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Probability Weighting and Input Use Intensity in a State-Contingent Framework

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By

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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 fertilizer adoption responses of food insecure farmers in Malawi, where Drought Tolerant (DT) maize was recently introduced. A field experiment, eliciting risk attitudes of farmers, is combined with a detailed farm household survey. A state-contingent production model with rank-dependent utility preferences is estimated. Over-weighting of small probabilities was associated with less use of fertilizer on all maize types and particularly so on the more risky improved maize types.

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

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

1. 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 possible response to this threat is the use of more drought-tolerant (DT) maize varieties (Burke and Lobell 2010; CIMMYT 2013; Magorokosho et al. 2010) in combination with changes to input choices and other aspects of the production process. Because climate is highly variable and experience with new varieties is necessarily limited, farmers' decisions on adoption will depend on risk attitudes and on the (actual and perceived) production technology.

Holden and Quiggin (2017) applied cumulative prospect theory (Kahneman and Tversky) and a state-contingent model of production under uncertainty (Chambers and Quiggin 2000) to model decisions of farmers in Malawi on whether to adopt a new technology, based on drought tolerant (DT) maize. The key findings were that more risk averse households were more likely to adopt

DT maize, less likely to adopt other improved maize varieties and less likely to dis-adopt traditional local maize. Exposure to past drought shocks stimulated adoption of DT maize and dis-adoption of local maize. More loss averse households were more likely to adopt DT maize.

In this paper, we use further data results from the same study to model the interaction between the choice of technology and the intensity of input use, with a particular focus on fertilizer. We focus on the role of probability weighting, in a rank-dependent utility (RDU) model (Quiggin 1982)[2]. This work extends a substantial literature on the relationship between risk attitudes and input use (Leathers and Quiggin 1991, Horowitz and Lichtenberg 1993, Bontems and Thomas 2000, 2006, Yesuf and Bluffstone 2009, Monjardino et al 2013), most of which has been undertaken within the expected utility (EU) model, which does not take account of probability weighting.

In discussion of input use and production risk, it is common to treat fertilizer as a risk-increasing input, since it typically yields higher returns in favorable states of nature. Conversely, pesticides and herbicides are often regarded as risk-reducing. Chambers and Quiggin (2000) argue that this terminology is misleading, since the effects of an input on the state-contingent distribution of outputs are not exogenously given, but depend on the production plan adopted by farmers. Chambers and Quiggin suggest instead that inputs should be defined as risk-complementary (risk-substituting) if the demand for those inputs increases (decreases) with the adoption of a more risky production plan. It follows that, other things equal, a more risk-averse farmer will use more risk-complementary inputs.

In the present study, we have evidence on risk attitudes both from direct questioning of farmers and from observed decisions on the adoption of DT maize, which gives rise to less risky output distributions.

[2] Cumulative prospect theory combines the rank-dependent approach to probability weighting with the reference point approach of the original prospect theory (Kahneman and Tversky 1979). Because our analysis showed little evidence that loss aversion plays an important role in decisions on fertilizer use, we focus on the RDU model without loss aversion.

2. Risk preferences and input use: A brief literature review

The question of whether concerns about risk are likely to encourage or discourage the use of inputs such as fertilizer has been discussed at length in the literature (Leathers and Quiggin 1991, Horowitz and Lichtenberg 1993, Bontems and Thomas 2000, 2006, Yesuf and Bluffstone 2009, Monjardino et al 2013, 2015). Most work has been done using expected utility (EU) theory with risk represented by a stochastic production function in which inputs can be classified as risk-increasing or risk-reducing.

Leathers and Quiggin (1991) use the Just-Pope production technology and treat fertilizer as a risk-increasing input. The key conclusions are that, under the standard hypothesis of non-increasing absolute risk aversion, use of a risk-increasing input will increase in response to either a reduction in risk aversion or a multiplicative reduction in yield risk.

Horowitz and Lichtenberg (1993) examine the effects of insurance and show that insured farmers use more fertilizer and pesticide. They infer that these inputs may be risk-increasing. This is consistent with the results of Leathers and Quiggin. However, the results are also open to the interpretation that insured farmers are more risk averse, in which case fertilizer and pesticide may be risk-reducing.

