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Modeling Preference and Willingness to Pay for Drought Tolerance (DT) in Maize in Rural Zimbabwe

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Summary. — Maize plays a leading role in the food security of millions in southern Africa, yet it is highly vulnerable to the moisture stress brought about by the erratic rainfall patterns that characterize weather systems in the area. Developing and making drought-tolerant maize varieties available to farmers in the region has thus long been a key goal on the regional development agenda. Farm-level adoption of these varieties, however, depends on local perceptions of the value they add, along with willingness to pay (WTP) for it. Focusing on Zimbabwe, this research aimed at estimating the implicit prices farmers are willing to pay for drought tolerance in maize compared to other preferred traits. Using a choice experiment framework, we generated 12,600 observations from a random sample of 1,400 households in communal areas within 14 districts of Zimbabwe. Taste parameters and heterogeneities were estimated using the generalized multinomial logit model (G-MNL). The results reveal drought tolerance, grain yield, covered cob tip, cob size, and semi-flint texture to be the most preferred traits by farm households in Zimbabwe. The WTP estimates show that farmers are willing to pay a premium for drought tolerance equal to 2.56, 7, 3.2, and 5 times higher than for an additional ton of yield per acre, bigger cob size, larger grain size, and covered cob tip, respectively. We suggest designing and implementing innovative ways of promoting DT maize along with awareness-raising activities to enhance contextual understandings of drought and drought risk to speed adoption of new DT maize varieties by risk-prone farming communities. Given the high level of rural literacy and the high rate of adoption of improved maize, trait-based promotion and marketing of varieties constitutes the right strategy.
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Key words — drought-tolerant maize, choice experiment, scale and taste heterogeneity, generalized multinomial logit, Zimbabwe

1. INTRODUCTION

Maize plays a crucial role in the livelihoods of people in Sub-Saharan Africa (SSA). It is the staple food crop for the majority of the population in the continent and reliance on maize is nearly universal for those in southern Africa, where it provides on average 40–50% of the calories consumed by the poor (Smale, Byerlee, & Jayne, 2011). Being a strategic crop in the region, maize has been a subject of political and academic interest for more than half a century, during which time there have been tremendous achievements in maize research in terms of the development of new and better adapted varieties (Byerlee & Eicher, 1997; Smale, 1995; Smale & Jayne, 2003). Despite the success stories around maize, poverty and food insecurity in the maize-based livelihood systems of southern Africa remain deep-rooted. High rates of population growth mean that since 1970 per capita grain production in SSA has declined by more than 10% (Minot, 2008). The key challenges that constrain agricultural productivity in southern Africa are drought, pests and diseases, soil degradation, unaffordability of farm inputs, lack of financial resources, erratic rainfall, and flooding (Kassie, Erenstein, Mwangi, LaRovere, Setimela, & Langyintuo, 2012).

Drought is a widespread phenomenon across large swathes of SSA with an estimated 22% of mid-altitude/subtropical and 25% of lowland/tropical maize growing in regions affected annually by seasonal water shortages (Chambers, 1989). Climate change is likely to increase average temperatures by of 2.1 °C in SSA, which will lead to even greater water scarcity, particularly in Southern Africa, in the coming decades (Hendrix & Glaser, 2007; Lobell, Burke, Tebaldi, Mastrandrea, Falcon, & Naylor, 2008). Studies have indicated that an increase in temperature of 2 °C would result in a

greater reduction in maize yields within SSA than a decrease in precipitation by 20% (Lobell & Burke, 2010).

Yield losses tend to be high in tropical countries that rely on a relatively unpredictable rainy season for crop growth. Past experience has demonstrated that the use of new varieties alongside improved management options can offset yield losses by up to 40% (Hendrix & Glaser, 2007). Specifically, drought and heat-tolerant crops will play an increasingly important part in adapting to this variation and to the long-term underlying trend toward a hotter and probably drier production environment. Hence the argument that, given the scarcity of water and its cardinal role in crop production, tolerance to drought and efficient water usage should be assigned the highest priority in developing future crops. Drought tolerance in maize is of enormous global importance, and is a trait which no farmer under rainfed conditions can afford to forgo (Greg O Edmeades, 2008; Lybbert & Bell, 2010). Using water at current rates when the world will have to support nine billion people or more in 2050 is simply not sustainable (Lobell et al., 2008).

