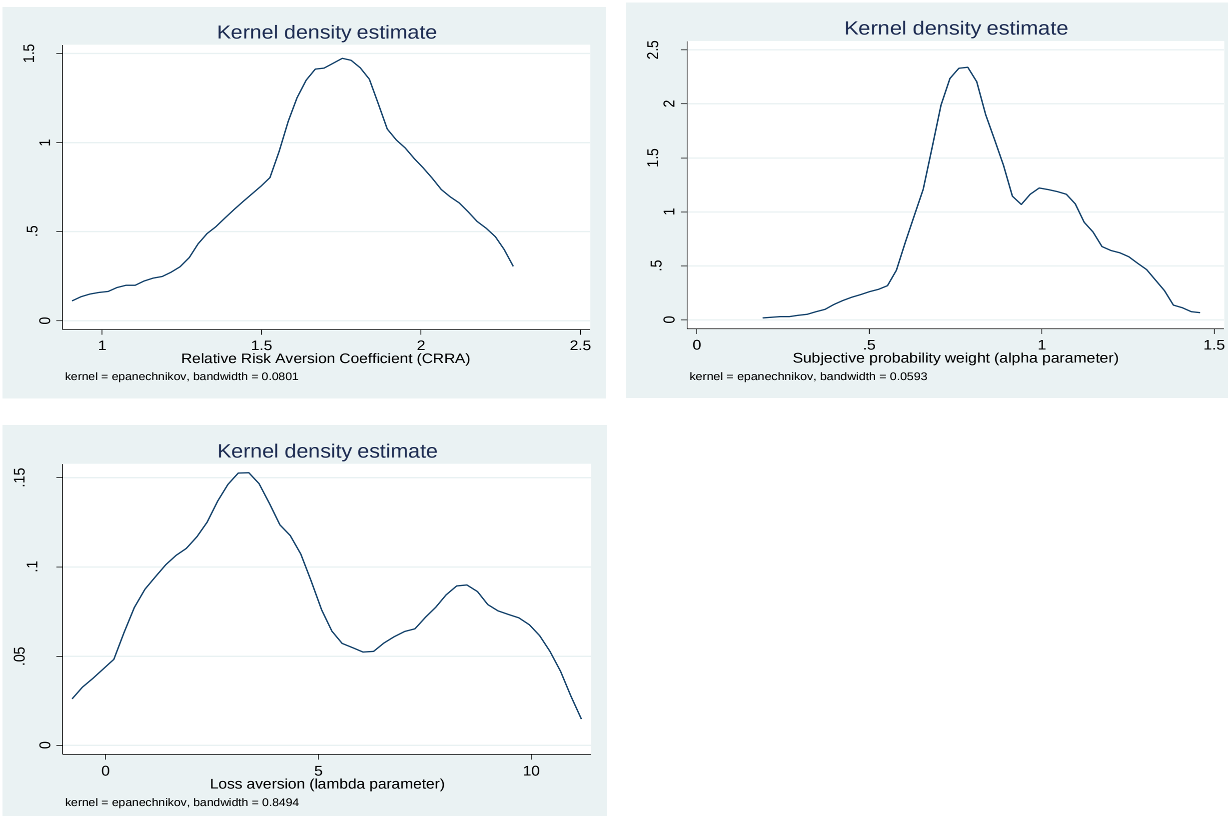

Figure 1. a) Relative risk aversion coefficient distribution, b) subjective probability weight (alpha parameter) distribution, c) loss aversion (lambda parameter) distribution.

Table 2. List of variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Planted DT maize, dummy	282	.507	.501	0	1
Planted OIMP maize, dummy	282	.397	.490	0	1
Planted local maize (LM), dummy	282	.553	.498	0	1
Maize area, local maize, ha	282	.279	.340	0	1.86
Maize area, DT maize, ha	282	.320	.479	0	3.26
Maize area, OIMP maize, ha	282	.245	.622	0	8.45
Total fertilizer on DT maize, kg	282	35.82	64.71	0	500
Total fertilizer on OIMP maize, kg	282	27.38	62.03	0	500
Total fertilizer on local maize, kg	282	28.07	56.34	0	400
Fertilizer use on OIMP maize, dummy	282	.298	.458	0	1
Fertilizer use on DT maize, dummy	282	.394	.489	0	1
Fertilizer use on local maize, dummy	282	.426	.495	0	1
Relative risk aversion coefficient	279	1.73	.291	.986	2.21
Subjective probabilty weight	278	.877	.213	.25	1.4
Loss aversion coefficient	278	4.61	2.97	.07	10.32
Number of shocks last 4 years	282	1.61	.867	0	4
Drought 2012, dummy	282	.780	.415	0	1
Drought 2011, dummy	282	.174	.380	0	1
Drought 2010, dummy	282	.085	.292	0	2
Average rainfall, mm	282	899.8	92.2	786.26	1014.9
Failed to get preferred variety, dummy	282	.337	.473	0	1
Farm size in ha	282	1.24	1.50	.086	19.18
Sex of respondent, male=1	281	.587	.493	0	1
Age of household head, years	282	43.24	14.51	21	85
Savings for fertilizer purchase, MK	282	3853	144	0	160000
Non-agricultural business, dummy	280	.461	.499	0	1
Formal employment, dummy	281	.146	.354	0	1
Received fertilizer coupon (FISP)	282	.557	.498	0	1
Received seed coupon (FISP)	282	.582	.494	0	1

7. Results

7.1. Maize type adoption

The results of the double hurdle models for adoption and intensity of adoption of the three types of maize are presented in Table 3, with average partial effects (APEs) presented in Table 4. The first three models in Table 3 exclude endogenous variables, while the last three models include endogenous variables. The APEs in Table 4 are only for the models that include the endogenous variables in Table 3.

As can be seen, the results for the key exogenous variables of interest are remarkably consistent across the specifications without and with endogenous variables and may indicate that omitted variable bias and endogeneity bias are not significant problems[31]. The first hurdle (to adopt or not to adopt) results show that relative risk aversion (CRRA) is positively correlated with adoption of DT maize and local maize, both being significant at the 1% level in both specifications (APEs are significant at the 5% level in Table 4), while relative risk aversion is negatively correlated with adoption of OIMP maize varieties (significant at the 5% level in both Tables 3 and 4). This is likely to reflect the fact that DT maize, due to its drought tolerance, and LM maize, due to its resistance to post-harvest pest risk, are considered safer options and are given higher priority by more risk averse households. Table 4 indicates that a farmer with CRRA=2 is 32.9% more likely to plant DT maize than a farmer with CRRA=1, while he is also 36.3% more likely to plant local maize and 28.8% less likely to plant OIMP maize. The average CRRA in the sample was 1.73.