Bontems and Thomas (2000, 2006) examine both risk aversion and the value of information, finding that both play a significant role in decisions on fertilizer use. The aggregate effect of risk aversion and information processing is estimated at about 20% of profit per acre. The positive weight attributed to risk aversion is consistent with the assumption that fertilizer is a risk-increasing input.

Yusuf et al (2009) examined new technology adoption and fertilizer use in Ethiopia. They concluded, contrary to most previous work that fertilizer is a risk reducing input. Gelo et al (2015), also examining Ethiopian data subject to climate risk conclude that fertilizer is risk increasing.

Most of this work was undertaken in the framework of Expected Utility theory. However, there is considerable evidence to support the more general rank-dependent utility (RDU) model, which incorporates probability weighting along with the traditional EUT concept of risk aversion arising from a concave utility function. The RDU model is a special case of the Cumulative Prospect Theory (CPT) model (Kahneman and Tversky), which allows for loss aversion as well as probability weighting. Unlike CPT, the RDU model has tractable comparative static properties (Quiggin 1991a).

We are only aware of one paper applying CPT to input use decisions. 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. There is clearly a need for more research to assess the external validity of their findings.

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

The theoretical framework used here, as in Holden and Quiggin (2017), is based on the state-contingent production technology (Chambers and Quiggin 2000). The exposition here will focus on the relationship between input demand and technology adoption, considered as forms of adaptation to climate change.

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, or as a change in the set of inputs and state-contingent outputs chosen from a given technology sets.

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

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

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 1991b, 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

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

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

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

with first-order condition

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

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

$$\text{Max}_{\text{iz}}\ E[u(p(\text{z-z}_0) - C(w,z))]$$

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

Using the ‘correspondence condition’ proposed by Quiggin (1991a), 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 probability extreme events (Kahnemann and Tversky 1979; Wu and Gonzales 1999; Gonzales and Wu 1999). Provided probability weighting leads to a greater weight on the less favorable state, an RDU maximizer will use more risk-substituting inputs and less risk-complementary inputs than an EU maximizer with the same utility function.

4. The case of fertilizer use and technological innovation in Malawi

Our context, is that of 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). These farmers must choose whether to adopt new drought tolerant (DT) varieties of maize, as against the alternatives of traditional local maize and other improved maize varieties (OIMP). Conditional on this choice, they must decide on other inputs to production, including the application of fertilizer. In this paper, we are primarily concerned with the fertilizer input choice.

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.

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).

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.

Exposure to shocks may affect risk attitudes. 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 A1 in Appendix 1 shows the distribution of the most severe shocks they perceived they had been affected by in 2011-12.

Risk preferences were measured using a combination of framed and artifactual field experiments. Elicitation procedures are described in Holden and Quiggin (2017). Here we focus on the CRRA parameter and the probability weighting parameter. Loss aversion was also elicited, nesting the RDU model within the CPT model of Kahneman and Tversky, but was not found to be significantly related to fertilizer demand. Hence, it is not reported here.

Summary statistics for the key variables are presented in Table A2 in Appendix 1.

5. Factors affecting input use decisions

Adoption decisions may have to be made before the state of nature is revealed[3]. Choices are therefore subject to technological and market risk. We will consider each of these in turn.

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

5.1. 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[4].

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.

5.2. 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

[4] 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. While one may question whether such drought perception data are endogenous and correlated with household characteristics including preferences, we found no such problem when regressing the lagged drought perception variables and the number of shocks variable on the these household variables (results are available from authors upon request).

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.

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.

5.3. 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 less efficient.

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

H1) Fertilizer use intensity is lower for more risk averse producers.

H2) Fertilizer use intensity is higher for low-risk DT maize than for high risk OIMP and LM maize.

H3) Subjective overweighting of low probability extreme events is associated with less intensive fertilizer use on maize.

H4) Subjective overweighting of low probability extreme events is more strongly associated with less fertilizer use on the more risky OIMP and LM maize than the less risky DT maize.

H5) Access to subsidized inputs enhances 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.