There are a number of global efforts aimed at developing maize germplasm with embedded drought tolerance (Lybbert & Bell, 2010). In SSA, the main initiative in this regard is the drought-tolerant maize for Africa (DTMA) project being implemented since 2006 by the International Maize and Wheat Improvement Center (CIMMYT), International Institute for Tropical Agriculture (IITA) and National Research/Extension Institutions of 13 countries in eastern, southern and western Africa.

While the development of these new varieties and related technologies is laudable, their impact depends very much on the extent to which they are adopted by farmers. Farmers' adoption decisions for improved maize varieties are governed by their willingness to pay for the different traits. While many stakeholders, including seed companies, play an important role in the dissemination of improved varieties, varieties must comprise the traits desired by farmers. The best way to assess demand for desired traits is to quantify their implicit prices. Hence, this study was designed to understand famers' preferences for the different traits of DT maize and to estimate the implicit prices of preferred traits with a deliberate focus on drought tolerance in the drought prone communal farming areas of Zimbabwe.

Several studies have examined trait preference and associated willingness to pay in a range of crops over the last 10 years (Carlsson, Frykblom, & Lagerkvist, 2007; Poudel & Johnsen, 2009; Smith & Fennessy, 2011; Wale & Yalew, 2007; Ward, Ortega, Spielman, & Singh, 2013). However, very few have employed theoretically and behaviorally plausible methods of choice experiment to do so (Asrat, Yesuf, Carlsson, & Wale, 2010; Blazy, Carpentier, & Thomas, 2011; Ward et al., 2013). Most studies have used mixed logit or random parameter logit to account for preference heterogeneity. Fiebig, Keane, Louviere, and Wasi (2010) pointed out that the mixed logit model is likely to be a poor approximation of the data-generating process if scale heterogeneity is important. Some authors have therefore investigated the behavioral implications of accounting for scale heterogeneity in contrast to a term in the utility function (Fiebig et al., 2010; Flynn, Louviere, Peters, & Coast, 2010; Louviere, Street, Burgess, Wasi, Islam, & Marley, 2008). In fact, there is a strong argument that the various model specifications investigated by researchers can simply be seen as different parameterizations, and that any gains in fit obtained in random scale models are the result of using more flexible distributions, rather than an ability to capture scale heterogeneity (Hess & Rose, 2012).

This study uses these recent models more for their ability to embed flexible distributions (Hess & Rose, 2012) than their arguable capability to disentangle scale heterogeneity. Given the number of traits, trait levels, choice sets and alternatives, our choice experiment on maize traits can hardly be considered as a difficult choice situation for farmers in rural Zimbabwe and scale heterogeneity is therefore less important in such familiar choice contexts (Fiebig et al., 2010).

In this study, we employ the generalized multinomial logit model (G-MNL) developed by (Fiebig et al., 2010) and the generalized mixed logit model proposed by (Greene & Hensher, 2010) to examine farmers' preferences for, and willingness to pay for, maize varieties in Zimbabwe. Specifically, we employ the models to estimate the taste parameters and preference heterogeneities, as well as the implicit prices of preferred maize traits in the WTP space framework. To the extent that the study is the first empirical estimation of WTP for drought tolerance in maize, the results have far-reaching policy implications for maize breeding programs, particularly in southern Africa, where it is the most important trait in selecting maize varieties for production (Chikobvu, Chiputwa, Langyintuo, La Rovere, & Mwangi, 2010; Kassie et al., 2012). The study utilizes data from a choice experiment undertaken by 1,400 households from 56 villages in rural Zimbabwe.