Furthermore, loss aversion is also significantly positively (at the 5% level in both specifications) correlated with adoption of DT maize. More loss averse households were therefore more likely to adopt DT maize. They may place greater weight on the expectation that DT maize will result in

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[31] Additional variations in the specifications, such as bootstrapped models to correct standard errors for possible heteroscedasticity, were also tested. Bootstrapped models in Stata 13 do not allow weighting with IPWs to correct for attrition bias and were therefore not preferred. However, the results were remarkably similar to the included results. The results from the alternative specifications are available upon request. Alternative double hurdle models to the *craggit* command in Stata (*dhreg* and *bootdhreg* commands) were also tested but did not allow weighting. They produced similar results.

Table 3. Double hurdle models by maize type and area planted to maize type without and with endogenous variables

Hurdle 1: Planted type of maize	Models without endogenous variables DT maize	OIMP maize	Local maize	Models with endogenous variables DT maize	OIMP maize	Local maize
Relative risk aversion coeff.	1.378***	-0.986**	1.132***	1.239***	-1.127**	1.134***
	(0.425)	(0.454)	(0.432)	(0.452)	(0.467)	(0.433)
Subjective probabilty weight	-0.362	0.117	-0.123	-0.604	0.154	-0.089
	(0.408)	(0.427)	(0.391)	(0.442)	(0.439)	(0.399)
Loss aversion coeff.	0.069**	0.026	-0.020	0.076**	0.024	-0.021
	(0.030)	(0.033)	(0.029)	(0.032)	(0.033)	(0.029)
Number of shocks last 3 years	0.128	0.118	-0.341****	0.192*	0.118	-0.322***
	(0.096)	(0.097)	(0.095)	(0.099)	(0.104)	(0.099)
Drought 2012, dummy	-0.089	0.260	0.175	-0.076	0.270	0.140
	(0.284)	(0.282)	(0.287)	(0.311)	(0.290)	(0.288)
Drought 2011, dummy	0.890***	-0.375	-0.385	0.926***	-0.390	-0.395
	(0.284)	(0.298)	(0.265)	(0.307)	(0.298)	(0.265)
Drought 2010, dummy	0.824*	-0.574	-0.010	0.871*	-0.575	-0.013
	(0.470)	(0.373)	(0.308)	(0.485)	(0.393)	(0.305)
Failed to get preferred variety,	-0.279	0.088	0.221	-0.266	0.059	0.242
dummy	(0.205)	(0.212)	(0.185)	(0.213)	(0.219)	(0.186)
Log of Farm size in ha	0.075	0.459	0.279	0.148	0.367	0.258
	(0.247)	(0.288)	(0.250)	(0.264)	(0.291)	(0.253)
Sex of respondent	-0.112	0.045	0.101	-0.168	0.019	0.130
	(0.185)	(0.184)	(0.180)	(0.198)	(0.192)	(0.182)
Average rainfall, mm	0.002	0.001	0.002	0.001	0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age	-0.008	-0.010	0.023****	-0.013**	-0.006	0.023****
	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)
Received subsidized fertilizer				0.227	-0.181	0.154
voucher				(0.208)	(0.226)	(0.192)
Received subsidized seed				0.678***	0.124	-0.078
voucher				(0.216)	(0.231)	(0.211)
Log of savings for fertilizer				-0.005	0.045*	0.005
purchase				(0.025)	(0.024)	(0.024)
Non-agricultural business,				-0.305*	0.446**	-0.044
dummy				(0.184)	(0.191)	(0.173)
Formal employment, dummy				0.159	-0.009	-0.057
				(0.284)	(0.291)	(0.260)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-6.024***	1.989	-4.004**	-5.457***	2.160	-4.290**
	(1.925)	(1.917)	(1.953)	(1.930)	(1.903)	(2.029)

Table 3, continued… Hurdle 2: Area planted by maize type	DT maize	OIMP maize	Local maize	DT maize	OIMP maize	Local maize
Relative risk aversion coeff.	-0.057	-0.357***	0.046	-0.068	-0.188**	0.035
	(0.092)	(0.119)	(0.061)	(0.080)	(0.084)	(0.054)
Subjective probabilty weight	0.216**	0.191**	0.042	0.257***	0.244**	0.054
	(0.094)	(0.094)	(0.057)	(0.082)	(0.097)	(0.048)
Loss aversion coefficient	-0.007	0.020***	0.000	-0.003	0.013*	0.000
	(0.008)	(0.008)	(0.005)	(0.008)	(0.007)	(0.004)
Number of shocks last 3 years	0.022	-0.009	-0.032*	0.011	-0.014	-0.023
	(0.021)	(0.026)	(0.020)	(0.021)	(0.021)	(0.017)
Drought 2012, dummy	0.048	-0.021	0.070	-0.015	0.033	0.074**
	(0.098)	(0.074)	(0.049)	(0.086)	(0.061)	(0.035)
Drought 2011, dummy	0.032	0.037	-0.052	0.023	-0.004	-0.024
	(0.059)	(0.044)	(0.044)	(0.043)	(0.036)	(0.032)
Drought 2010, dummy	-0.082	0.041	-0.043	-0.083	0.050	-0.045
	(0.070)	(0.077)	(0.054)	(0.054)	(0.056)	(0.036)
Failed to get preferred variety,	-0.080*	-0.019	-0.009	-0.032	-0.028	0.035
dummy	(0.049)	(0.042)	(0.033)	(0.047)	(0.032)	(0.023)
Log of Farm size in ha	0.582****	0.565****	0.362****	0.496****	0.533****	0.388****
	(0.094)	(0.101)	(0.046)	(0.111)	(0.086)	(0.034)
Sex of respondent in household	-0.055	0.038	-0.017	-0.038	0.046	-0.011
	(0.036)	(0.044)	(0.030)	(0.032)	(0.041)	(0.024)
Average rainfall, mm	0.000	0.001***	0.000	0.000	0.001	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Received subsidized fertilizer				-0.015	0.063	0.025
voucher				(0.035)	(0.043)	(0.022)
Received subsidized seed				0.013	-0.057	-0.024
voucher				(0.046)	(0.039)	(0.026)
Log of savings for fertilizer				0.006	-0.000	0.003
purchase				(0.005)	(0.005)	(0.003)
Non-agricultural business,				0.001	0.022	-0.021
dummy				(0.034)	(0.034)	(0.022)
Formal employment, dummy				0.021	-0.044	0.006
				(0.056)	(0.038)	(0.027)
Log of OIMP maize area				-0.097		-0.107
				(0.133)		(0.093)
Log of local maize area				-0.036	-0.206**	
				(0.092)	(0.097)	
Log of DT maize area					-0.119	-0.012
					(0.079)	(0.063)
Log of pre-state of nature labor				0.123****		
input on DT maize				(0.035)		
Log of pre-state of nature labor					0.142****	
Input on OIMP maize					(0.023)	