We adopt the classical approach to hypothesis testing, in which each of H1-5 is tested against the null hypothesis H0, which may be stated as "there is no difference in fertilizer use intensity associated with the variable under examination".

6. Data and estimation

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.

Exposure to shocks may affect risk attitudes. 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 A1 in Appendix 1 shows the distribution of the most severe shocks they perceived they had been affected by in 2011-12.

Elicitation procedures are described in Holden and Quiggin (2017). Here we focus on the CRRA parameter and the probability weighting parameter. A single parameter for the probability weighting was calibrated from three multiple price lists following Tanaka et al. (2010). Loss aversion was also elicited, nesting the RDU model within the CPT model of Kahneman and Tversky, but was not found to be significantly related to fertilizer demand. Hence, it is not reported here. A large share of the sample was found to have a probability weighting function with inverted S-shape. This is consistent with most other studies of probability weighting functions (Gonzales and Wu 1999, Wu and Gonzales 1999). We used the following single-parameter weighting function and the multiple price list approach of Tanaka et al. (2010):

$$w(p) = 1/\exp\left(\ln(1/p)\right)^{\alpha}$$

An $\alpha < 1$ implies overweighting of low probabilities and an inverted S-shape. Figure 1 shows the distribution of the α parameter in our sample. We see that the large majority have values below one and therefore overweight small probabilities.

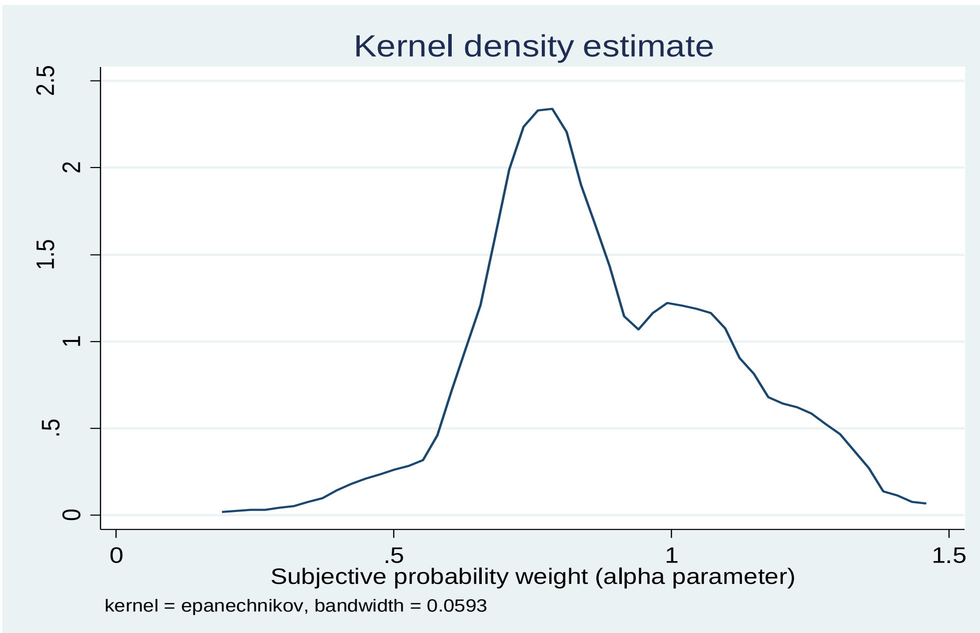

Figure 1. Distribution of the α parameter in the sample.

Summary statistics for the key variables are presented in Table A2 in Appendix 1.

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.

6.1. Estimation strategy

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 fertilizer are therefore captured by the two sets (system) of equations below;

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

where F_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 and S_i^F are dummy variables indicating whether the farmer has access to subsidized seed or fertilizer in the form of a maize seed or fertilizer vouchers, 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, and α_i is the subjective probability weighting parameter. 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.