The rest of the paper is structured as follows. The next section discusses maize production in Zimbabwe. Section three describes the survey design and the data used in the analysis. This is followed by a specification of the model. The fourth section presents the empirical results. Conclusions are presented in the final section.

2. MAIZE IN ZIMBABWE

Zimbabwe's economy is agriculture-based and hence its performance is mainly dependent on agricultural production rates. In 2011, agriculture contributed 20.4% to the Gross Domestic Product (GDP) (Anseeuw, Kapuya, & Saruchera, 2012). When agriculture performs badly, overall economic growth is compromised as was the case in 2012 when GDP growth was downsized from forecasts of 9.4–5.6%, because of an estimated 13.2% decline in agricultural production (Biti, 2012). Agriculture employs over 30% of the total formal workforce (Kapuya et al., 2009). It is the main source of livelihood for over 70% of Zimbabwe's population, either directly through production or indirectly through value addition (Anseeuw et al., 2012).

Maize is the primary staple food crop for close to 98% of the 12.7 million people in the country (CIA, 2012). In surplus years, maize is a source of income for 60% of the rural population (Rukuni, Tawonezvi, Eicher, Munyuki-Hungwe, & Matondi, 2006). It is because of the importance of maize in the diet of many Zimbabweans that the crop is considered to be of national strategic importance in terms of nutrition and food security. Over a third of the Ministry of Agriculture's inputs budget is spent on procuring seed maize for distribution to poor and vulnerable households annually. The remaining sum goes toward fertilizers for maize production. In 2010, direct support through maize and fertilizer inputs from government was worth US$32 million. The figure increased to US$45 million in 2011–12 although it dropped in 2012–13 to US$22 million as the result of a national economic shortfall (Jongwe, 2013).

Smallholder farmers in post-independence Zimbabwe started to face serious challenges after the World Bank and IMF-driven economic structural adjustment programs

[ESAPs] forced the country to cut consumer subsidies, severe cutbacks in government spending (including the social sectors), extensive liberalization of price and import controls, and promotion of exports, particularly the expansion of non-traditional exports, that is, manufactured goods (Kanji, 1995; Saunders, 1996). The ESAP experiences in Africa have generally been reported to be unfavorable at macro level with some mixed results at micro level (Christiaensen, Demery, & Paternostro, 2002; Heidhues & Obare, 2011). These authors argued that to the extent that SAPs failed to promote growth, no improvement in poverty can be expected from growth effects. The winners have been net surplus producers of agricultural products among rural households, particularly those with export crops, while the losers have been net consuming poor households and the urban poor (Christiaensen et al., 2002; Heidhues & Obare, 2011).

The inconvenient truth continued for farmers in the communal areas of Zimbabwe after the fast track land reform which started in late 1990s and was legalized in 2000. The intention of the 2000 FTLRP was to reallocate Zimbabwe's land more equitably (FINMARK, 2016). Smallholder landholdings increased from 50% of the total land area to 66%, while land for large-scale farming was reduced from 34% to 20.6% (MAMID, 2010). With reductions in the commercial farms, a new breed of small-scale farmers emerged to alter the composition of the agricultural sector. From approximately 4,000 commercial farmers, Zimbabwe's agricultural sector currently comprises approximately 460,000 A1 smallholder and communal farmers (ACB, 2016; FINMARK, 2016).

Subsequently, the land area planted to maize (a key smallholder crop) increased in line with the increase in smallholder farming unit areas (Rukuni et al., 2006). After the FTLR program, over 50% of the country's 3,220,000 ha of arable land has been cropped with maize. Maize occupies over 75% of the land dedicated to cereal production (Anseeuw et al., 2012). During 2001–05, there was a 16% increase in the area under maize (from 1.2 million ha to 1.7 million ha). This was a period of massive land redistribution under the FTLR program, when at least three million hectares of land were redistributed to over 80,000 farming households (Moyo, 2011). The volatility in land area dedicated to maize production evident from 2006 to 2009 (while remaining above 1.5 million ha each year), is most likely a response to (among other factors) maize prices, access to and availability of agricultural inputs.