Log of pre-state of nature labor						0.120****
Input on LM maize						(0.016)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.556	-0.772*	-0.029	-0.858**	-0.870**	-0.330
	(0.541)	(0.449)	(0.277)	(0.437)	(0.354)	(0.226)
Sigma constant	0.197****	0.188****	0.146****	0.174****	0.150****	0.116****
	(0.018)	(0.018)	(0.010)	(0.014)	(0.015)	(0.008)
Wald chi2	90.549	9263.163	56.858	110.142	8671.206	59.098
Prob > chi2	0.000	0.000	0.001	0.000	0.000	0.002
Number of observations	277	277	277	276	276	276

Note: *, **, ***, *** indicate that coefficients are significant at 10, 5, 1, and 0.1% levels, respectively. Standard errors in parentheses. Models weighted with inverse probability weights to correct for attrition bias, based on baseline survey household characteristics. Models estimated using Craggit command in Stata 13. The table gives average marginal effects.

Table 4. Average partial effects (APEs) with bootstrapped standard errors for key variables

Maize type	DT		OIMP		LM	
Hurdle 1: Growing maize type	APE	Bootstr. SE	APE	Bootstr. SE	APE	Bootstr. SE
Relative risk aversion coefficient	0 .329**	0.132	-0.288**	0.132	0.363**	0.146
Subjective probabilty weight (alpha)	-0.160	0.125	0.039	0.126	-0.035	0.135
Loss aversion coefficient (lambda)	0.020**	0.009	0.006	0.009	-0.007	0.011
Number of shocks last 3 years	.051*	0.031	0.030	0.031	-0.104***	0.034
Drought 2011, dummy	0.246**	0.100	-0.099	0.092	-0.121	0.102
Drought 2010, dummy	0.232	0.383	-0.147	0.189	-0.005	0.117
Log of Farm size in ha	0.039	0.088	0.094	0.081	0.086	0.091
Age of household head	-0.003*	0.002	-0.001	0.002	0.007****	0.002
Received subsidized seed voucher	0.180***	0.061	0.032	0.067	-0.027	0.073
Non-agricultural business, dummy	-0.072	0.055	0.098*	0.055	-0.014	0.059
Hurdle 2: Log of planted area to maize type						
Relative risk aversion coefficient	0.080	0.061	-0.235***	0.075	0.164**	0.065
Subjective probabilty weight (alpha)	0.046	0.062	0.090	0.072	0.010	0.064
Loss aversion coefficient (lambda)	0.005	0.005	0.010*	0.005	-0.003	0.005
Number of shocks last 3 years	0.021	0.015	0.009	0.018	-0.052***	0.018
Drought 2011, dummy	0.039	0.040	0.003	0.044	-0.039	0.045

Drought 2010, dummy	-0.009	0.125	-0.012	0.111	-0.018	0.054
Log of Farm size in ha	0.202***	0.066	0.218***	0.064	0.208****	0.043
Age of household head	-0.001	0.001	-0.0004	0.001	0.004****	0.001
Received subsidized seed voucher	0.027	0.035	-0.034	0.040	-0.024	0.033
Non-agricultural business, dummy	-0.009	0.027	0.032	0.030	-0.029	0.027

Note: Average partial effects for the models in Table 3 including endogenous variables. Bootstrapped standard errors based on 400 replications programmed based on Burke (2009). *, **, ***, *** indicate that coefficients are significant at 10, 5, 1, and 0.1% levels, respectively.

smaller losses in drought years. However, a one unit higher lambda (loss aversion parameter) is associated with only a 2% higher probability of planting DT maize (Table 4).

The lagged drought exposure dummy variables are significantly positively correlated with adoption of DT maize in both model specifications in Table 3, while the APE in Table 4 is only significant for the one year lagged drought variable. The one year lagged drought dummy is significant at the 1% level in both specifications in Table 3, and the APE is significant at the 5% level in Table 4. Farmers exposed to drought in 2011 were 24.6% more likely to plant DT maize in 2012. The two year lagged drought dummy is significant at the 10% level in Table 3 and insignificant in Table 4. The APE in Table 4 for DT maize is, however, positive and has a value close to that of the one year lagged drought APE.

On the other hand, the variable for the number of shocks that households have been exposed to over the preceding four years is significant (at the 0.1% and 1% levels) and has a negative sign in the LM models in Table 3. Additionally, the APE is significant at the 1% level in Table 4. Exposure to one extra shock (of any kind) is associated with a 10.4% lower probability of planting local maize and a 5.2% higher probability of planting DT maize[32]. This is consistent with higher shock exposure triggering dis-adoption of local maize. The parameters for this variable are positive for DT and OIMP maize but are significant at the 10% level only in the case of DT maize when endogenous variables are included. The drought shocks are also included in the count of the

[32] This is after we have controlled for lagged drought shock with the dummy variables.

number of shocks. This may imply that it is drought shocks in particular that stimulate DT maize adoption, while the number of shocks is more important than drought shocks per se to the dis-adoption of local maize.

Among the other exogenous variables, only age was significant in the models for LM maize in both specifications, where it had a positive sign and was significant at the 0.1% level in both models in Tables 3 and 4. Older household heads are more likely to continue to grow local maize. An increase in the age of the household head by 10 years is associated with a 7% higher probability of planting local maize. Age was negatively associated with adoption of DT maize but was significant (at the 5% level) only in the specification that included endogenous variables, while the APE was significant (at the 10% level) only in Table 4. An increase in age by 10 years is associated with a 3% lower probability of planting DT maize. This may be because older people are more skeptical about the adoption of new technologies, such as DT maize.

Among the endogenous variables included in the second set of models, the dummy for having received a maize seed voucher under the subsidy program was positively associated with adoption of DT maize (significant at the 1% level in Tables 3 and 4). The recipient of a seed voucher from the subsidy program in 2012 was associated with an 18% higher probability of planting DT maize. This is consistent with the findings of Holden and Fisher (2015) that the input subsidy program has contributed to the adoption of DT maize. Saving for fertilizer purchases and having non-agricultural business income were positively associated with adoption of OIMP maize, and this may indicate that liquidity can constrain adoption of OIMP maize seeds, which were more likely to be distributed independently of the input subsidy program.