6.2. 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[5]. 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 jointly and for each maize type as censored tobit models[6].

$$\text{4)}\quad F_i^M = \gamma_0^M + \gamma_1^M crra_i + \gamma_2^M \alpha_i + \gamma_{31}^M D_i^{2012} + \gamma_{32}^M D_i^{2011} + \gamma_{33}^M D_i^{2010} + \gamma_4^M NS_i + \gamma_5^M FG_i + \gamma_6^M R_v + \gamma_7^M EX_i + \left(\gamma_8^M EN_i + \gamma_9^M S_i^S + \gamma_{10}^M S_i^F + \gamma_{11}^M M_i^{\neq M} + \gamma_{12}^M F_i^{\neq M}\right) + \gamma_{13}^M D_v + v_i^{LM}; ipw_i^M$$

The dependent variables are in kg fertilizer and are left censored. 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. Tables 1 and 2 present average marginal effects.

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[5] See Holden and Fisher (2015) for the details on the classification of maize varieties into these three maize types.
[6] Double hurdle models were also tested but failed to converge.

7. Results: Fertilizer use intensity by maize type

7.1. Main model results

Fertilizer use intensity is analyzed using censored tobit models that are pooled (Table 1) or conditional on the type of maize being planted by households (Table 2). 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 quantities were measured as kg fertilizer. Tables 1 and 2 present the results for models both without and with a set of endogenous variables. We also tested double hurdle models but these did not converge[7] and censored tobit models appeared to be most appropriate.

Tables 1 and 2 show 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 one model in Table 2, the first model with OIMP maize without endogenous variables. The subjective probability weight (alpha parameter), however, is positive and highly significant (at 1% or 0.1% levels) in all models in Tables 1 and 2. This indicates that fertilizer use intensity is significantly lower for farmers who overweight low probability extreme events more. Figure 2 illustrates the actual distribution of fertilizer use[8] 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 higher average rainfall and in areas not exposed to droughts two years earlier. It is possible that the one year lag is insignificant because there was no serious drought in 2011. 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 positive and highly significant (at the 0.1% level in the pooled model in Table 1 and at 10% level

[7] The low number of censored observations may explain this.
[8] Untransformed fertilizer use, to get a better idea of the actual amounts used.

for OIMP and local maize and at 1% level for DT maize. Saving for fertilizer purchases is positive and significant at 0.1% level in the pooled model and the DT and local maize models while insignificant in the OIMP model. This result suggests that a liquidity constraint may limit fertilizer use intensity. The dummy for non-agricultural business is significant at the 0.1% level and positive in the OIMP maize model and significant at 0.1% level and negative in the LM model. While the first result is consistent with a liquidity constraint alleviated by access to non-farm income, the latter result is more puzzling.

One of the implications of these findings is that fertilizer subsidies therefore counteract 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.

Table 1. Pooled models for all maize types

	Parsimonious	With Endog. Var.
Relative risk aversion	-25.274	-13.681
	(32.826)	(32.819)
Subj. probability weight	96.137****	97.579****
	(23.753)	(26.340)
Number of shocks last 3 yrs	-3.751	1.983
	(5.137)	(4.267)
Drought 2012, dummy	6.500	-1.074
	(25.015)	(26.956)
Drought 2011, dummy	8.133	8.953
	(19.593)	(16.650)
Drought 2010, dummy	-23.230	-17.946
	(14.561)	(14.301)
Average rainfall	-0.121*	-0.114
	(0.073)	(0.076)
Farm size, GPS meas., ha	15.662****	14.642****
	(2.979)	(3.347)
Sex of respondent, male=1	-9.810	-2.693
	(9.719)	(9.438)
Subsidized fertilizer, dummy		53.447****
		(14.685)
Savings for fertilizer, MK		0.001****
		(0.000)
Non-agric. business, dummy		2.548
		(11.815)
Formal employment, dummy		16.586
		(10.149)
DT maize, dummy	36.498***	26.563**
	(13.583)	(12.539)
Local maize, dummy	-15.783	-19.206
	(13.075)	(11.916)
Village FE	Yes	Yes
Constant	152.559*	71.840
	(82.711)	(91.204)
Sigma constant	75.320****	71.104****
	(7.094)	(6.807)
Log likelihood	-1331.058	-1312.871
Prob > F	0.000	0.000
Number of observations	277	277
Left-censored obs.	53	53

Note: Dependent variable: kg Fertilizer. *, **, ***, *** indicate that coefficients are significant at 10, 5, 1, and 0.1% levels, respectively. Cluster robust standard errors in parentheses, clustering at village level.