In the 2010–11 season, land dedicated to maize production increased by 20% to a record 2 million ha. This increase could also be explained by another wave of land redistribution. In this season, about 750,000 hectares of land which had not been previously distributed during 2001–05 were redistributed to mostly A1 and A2 farmers (Moyo, 2011). The area under maize retreated to 1.69 million ha in the 2011–12 season. This decline in land allocated to maize could be partly attributed to a shift in crop enterprise choice toward cash crops such as tobacco, with the substitution being mostly linked to low maize prices (below production costs thus rendering commercial activity unviable); dilapidation of infrastructure; instructional problems as well as untargeted and untimely policy decisions that affected the growth of the maize subsector (Anseeuw et al., 2012; Kapuya, Meyer, & Kirsten, 2013; Zikhali, 2008).

While the land allocated to maize has been increasing, national yield per unit area has been declining. Average maize yield declined from a record high of 1700 kg/ha in 1996 to 1,230 kg/ha in 2001. From 2001 to date, Zimbabwe has struggled to produce one ton of maize per ha, producing on average, only 0.8 ton/ha for the last 10 years. Explanations for this include mid-season dry spells or droughts, inputs shortages, the unstable socio-political environment, and a lack of production skills (AfDB/OECD, 2003; FAO/WFP, 2010). Communal areas are characterized by low rainfall ranging from less than 450–750 mm per annum (ILCA, 1993). These areas also experience mid-season dry-spells and fluctuating rainfall patterns, leading, in most cases to poor harvests. Therefore, eliciting the preferences of the most important crop for smallholder farmers and estimating the relative implicit prices farmers are willing to pay for the key traits would certainly be an important input to the research and development initiatives that aim at improving livelihoods in these demanding socio-economic and bio-physical circumstances.

3. METHODOLOGY

(a) Sampling and choice experiment

About 80% of the 1.7 million farm households of Zimbabwe live in communal areas. Communal areas are lands held under customary tenure, much of it in arid areas with poor soil, established as reserves for black Zimbabweans following the requirements of the Southern Rhodesia Order-in-Council in 1898 (Dore, 2009). These areas are characterized by chronic food insecurity and extreme poverty. Livelihoods in communal areas are based on rainfed maize production systems with low external inputs usage and low productivity. About 60% of the national land allocation to maize is in communal areas, but these areas only account for 28% of national maize production (Dore, 2009; Stanning, 1989).

Identification of rural households for sampling began with the identification of natural regions where maize is widely grown and plays an important role for food security. Zimbabwe is divided into five natural agro-ecological regions (Figure 1).

Maize is the single most important crop in regions II, III, and IV. Its importance is growing in region V as well at the expense of small cereals such as sorghum and finger millet. Fourteen districts were purposively and proportionately selected from these four regions. District selection was guided by levels of maize production and potential population exposure to drought-tolerant maize varieties. The proportion implies the relative importance (in terms of acreage and production) of maize in the natural regions. Table 1 shows the estimated natural region coverage of sample districts.

Accordingly, we identified eleven districts that fall within natural regions II and III; two districts within natural regions III and IV, and one district within regions IV and V. Then, four villages were randomly selected from each district, providing a total of 56 villages. In each case the sampling frame was the list of all farming households in the village. Twenty-five households were randomly selected from each village household list for a total sample of 1,400 households.