Next, we examine factors associated with the intensity of adoption of different types of maize. Intensity of adoption is measured as the land area (log-transformed) planted with a specific type of maize. The second hurdle results in Tables 3 and 4 demonstrate that factors that affect the intensity of adoption differ from those that affect the first stage adoption decision.

Relative risk aversion is negatively associated with intensity of adoption of OIMP maize but not significantly related to intensity of adoption of DT maize. For local maize, only the APE in Table 4 is significant (at the 5% level) and has a positive sign. A farmer with CRRA=2 is planting an area of OIMP maize that is 23.5% smaller than a farmer with CRRA=1, while he plants an area of local maize that is 16.4% larger.

The prospect theory (CPT) experiments revealed high levels of loss aversion (average lambda=4.61) and the dominance of an inverted S-shaped subjective probability weighting function, with an average alpha=0.877.

The subjective probability weight (alpha) parameter is significantly and positively correlated with the intensity of adoption of DT and OIMP maize (both being significant at least at the 5% level in both specifications in Table 3), although for the APEs, the variable is not significant. The APEs of the alpha parameter are also small and therefore appear to have little impact on the intensity of adoption. More loss averse individuals, on the other hand, exhibit significantly (at the 1% and 10% levels in Table 3 and at the 10% level in Table 4) higher levels of adoption intensity of OIMP maize, a result that is somewhat surprising. Here also, the APE is low: a one unit increase in the lambda loss aversion parameter is associated with a 1% increase in the area of OIMP maize.

Few of the other exogenous variables were consistent (in terms of sign and significance levels) across the two specifications (without and with endogenous variables). The exception is farm size, which is highly significant (at the 0.1% level) and has a positive sign in all models. The intensity of adoption responded almost equally to a change in farm size for all maize types. A 10% increase in farm size is associated with a 2.0% increase in the area of DT maize, a 2.2% increase in the area of OIMP maize and a 2.1% increase in the area of local maize. This illustrates that the intensity of adoption is constrained by the (small) farm sizes in the study areas.

Few of the endogenous variables are also significantly correlated with the intensity of adoption. The exceptions are the *ex ante* labor input variables, which were strongly positively correlated with intensity of adoption for all three maize types. This demonstrates the complementarity of land and labor in this hoe-based farming system. The negative signs for the intensity of adoption of alternative maize types indicate that they are substitutes, but the lack of statistical significance (with one exception) also indicates that growing one maize type does not necessarily rule out growing other types.

We summarize by assessing the results in relation to our hypotheses. The findings related to relative risk aversion mostly support hypothesis H1), which states that "*Relative risk aversion is associated with a higher probability and a higher intensity of adoption of DT and LM maize and the opposite for OIMP maize*." None of the empirical evidence provides a basis for rejecting parts of the hypothesis. Hypothesis H2) states that "*Loss aversion is associated with a higher probability* *of DT maize adoption and a lower probability of OIMP maize adoption."* We found that loss aversion was positively correlated with adoption of DT maize but not negatively related to adoption of OIMP maize. On the contrary, loss aversion was positively associated with the intensity of OIMP maize adoption. Hypothesis H2) may therefore be rejected in the case of OIMP but not in the case of DT maize. The first part of hypothesis H3 states that "*Subjective overweighting of low probability extreme events is associated with less adoption of OIMP maize* …" We found no support for this hypothesis. The elicited subjective probability weights were not significantly associated with either adoption or intensity of adoption of any of the maize types. Hypothesis H4) states that "*Shock exposure in the form of droughts in previous years is associated with increased adoption of DT maize and dis-adoption of LM maize*." The results support this hypothesis, which therefore cannot be rejected. The first part of hypothesis H5) states that "*Access to subsidized inputs enhances adoption of DT maize* …" The results strongly support this hypothesis. The input subsidy program appears to have been instrumental in promoting adoption of DT maize.

7.2. Fertilizer use intensity by maize type

Fertilizer use intensity by maize type is analyzed using censored tobit models that are conditional on the type of maize being planted by households. To correct for attrition and sample selection bias related to planting specific types of maize, inverse probability weights from probit models for planting each type of maize were used, with the baseline household sample and characteristics as right-hand side variables. Input variables were log-transformed. Table 5 presents the results for models both without and with a set of endogenous variables, as in the case of maize type adoption. However, in the case of intensity of fertilizer use, double hurdle models did not work, and censored tobit models appeared to be most appropriate.

Table 5 shows that the key variables produced quite similar results in the cases without and with the endogenous variables. Relative risk aversion had a negative sign in all models but was significant only in the first model with OIMP maize. The subjective probability weight (alpha parameter), however, is positively significant in five of six models. The highest levels of significance are found in the DT maize models (significant at the 1% and 0.1% levels), while the parameters are larger in magnitude and significant at the 1% and 5% levels in the case of OIMP maize. This indicates that fertilizer use intensity is significantly lower for farmers who overweight low probability extreme events more and particularly so for the improved maize varieties. Figure 2 illustrates the actual distribution of fertilizer use[33] on OIMP, DT and LM maize for respondents with alpha<0.75 versus respondents with alpha>0.75. We see that fertilizer use distributions are much lower for the first group and particularly so for the OIMP maize.

There are no strong shock effects on fertilizer use intensity, but average rainfall is associated with a higher intensity of fertilizer use on OIMP maize, while for DT maize, farmers apply more fertilizer in areas with lower average rainfall. The latter may be because they believe it is less risky to apply fertilizer to DT maize in such areas. Male-headed households tended to use less fertilizer on LM maize than female-headed households. The latter result is in line with females having a stronger preference for local maize, which may be related to its superior post-harvest and food qualities. Some learning may enhance the potential of DT maize varieties, as the level of technical efficiency is found to be low in smallholder maize production in Malawi after controlling for drought and land quality (Holden and O'Donnell 2015).

With regard to the included endogenous variables, receipt of a voucher for subsidized fertilizer is positively and significantly related (at the 1% and 0.1% levels) to intensity of fertilizer use for all three types of maize. Saving for fertilizer purchases is significant (at the 5% and 10% levels) and positive in the models for DT and LM maize, while the dummy for non-agricultural business is significant (at the 1% level) and positive in the OIMP maize model. This result suggests that a liquidity constraint may limit fertilizer use intensity,

Fertilizer subsidies therefore appear to counteract irrational behavior in the form of subjective overweighting of low probability extreme events, behavior that is associated with lower fertilizer use and low fertilizer use due to binding liquidity constraints. The latter finding is consistent with the findings of Holden and Lunduka (2014), while the first result indicates that irrational behavior also plays a significant role.