Table 2. Censored tobit models for intensity of fertilizer use by maize type without and with endogenous variables (table with selected key variables).

	Parsimonious models			**With endogenous variables**		
	DT	OIMP	LM	DT	OIMP	LM
Relative risk aversion	-48.584	-104.617**	-26.492	-41.447	-19.240	-25.260
	(54.806)	(48.373)	(33.167)	(50.039)	(61.866)	(34.900)
Subj. probability weight	68.834**	178.206****	138.849***	156.619****	186.520***	116.428***
	(29.640)	(49.366)	(47.542)	(41.363)	(64.311)	(44.336)
Number of shocks last 3 yrs	-10.146	6.572	-13.303	9.247	16.392	-7.996
	(7.113)	(23.392)	(9.753)	(6.530)	(19.806)	(8.488)
Drought 2012, dummy	-13.184	-5.338	-59.271	-52.512**	-24.161	-26.762
	(33.282)	(46.203)	(42.548)	(25.053)	(23.837)	(31.672)
Drought 2011, dummy	5.697	5.400	14.326	-6.965	6.834	13.484
	(28.738)	(27.936)	(21.775)	(21.532)	(17.489)	(22.898)
Drought 2010, dummy	-8.758	-55.576**	-83.095****	-19.156	-43.740	-59.586***
	(16.179)	(21.740)	(19.898)	(17.038)	(41.653)	(20.448)
Average rainfall	0.121	0.067	0.315***	-0.017	-0.040	0.132*
	(0.152)	(0.203)	(0.096)	(0.111)	(0.161)	(0.074)
Farm size, GPS meas., ha	51.227****	-29.826****	12.587****	34.802****	-27.509****	12.709****
	(4.036)	(8.280)	(3.162)	(7.051)	(6.747)	(2.498)
Sex of respondent, male=1	-19.578	23.998	-12.071	-0.174	34.536	-12.251
	(25.544)	(21.121)	(15.162)	(24.699)	(25.368)	(16.986)
Subsid. fertilizer, dummy				60.771***	52.207*	33.125*
				(19.402)	(29.591)	(17.575)
Savings for fertilizer, MK				0.002****	0.000	0.001****
				(0.001)	(0.001)	(0.000)
Non-agric. business, dummy				-7.072	66.402****	-58.397****
				(10.806)	(20.495)	(15.367)
Formal employ., dummy				43.964*	-50.197*	-3.766
				(24.557)	(27.349)	(23.797)
Village FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-26.853	11.630	-275.023****	-17.486	-104.097	-129.380**
	(209.756)	(256.922)	(76.426)	(143.060)	(239.725)	(60.247)
Sigma constant	49.096****	77.802****	26.465**	41.811****	65.821****	23.796**
	(13.931)	(8.273)	(11.836)	(10.856)	(9.627)	(10.812)
Log likelihood	-6659.218	-3373.851	-17100.000	-6437.997	-3258.959	-16700.000
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
Number of observations	133	106	138	133	106	138
Left-censored obs.	19	21	30	19	21	30

Note: Dependent variable: kg Fertilizer. *, **, ***, *** 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.