In identifying traits for the choice experiment (other than seed price) a pair-wise comparison was used to identify ten maize traits with smallholder farmers. Then the list was shortened to six traits with maize breeders at CIMMYT and Zimbabwe's Department of Research and Specialist Services (DR&SS). The final set of traits included grain yield measured in tons/acre, maize cob size, grain (kernel) size, drought tolerance, grain (kernel) texture, cob tip (husk) cover and seed price. These traits were once again discussed with farmers and researchers to ensure common understandings of traits descriptions and identification features were established. Then,
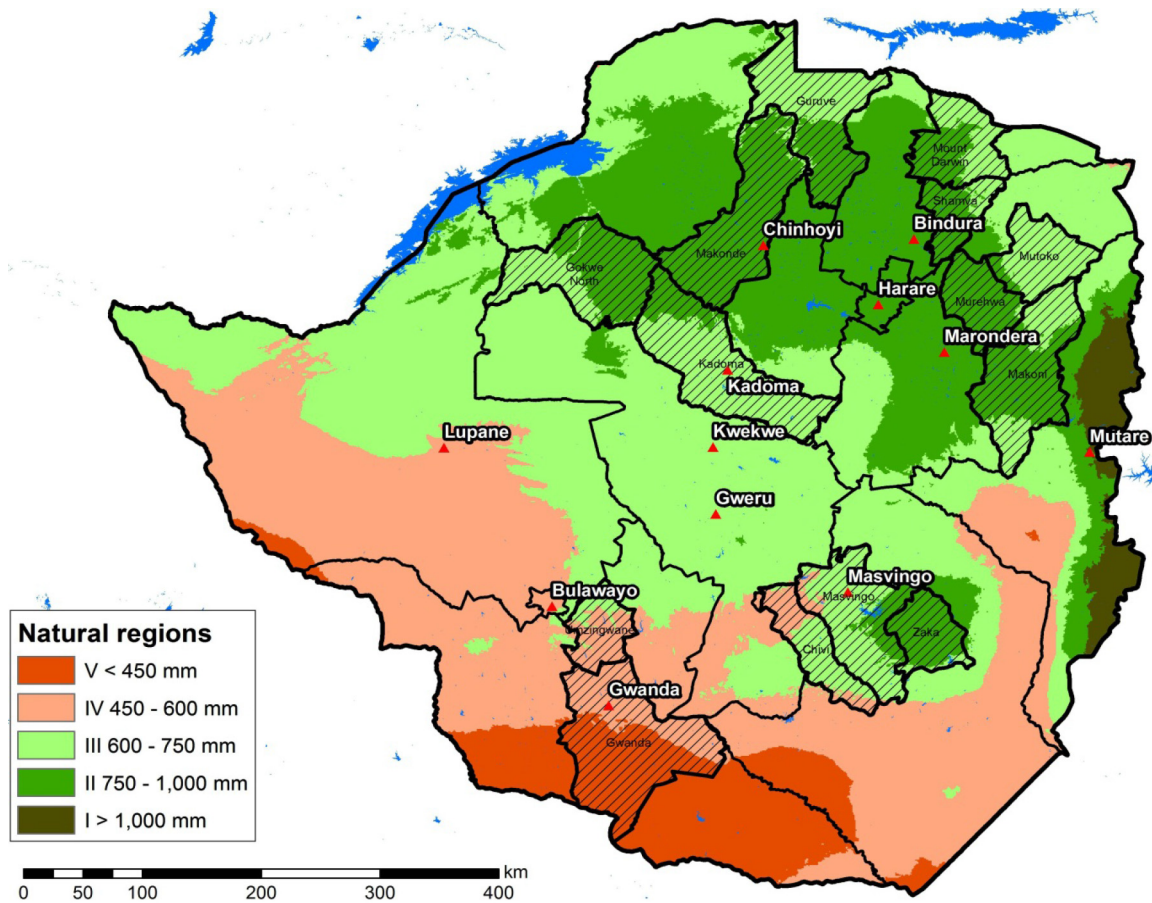
Figure 1. *Natural regions of Zimbabwe and study districts (districts marked in patterns)*

Table 1. *Estimated natural region coverage of sample districts*

District	% NR I	% NR II	% NR III	% NR IV	% NR V
Chivi	–	–	60	40	–
Masvingo	–	20	75	5	–
Zaka	–	90	10	–	–
Makoni	–	60	40	–	–
Mount Darwin	–	50	50	–	–
Guruve	–	50	50	–	–
Gokwe North	–	60	40	–	–
Kadoma	–	30	70	–	–
Mutoko	–	5	95	–	–
Murehwa	–	95	5	–	–
Makonde	–	90	10	–	–
Shamva	–	70	30	–	–
Gwanda	–	–	–	40	60
Umzingwane	–	–	30	70	–

an efficient design was developed using SAS software by employing the macros developed by Kuhfeld (2010). The design generated 36 profiles of maize grouped in two's resulting in 18 choice sets. We included opt out option in each of the choice sets and blocked the choice sets into two so that each respondent would be presented with nine choice sets of three alternatives. The traits and trait levels used in the choice experiment are indicated in Table 2 below.