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[33] Untransformed fertilizer use, to get a better idea of the actual amounts used.

Table 5. Censored tobit models for intensity of fertilizer use by maize type without and with endogenous variables.

	Models without endogenous variables			Models with endogenous variables		
RHS variables	Fertilizer on DT	Fertilizer on OIMP	Fertilizer on LM	Fertilizer on DT	Fertilizer on OIMP	Fertilizer on LM
Relative risk aversion coefficient	-0.433	-3.235***	-0.587	-0.811	-1.413	-0.761
	(0.816)	(1.063)	(0.904)	(0.653)	(0.973)	(0.776)
Subjective probabilty weight	2.054***	3.613***	1.297	2.082****	2.912**	1.292*
	(0.754)	(1.192)	(0.818)	(0.571)	(1.126)	(0.736)
Loss aversion coefficient	-0.022	0.051	0.010	0.012	0.004	-0.009
	(0.065)	(0.066)	(0.067)	(0.055)	(0.056)	(0.059)
Number of shocks last 3 years	-0.018	-0.254	-0.304	0.222	-0.101	0.047
	(0.158)	(0.250)	(0.270)	(0.140)	(0.232)	(0.246)
Drought 2012, dummy	0.109	-0.740	0.017	-0.171	-0.841	-0.207
	(0.662)	(0.684)	(0.615)	(0.512)	(0.563)	(0.593)
Drought 2011, dummy	-0.262	1.011*	0.157	-0.220	0.598	0.527
	(0.434)	(0.583)	(0.625)	(0.313)	(0.559)	(0.573)
Drought 2010, dummy	0.220	-0.959	-0.591	0.266	-0.748	-0.562
	(0.334)	(0.817)	(0.711)	(0.319)	(0.878)	(0.583)
Average rainfall, mm	-0.009**	0.011***	-0.003	-0.009***	0.007**	-0.003
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Failed to get preferred variety, dummy	-0.559	0.196	-0.227	-0.006	0.367	-0.017
	(0.366)	(0.418)	(0.449)	(0.307)	(0.366)	(0.403)
Log of Farm size in ha	0.769	0.398	0.022	-0.873*	-1.174	-0.894
	(0.525)	(0.771)	(0.544)	(0.513)	(0.818)	(0.759)
Sex of respondent in household	-0.367	0.241	-0.935**	0.071	0.207	-0.714*
	(0.304)	(0.427)	(0.421)	(0.244)	(0.403)	(0.361)
Received subsidized fertilizer voucher				1.958****	1.254***	1.920****
				(0.331)	(0.473)	(0.427)
Received subsidized seed voucher				-0.475	-0.519	-0.104
				(0.351)	(0.473)	(0.384)
Log of savings for fertilizer purchase				0.078**	-0.004	0.074*
				(0.030)	(0.054)	(0.044)
Non-agricultural business, dummy				-0.074	1.079***	-0.152
				(0.301)	(0.388)	(0.341)
Formal employment, dummy				-0.317	0.009	0.009
				(0.375)	(0.445)	(0.613)
Log of DT maize area				2.439****		
				(0.589)		
Log of OIMP maize area					3.278***	
					(1.220)	
Log of local maize area						3.539**
						(1.475)

Log of pre-state of nature labor DT				0.249		
				(0.156)		
Log of pre-state of nature labor OIMP					-0.328	
					(0.286)	
Log of pre-state of nature labor LM						0.235
						(0.231)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	12.220***	-4.561	7.266*	10.512***	-3.561	3.836
	(4.171)	(3.501)	(4.134)	(3.258)	(3.323)	(3.817)
Sigma constant	1.563****	1.738****	1.943****	1.225****	1.496****	1.634****
	(0.156)	(0.171)	(0.166)	(0.112)	(0.141)	(0.132)
Log likelihood	-338.241	-266.369	-379.935	-294.977	-246.207	-345.089
Prob > F	0.000	0.000	0.009	0.000	0.000	0.000
Number of observations	136	98	144	136	98	143
Left-censored obs.	20	19	32	20	19	32

Note: Dependent variable: log(kg Fertilizer+1). *, **, ***, *** indicate that coefficients are significant at 10, 5, 1, and 0.1% levels, respectively. Standard errors in parentheses. Models weighted with inverse probability weights to correct for attrition bias and sample selection into maize type, based on baseline survey household characteristics. The models are conditional on each maize type being grown by the household. The coefficients are average marginal effects.