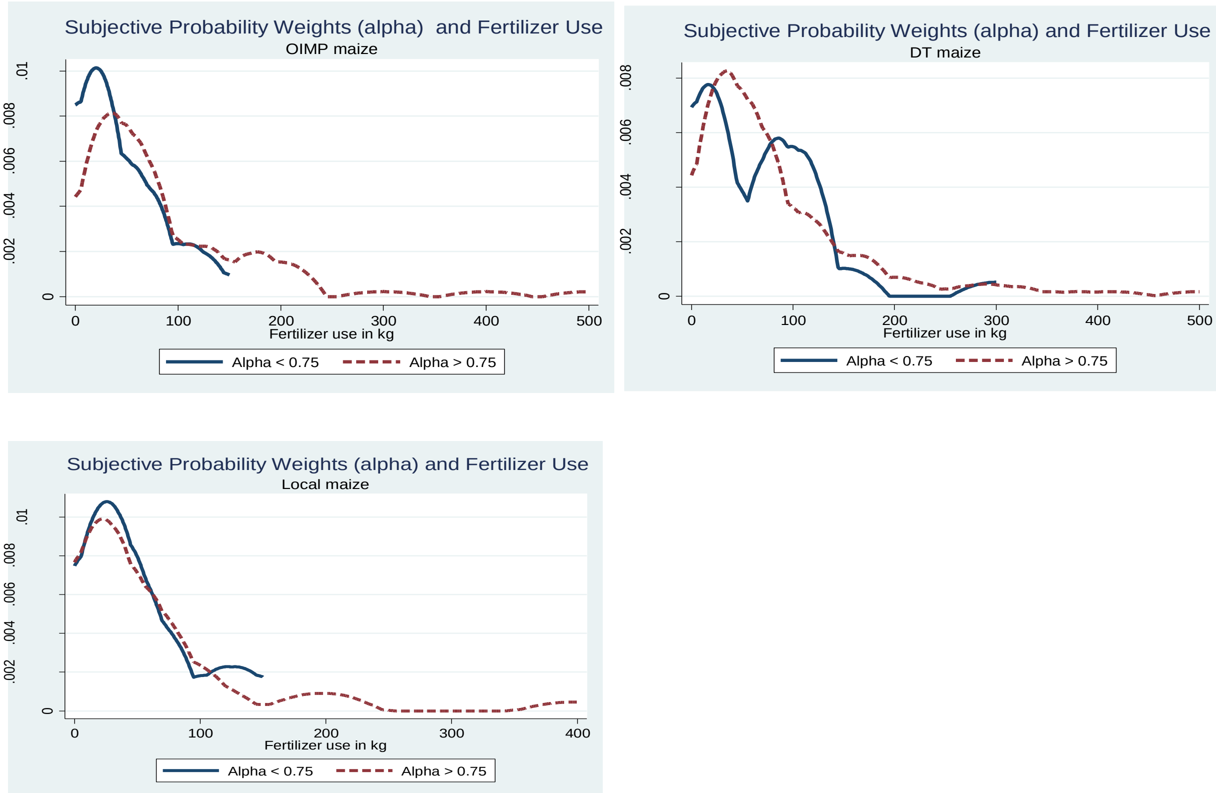

Figure 2. Subjective probability weights and fertilizer use intensity on OIMP, DT and local maize

We can now assess the hypotheses regarding fertilizer use intensity. Hypothesis H1 states that "*Fertilizer use intensity is lower for more risk averse producers*". The coefficients for relative risk aversion were negative in all models but only significant in the model for OIMP maize without endogenous variables. Hypothesis H2 states that "*Fertilizer use intensity is higher for low-risk DT maize than for high risk OIMP and LM maize*". Table 1 shows that fertilizer use on DT maize is significantly (at 1% and 5% levels in models without and with the endogenous variables) larger than on OIMP and LM maize. Hypothesis H2 is therefore supported by the data.

Hypothesis H3 states that *"Subjective overweighting of low probability extreme events is associated with less use of fertilizer*." This hypotheses is strongly supported by our data as the subjective probability weight variable is highly significant and with positive sign in all models. Hypothesis H4 states that "*Subjective overweighting of low probability extreme events is more strongly associated with less fertilizer use on the more risky OIMP and LM maize than the less risky DT maize*". Table 2 shows that the highest coefficients are found for OIMP maize, which may be perceived as the riskiest type of maize to which fertilizer is applied, but it is significantly larger than that of DT maize only in the models without endogenous variables. 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.

7.2. 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.

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 being 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 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 intensity of adoption of fertilizer on 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 probability weighting affect fertilizer use intensity.

Perhaps surprisingly, our study revealed only weak correlations between risk aversion and fertilizer used intensity, with higher risk aversion being associated with lower fertilizer use intensity on the most risky type of improved maize. We found strong and robust positive correlation between over-weighting of low probabilities and lower levels of fertilizer use while intensity of fertilizer use was higher on the new DT type of maize, consistent with our theory. Fertilizer subsidies enhanced fertilizer use intensity on all maize types and this served to compensate for the under-investment in fertilizer use due to the subjective over-weighting of low probability drought-risk in the study areas. Fertilizer subsidies may therefore not only stimulate input use due to a relaxation of liquidity constraints but also due to an adjustment for systematic irrational behavior related to probability judgements.