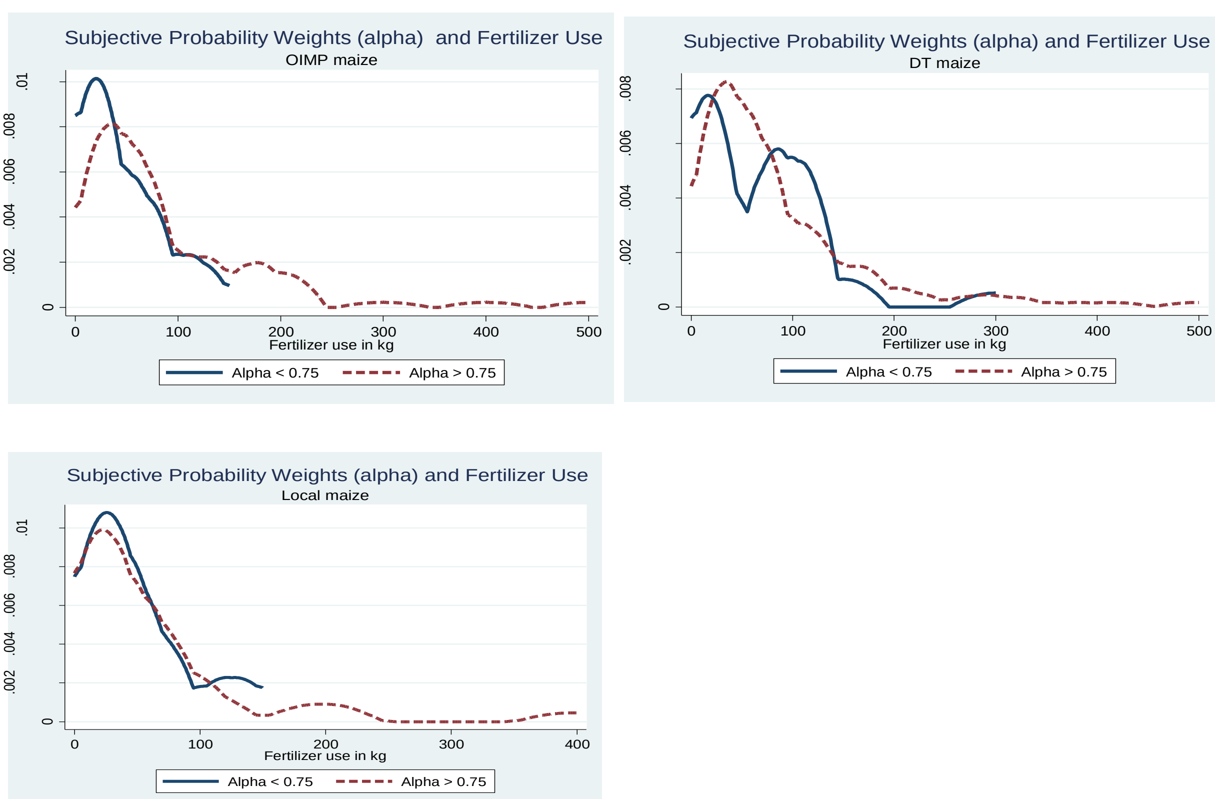

Figure 2. Subjective probability weights and fertilizer use intensity on OIMP, DT and local maize

Area planted for each maize type is strongly and positively related to the intensity of fertilizer use, indicating that land and fertilizer are also complementary inputs in production, while labor use is less closely related to fertilizer use intensity. This may be because fertilizer application requires little labor.

We can now assess the remaining hypotheses regarding fertilizer use intensity. The second part of hypothesis H3) states that *"Subjective overweighting of low probability extreme events is associated with less use of fertilizer on OIMP and local maize*." Our findings reveal such an effect for all types of maize, but it was strongest for OIMP maize, which may be perceived as the riskiest type of maize to which fertilizer is applied. The hypothesis, therefore, cannot be rejected. Finally, hypothesis H5) states that *"Access to subsidized inputs enhances the intensity of fertilizer use on all types of maize."* This hypothesis is strongly supported by the results.

7.3. Robustness checks

We have demonstrated that the key preference and shock variables are robust to the model specifications both without and with the endogenous variables in the models with log transformed input variables. The key results are also very similar in models with untransformed variables and with specifications in which the number of included endogenous variables is altered. This was the case for the maize type adoption models and the fertilizer intensity models. While we used IPWs to correct for attrition bias, the models without IPWs produced very similar results.

We do not have a good measure of household income, as the off-farm income data are weak and do not include consumption data that would have allowed us to create a measure of total consumption expenditure. Farm size (land) is the best wealth indicator we have. The off-farm income access dummies and savings variables, together with the input subsidy access variables, revealed that poverty and liquidity constraints can constrain adoption of both fertilizer and improved maize seeds. However, controlling for these factors did not change the way relative risk aversion and subjective probability weighting affected technology adoption and the intensity of adoption.

7.4. Correlation versus causality

We have relied on cross-sectional survey data and must therefore be cautious in drawing causal conclusions from our results. However, the fact that the preference parameters were derived through field experiments and that we could draw on a natural experiment in the form of a significant drought shock in 2012 along with less severe lagged drought shocks and other shocks give us reasons to argue that we can draw some causal implications from the findings. The fact that DT maize adoption was a relatively new phenomenon, with an increase in the adoption rate from 2% to 45% between 2006 and 2012, also indicates that we may have reason for confidence in a causal relationship from risk preference parameters and shocks to technology adoption. This does not rule out that there may be an element of reverse causality or correlation and therefore some bias in the estimates. The robustness checks that were implemented, however, indicate that such biases are small in our data.

8. Conclusion

Climate change is likely to increase climate risk, and more severe and more frequent droughts are likely to occur in some parts of the world, including the southern part of Africa in which Malawi is situated. Malawi has a population and an economy that is highly dependent on rain-fed agriculture, with maize the main staple crop that is susceptible to drought. International efforts have resulted in the development of improved high-yielding and more drought-tolerant maize varieties.

This study has investigated the adoption decisions of poor smallholder farmers in Malawi with regard to different maize types and fertilizer use on these maize types. Field experiments were used to elicit risk preference prospect theory parameters. These were combined with detailed household-farm plot data, with farmers' fields measured using GPS. This allowed for a detailed investigation of factors associated with the adoption and intensity of adoption of different maize types. To our knowledge, this is the first study of its kind to include such a detailed investigation of how drought shocks, risk preferences and prospect theory parameters affect the adoption and intensity of adoption of alternative maize technologies and fertilizer use.

The findings have an important implication for the identification of the productivity impacts of DT maize, as opposed to other maize varieties, from farm survey data. Impact studies that use survey data and do not control for the effects of risk preferences and subjective probability weighting on adoption and intensity of adoption of the maize varieties as well as fertilizer use will get biased estimates of these impacts.

More generally, this study shows that modern developments in state-contingent production theory and the theory of choice under uncertainty can be integrated and used to analyze producer decisions. In combination with advanced techniques for the elicitation of preferences and the estimation of discrete choice models, these developments promise new insight into the perennial problem of managing climatic risk in agriculture.

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Appendix. Field experiment design: Risk preference experiments

Instructions to enumerators: Arrange the experiment for all households in a village within one day. Use school or another facility where a large room with tables and chairs are available. Ensure that the area is protected from interference by other people and prevent that those who have played interact with those that have not played the experiments. With four enumerators you may interview/play with four respondents at the same time such but ensure that those who play cannot communicate or observe each other. All games should be played with the head of the household.

They should get a participation amount (MK 1000) that they have to be prepared to lose (some of) in the experiments). There is a large number of tasks to be evaluated by each of the respondents. You have to take the time that is needed for them to think about each task such that they understand it and make proper selection based on their own preferences. Explain to them that a lottery will be used to identify which of the series of games that they will play that will be real and give them a real payout.

Risk preference experiments: Overview

First four series: Choice between alternative maize varieties. Two types of years: Bad years (drought) and good years (no drought). Varying probability of bad year (number of bad years out of 10) & varying yield outcome levels for varieties in good and bad years (in kg/ha). When they choose the Variety they do not know what type of year they will get (good or bad), only the chance (in number of years out of ten) of a bad year. Based on this they should choose their preferred variety. Lotteries come in series, where your task is to identify the switch point in each series where typically only one variable (e.g. the probability of good or bad years) changes at the time. Rational behavior implies that there will be only one switch point in each of the series (or in some cases they will not switch at all). If they switch back and forth this is an indication that they have not understood the game or answer carelessly. Your task is to make sure that they understand and make careful (preferred choices). You therefore need to be patient, especially in the beginning to make them understand. Demonstrate the probabilities with fingers or cards (use 10 playing cards). Demonstrate the outcomes with money. . Such demonstration methods should be standardized across enumerators in initial testing of the experiments.

After careful completion of the whole interview and making of choices, there will be a random sampling of the series and game in the series that will give the actual payout. After this the household head will be given her/his reward based on the outcome of this sampling and actual choices made. After that they are asked to go home and not talk to other households who have not yet been interviewed or played the game. It is important that they respect this.

Risk of starting point bias: Randomize the task you start with in each series (pull a card). After the first response move towards the end point in the direction you expect a switch to check whether you get it. Narrow in on the switch point by moving to the middle between the last prospects if there was a switch, continue halfway forward otherwise.

Instructions to players (household heads):

We have rewarded you with an initial payment of MK 1000 for coming to play the game. You are likely to win more but may also expect to lose some of the MK 1000 in the games to be played. Rewards depend on outcomes in lotteries and choices made by you during the game. If you make careful decisions you are more likely to get preferred rewards over less preferred rewards. The experiments include choices of maize varieties with different outcomes in drought years and years with good rainfall, alternative lotteries with money, lotteries with payments at different points in time, and lotteries with maize seeds (2 kg bags) and fertilizers (5 kg bags).

The rewards will vary in the different lotteries which come in series.

At the end a lottery will be used to identify which of the choice series will be for real payout. After you have received your reward(s) you should go home and not talk to anybody who have not yet played the game. That is very important.

Choice series 1 (Chose between Variety 1 and Variety 2 when probability of drought varies)

		Variety 1 (Lottery A)				Variety 2 (Lottery B)			
		Yields in kg/ha				Yields in kg/ha			
Task	Probability of bad year, %	Bad year	Good year	Expected yield	Choice	Bad year	Good year	Expected yield	Choice
11	10	1000	2000	1900		100	4000	3610	
12	20	1000	2000	1800		100	4000	3220	
13	30	1000	2000	1700		100	4000	2830	
14	40	1000	2000	1600		100	4000	2440	
15	50	1000	2000	1500		100	4000	2050	
16	60	1000	2000	1400		100	4000	1660	
17	70	1000	2000	1300		100	4000	1270	
18	80	1000	2000	1200		100	4000	880	

Choice series 2(Chose between Variety 3 and Variety 2 when probability of drought varies)

		Variety 3 (Lottery A)				Variety 2 (Lottery B)			
		Yields in kg/ha				Yields in kg/ha			
Task	Probability of bad year, %	Bad year	Good year	Expected yield	Choice	Bad year	Good year	Expected yield	Choice
21	10	1000	1500	1450		100	4000	3610	
22	20	1000	1500	1400		100	4000	3220	
23	30	1000	1500	1350		100	4000	2830	
24	40	1000	1500	1300		100	4000	2440	
25	50	1000	1500	1250		100	4000	2050	
26	60	1000	1500	1200		100	4000	1660	
27	70	1000	1500	1150		100	4000	1270	
28	80	1000	1500	1100		100	4000	880	

Choice series 3(Chose between Variety 3 and Variety 4 when probability of drought varies)

		Variety 3 (Lottery A)				**Variety 4 (Lottery B)**			
		Yields in kg/ha				**Yields in kg/ha**			
Task	Probability of bad year, %	Bad year	Good year	Expected yield	Choice	Bad year	Good year	Expected yield	Choice
31	10	1000	1500	1450		500	4000	3650	
32	20	1000	1500	1400		500	4000	3300	
33	30	1000	1500	1350		500	4000	2950	
34	40	1000	1500	1300		500	4000	2600	
35	50	1000	1500	1250		500	4000	2250	
36	60	1000	1500	1200		500	4000	1900	
37	70	1000	1500	1150		500	4000	1550	
38	80	1000	1500	1100		500	4000	1200	
39	90	1000	1500	1050		500	4000	850	

Choice series 4(Chose between Variety 3 and Variety 5 when probability of drought varies)

		Variety 3 (Lottery A)				**Variety 5 (Lottery B)**			
		Yields in kg/ha				Yields in kg/ha			
Task	Probability of bad year, %	Bad year	Good year	Expected yield	Choice	Bad year	Good year	Expected yield	Choice
41	10	1000	1500	1450		800	4000	3680	
42	20	1000	1500	1400		800	4000	3360	
43	30	1000	1500	1350		800	4000	3040	
44	40	1000	1500	1300		800	4000	2720	
45	50	1000	1500	1250		800	4000	2400	
46	60	1000	1500	1200		800	4000	2080	
47	70	1000	1500	1150		800	4000	1760	
48	80	1000	1500	1100		800	4000	1440	
49	90	1000	1500	1050		800	4000	1120	

Instructions to players: The following experiments involve money (MK) rather than maize yields. Here is a chance of winning real money in these experiments. One of the experiments will be chosen for real payout. Your choices will affect a potential payout from the experiments. You should therefore make careful judgment and decisions. The game for payout will be sampled after you have responded to a series of lottery choices.

Choice series 5: Chose between Lottery A and Lottery B when probability of bad outcome varies

		Lottery A				Lottery B			
		Outcome in MK				Outcome in MK			
Task	Probability of bad outcome, %	Bad	Good	Expected	Choice	Bad	Good	Expected	Choice
51	10	1000	2000	1900		100	4000	3610	
52	20	1000	2000	1800		100	4000	3220	
53	30	1000	2000	1700		100	4000	2830	
54	40	1000	2000	1600		100	4000	2440	
55	50	1000	2000	1500		100	4000	2050	
56	60	1000	2000	1400		100	4000	1660	
57	70	1000	2000	1300		100	4000	1270	
58	80	1000	2000	1200		100	4000	880	
59	90	1000	2000	1100		100	4000	490	

Choice series 6: Chose between Lottery A and Lottery B when probability of bad outcome varies

		Lottery A				Lottery B			
		Outcome in MK				Outcome in MK			
Task	Probability of bad outcome, %	Bad	Good	Expected	Choice	Bad	Good	Expected	Choice
61	10	1000	1500	1450		100	4000	3610	
62	20	1000	1500	1400		100	4000	3220	
63	30	1000	1500	1350		100	4000	2830	
64	40	1000	1500	1300		100	4000	2440	
65	50	1000	1500	1250		100	4000	2050	
66	60	1000	1500	1200		100	4000	1660	
67	70	1000	1500	1150		100	4000	1270	
68	80	1000	1500	1100		100	4000	880	
69	90	1000	1500	1050		100	4000	490	