References

Bontems, P. and Thomas, A. (2000). Information Value and Risk Premium in Agricultural Production: The case of Split Nitrogen Application for Corn. *American Journal of Agricultural Economics* 82: 59-70.

Bontems, P. and Thomas, A. (2006). Regulating nitrogen pollution with risk averse farmers under hidden information and moral hazard. *American Journal of Agricultural Economics* 88(1): 57-72.

Burke, M., & Lobell, D. (2010). Food security and adaptation to climate change: What do we know? In Lobell, D. and Burke, M. (eds.) *Climate Change and Food Security*, http://link.springer.com/book/10.1007%2F978-90-481-2953-9.

Burke, W. J. (2009). Fitting and interpreting Cragg's tobit alternative using Stata. *The Stata Journal* 9(4): 584-592.Chambers, R.G. and Quiggin, J. (2000) *Uncertainty, Production, Choice and Agency: The State-Contingent Approach,* Cambridge University Press, Cambridge.

Chambers, R.G. and Quiggin, J. (2000) *Uncertainty, Production, Choice and Agency: The State-Contingent Approach,* Cambridge University Press, Cambridge.

Chateauneuf, A., Cohen, M. and Meilijson, I. (2004). Four notions of mean-preserving increase in risk, risk attitudes and applications to the rank-dependent expected utility model. *Journal of Mathematical Economics* 40(5): 547-71.

CIMMYT (2013). The Drought Tolerant Maize for Africa project. DTMA Brief, September. International Maize and Wheat Improvement Center. http://dtma.cimmyt.org/index.php/about/background.

Dorward, A., & Chirwa, E. (2011). The Malawi agricultural input subsidy programme: 2005/06 to 2008/09. *International Journal of Agricultural Sustainability*, 9(1): 232-247.

Gonzalez, R., & Wu, G. (1999). On the shape of the probability weighting function. *Cognitive Psychology* 38(1): 129-166.

Holden, S. T. (2014). Risky Choices of Poor People: Comparing Risk Preference Elicitation Approaches in Field Experiments. CLTS Working Paper No. 10/2014. Centre for Land Tenure Studies, Norwegian University of Life Sciences, Aas, Norway.

Holden, S. T. and Fischer, M. (2015). Can Adoption of Improved Maize Varieties Help Smallholder Farmers Adapt to Drought? Evidence from Malawi. CLTS Working Paper No. 1/2015. Centre for Land Tenure Studies, Norwegian University of Life Sciences, Aas, Norway.

Holden, S. T. and Lunduka, R. (2013). Who benefit from Malawi's farm input subsidy program? *Forum for Development Studies* 40: 1-25.

Holden, S. T. and Lunduka, R. (2014). Input Subsidies, Cash Constraints and Timing of Input Supply. *American Journal of Agricultural Economics* 96(1): 290–307.

Holden, S. T. and O'Donnell, C. J. (2015). Maize Productivity and Input Subsidies in Malawi: A State-Contingent Stochastic Production Frontier Approach. School of Economics and Business Working Paper No. 2/2015. Norwegian University of Life Sciences, Aas, Norway.

Holden, S. T. and Quiggin, J. (2017). Climate risk and state-contingent technology adoption: shocks, drought tolerance and preferences. *European Review of Agricultural Economics*, doi: 10.1093/erae/jbw016

Horowitz, J.K. and Lichtenberg, E. (1993). Insurance, moral hazard, and chemical use in agriculture. *American Journal of Agricultural Economics* 75(4):926-935.

Intergovernmental Panel on Climate Change (IPCC) (2014). Climate Change 2014: Impacts, adaptation, and vulnerability. Part B: Regional Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Barros, V.R., Field, C.B., Dokken, D.J., Mastrandrea, M.D., Mach, K.J., Bilir, T.E., Chatterjee, M., Ebi, K.L., Estrada, Y.O., Genova, R.C., Girma, B., Kissel, E.S., Levy, A.N., MacCracken, S., Mastrandrea, P.R., & White L.L., (eds.)]. Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

Kahnemann, D. and Tverrsky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica* 47: 263-291.

Leathers, H.D. and Quiggin, J.C. (1991). Interactions between agricultural and resource policy: the importance of attitudes toward risk. *Am. J. Agric. Econ.* 73 (3): 757–764.

Liu, E. M. and Huang, J. (2013). Risk Preferences and Pesticide Use by Cotton Farmers in China. *Journal of Development Economics* 103: 202-215.

Magorokosho, C., Vivek, B., MacRobert, J., & Tarekegne, A. (2010). Characterization of maize germplasm grown in eastern and southern Africa: Results of the 2009 regional trials coordinated by CIMMYT. Harare, Zimbabwe: CIMMYT.

Monjardino, M., McBeath, T.M., Brennan, L. and Llewellyn, R.S.(2013). Are farmers in low-rainfall cropping regions under-fertilising with nitrogen? A risk analysis. *Agricultural Systems* 116: 37-51.

Monjardino, M., McBeath, T., Ouzman, J., Llewellyn, R. and Jones, B.(2015). Farmer risk-aversion limits closure of yield and profit gaps: A study of nitrogen management in the southern Australian wheatbelt. *Agricultural Systems* 137: 108-118.

Quiggin, J. (1991a). Comparative statics for Rank-Dependent Expected Utility theory. *Journal of Risk and Uncertainty* 4(4): 339-50.

Quiggin, J. (1991b). Increasing risk: another definition. In *Progress in Decision, Utility and Risk Theory*, (Ed, Chikan, A.) Kluwer, Amsterdam.

Quiggin, J. (1982). A theory of anticipated utility. *Journal of Economic Behavior and Organization*, 3(4), 323-43.

Quiggin, J. and Horowitz, J. (2003). Costs of adjustment to climate change. *Australian Journal of Agricultural and Resource Economics* 47: 429-446.

Ricker-Gilbert, J., Jayne, T. S. and Chirwa, E. W. (2011). Subsidies and Crowding out: A Double-Hurdle Model of Fertilizer Demand in Malawi, *American Journal of Agricultural Economics* 93: 26-42.

Rothschild, M. and Stiglitz, J. (1970), Increasing risk: I. A definition, *Journal of Economic Theory* 2(4): 225-43.

Sandmo, A. (1971). On the theory of the competitive firm under price uncertainty. *The American Economic Review* 61 (1): 65-73.

Savage, L. J. (1954). *The foundations of statistics*. Wiley, New York.

Tanaka, T., Camerer, C. F. and Nguyen, Q. (2010). Risk and Time Preferences: Linking Experimental and Household Survey Data from Vietnam. *American Economic Review* 100(1): 557-571.

Wu, G., & Gonzalez, R. (1999). Nonlinear decision weights in choice under uncertainty. Management Science 45(1), 74-85.

Yesuf, M. and Bluffstone, R.A. (2009). Poverty, risk aversion, and path dependence in low-income countries: Experimental evidence from Ethiopia. *American Journal of Agricultural Economics* 91(4): 1022-1037.

Appendix 1. Descriptive statistics

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 A1. 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.

Table A2. 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

Additional included variables

The next variables are the shock variables (drought shock dummies, 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[9] 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[10]. The key findings we present were very robust to alternative model specifications[11], 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[12] 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). ipw_i is the inverse probability weight, included to control for attrition in the sample[13]. Village fixed effects were also used to control for cross

[9] Exogenous in the sense that they cannot easily be changed in the short run.
[10] 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).
[11] 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.
[12] By *ex ante* labor allocation, we mean labor allocated before the state of nature (in the form of drought in this case) is revealed.
[13] 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.

village differences in market access, prices and the distribution of improved maize seeds through and outside the subsidy program.

Appendix 2. Detailed results

Table A4. Censored tobit models for intensity of fertilizer use by maize type without and with endogenous variables (complete models).

	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 probability 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.

Appendix 3. 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	Expected yield	Choice	Probability of bad outcome, %	Bad	Good	Expected yield	Choice
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:_________________________