Choice series 7: Chose between Lottery A and Lottery B when probability of bad outcome varies

		Lottery A				**Lottery B**			
		Outcome in MK				**Outcome in MK**			
Task	Probability of bad outcome, %	Bad	Good	Expected	Choice	Bad	Good	Expected	Choice
71	10	1000	1500	1450		500	4000	3650	
72	20	1000	1500	1400		500	4000	3300	
73	30	1000	1500	1350		500	4000	2950	
74	40	1000	1500	1300		500	4000	2600	
75	50	1000	1500	1250		500	4000	2250	
76	60	1000	1500	1200		500	4000	1900	
77	70	1000	1500	1150		500	4000	1550	
78	80	1000	1500	1100		500	4000	1200	
79	90	1000	1500	1050		500	4000	850	

Choice series 8: Chose between Lottery A and Lottery B when probability of bad outcome varies

		Lottery A				**Lottery B**			
		Outcome in MK				Outcome in MK			
Task	Probability of bad outcome, %	Bad	Good	Expected	Choice	Bad	Good	Expected	Choice
81	10	1000	1500	1450		800	4000	3680	
82	20	1000	1500	1400		800	4000	3360	
83	30	1000	1500	1350		800	4000	3040	
84	40	1000	1500	1300		800	4000	2720	
85	50	1000	1500	1250		800	4000	2400	
86	60	1000	1500	1200		800	4000	2080	
87	70	1000	1500	1150		800	4000	1760	
88	80	1000	1500	1100		800	4000	1440	
89	90	1000	1500	1050		800	4000	1120	

Prospect theory series: In each of the following series probabilities stay constant across tasks but vary across prospects. Prospect A is kept constant within a series but good outcome is increasing with task number in Prospect B. Identify the switch point like in earlier series (expect switch from Prospect A to Prospect B at some point).

PT1	Prospect A					Prospect B				
Task	**Probability of bad outcome, %**	**Bad**	**Good**	**Expected yield**	**Choice**	**Probability of bad outcome, %**	**Bad**	**Good**	**Expected yield**	**Choice**
P1	60	1000	4000	2200		90	500	7000	1150	
P2	60	1000	4000	2200		90	500	10000	1450	
P3	60	1000	4000	2200		90	500	13000	1750	
P4	60	1000	4000	2200		90	500	16000	2050	
P5	60	1000	4000	2200		90	500	19000	2350	
P6	60	1000	4000	2200		90	500	22000	2650	
P7	60	1000	4000	2200		90	500	25000	2950	
P8	60	1000	4000	2200		90	500	28000	3250	
P9	60	1000	4000	2200		90	500	35000	3950	
P10	60	1000	4000	2200		90	500	50000	5450	

PT2	Prospect A					Prospect B				
Task	**Probability of bad outcome, %**	**Bad**	**Good**	**Expecte d yield**	**Choice**	**Probability of bad outcome, %**	**Bad**	**Good**	**Expecte d yield**	**Choic e**
P11	10	1500	2000	1950		30	250	2500	1825	
P12	10	1500	2000	1950		30	250	2750	2000	
P13	10	1500	2000	1950		30	250	3000	2175	
P14	10	1500	2000	1950		30	250	3250	2350	
P15	10	1500	2000	1950		30	250	3500	2525	
P16	10	1500	2000	1950		30	250	3750	2700	
P17	10	1500	2000	1950		30	250	4000	2875	
P18	10	1500	2000	1950		30	250	4500	3225	
P19	10	1500	2000	1950		30	250	5000	3575	
P20	10	1500	2000	1950		30	250	6000	4275	

Payment for Risk preference games: Use 6 cards (1-6) to identify which of the 6 series with money above should be selected for payout. Then allow households to pick a card out of 10 to identify which of the tasks in the selected series will be used for payout. You use the Prospect they have chosen for that task, prospect A or B. For that chosen Prospect you identify the probability of Good and Bad outcomes and assign card numbers to each, e.g. 40% probability of Good outcome in PT1 game implies that you assign cards 1-4 to Good and cards 5-10 to Bad outcome. After that you shuffle the cards and ask the farmer to pull one card. If the card is 1-4 you pay them the Good outcome of MK 4000 for PT1 and you give them MK 1 000 if the card number they pick is above 4.

Payment in risk preference experiments:

Series chosen for payout (Respondent pulls 1 out of 6 cards):________________

Task chosen for payout (Respondent pulls 1 of 9 or 10 cards:________________

Identify whether the Respondent had chosen Prospect A or B for that Task: Prospect chosen:__________

Allocate cards according to probabilities in Task chosen, and ask respondent to pull a card to assess whether the number is associated to the Bad or Good Outcome.

Card pulled:_________

Card implies: 1=Win, 0=Loss

Amount won:__________

Signature for amount received:________________

Loss Aversion (money)

- The household head has been given 1000 MK that s/he will have to risk all or some of in the following game.
  - **Instructions to players**: You have a choice between participating in two lotteries. Each of them has a 50% chance of winning, and 50% chance of losing (by tossing a coin). First choice: “Lottery A will give you MK 1250 extra if the coin toss lands on Head, and you have to give back MK 200 if it lands on Tail. Lottery B will give you MK 1500 extra if coin lands on Head but you will lose all the MK 1000 if it lands on Tail. Do you choose Lottery A or Lottery B?
- **Instructions to instructors**: Introduce each of the seven lottery choices in a similar way as above to determine the switch point from Lottery A to Lottery B. Tick the preferred lottery (A or B) in each row. Only one of these seven games will be randomly sampled and played for real (by selecting one card out of seven numbered from 1 to 7. For the selected task you see whether they chose Prospect A or B. For the prospect they chose you toss the coin to identify whether they win or lose.
- There should typically be one switch point where they switch from Lottery A to Lottery B (consistent behavior) but always choosing one of the lotteries would also be consistent.

	Prospect A					Prospect B				
Task	Probability of bad outcome, %	Win	Loss	Expected yield	Choice	Probability of bad outcome, %	Win	Loss	Expected yield	Choice
L1	50	1250	-200	525		50	1500	-1000	250	
L2	50	200	-200	0		50	1500	-1000	250	
L3	50	50	-200	-75		50	1500	-1000	250	
L4	50	50	-200	-75		50	1500	-800	350	
L5	50	50	-400	-175		50	1500	-800	350	
L6	50	50	-400	-175		50	1500	-700	400	
L7	50	50	-400	-175		50	1500	-550	475	

Mark the play that was sampled to be real: **Game no**:______

Outcome of the game: Amount lost:_____________ Amount won:_________

Signature of player:_________________________