Drought tolerance in maize is a complex and composite trait manifested in different ways at different growth stages of the plant. At the early stage seedling vigor and leaf rolling are important features, where varieties which take longer to roll leaves under early season drought stress are considered drought tolerant. At flowering, anthesis-silking interval (ASI) is the characteristic of concern. Shorter or narrower ASI equates to drought tolerance because it increases the probability of fertilization. After flowering, a slower rate of leaf senescence or stay-green capacity under moisture stress indicates drought tolerance. At harvesting, ears per plant, number of kernels per ear and grain yield are the key criteria. Higher values of these traits indicate drought tolerance (Cairns *et al.*, 2013; Edmeades, 2013).

Table 2. *Maize traits and trait levels used in the choice experiment*

Variable	Description	Levels	Reference level
Yield	Grain yield measured in ton/acre, ranging from 0.5 to 3.5 ton/acre in communal areas.	0.5, 1.5, 2.5, 3.5	
Cob size	Observation based on the relative maize cob size (based on length and diameter).	Small, Medium, Big	Small
Grain size	Observation based on the relative kernel size.	Small, Large	Small
Drought tolerance	The ability of a maize variety to have high seedling vigor and leaf senescence with leaves not rolling or rolling less under moisture stress	Not tolerant, tolerant	Not tolerant
Grain texture	Hard, semi-hard, or soft seed coat.	Dent, semi-flint, flint	Dent
Tip (husk) cover	Describes the extent to which the end of the maize cob is covered with sheath leaves.	Not covered, covered	Not covered
Seed price	Maize seed price in USD/kg. Seed price ranges from 1.5 to 3.5 USD/kg—including both open pollinated and hybrid maize.	1.5, 2.5, 3.0, 3.5	

After harvesting: the standard yield loss level expected under "representative drought conditions" is 25–30% on average (La Rovere et al., 2010). A variety that shows much lower yield loss under the same drought condition as others is considered drought tolerant. The other way of identifying drought-tolerant varieties is by using a molecular marker, thus confirming the presence of a gene or allele responsible for drought tolerance. This approach has been of little help so far because gene presence does not necessarily guarantee trait expression (Cairns et al., 2013; Edmeades, 2013). Definitions of drought tolerance and tolerance levels used with farmers focused on the pre-harvest manifestations of the trait.

The survey was undertaken in all 14 sample districts by five enumerators and one national coordinator. Each respondent was asked to choose his/her preferred alternative maize profile in nine choice situations. This makes the total number of completed choice situations 12,600 (i.e., 1,400 * 9). In only 39 (0.3%) of the choice situations respondents preferred to opt out to other alternatives. This low level of opting out could imply that either the choice sets had plausible options that were appealing enough or the maize varieties currently under production are not drought tolerant such that farmers wanted to have one of the two varieties.

Most (77.4%) of the sample households were male headed and the average age household head being 38 years (with a range of 12–94 years). Years of schooling of the household head was on average about 9 years (with a range of 0–18 years). The average household size was about six persons with the number of female members slightly higher than that of male members. The livelihood mainstay for sample households was crop and livestock farming. Three out of four respondents depended on farming whereas about 12% indicated petty trading or other own business to be their mainstay. Temporary and permanent employment was also reported by 10.7% of the respondents as their primary source of livelihood. The average farmland holding was found to be about seven acres; i.e., 2.83 ha. On average, the sample households allocated 60% of their land to maize highlighting the importance of maize in their livelihoods (Table 3).

Respondents were asked to identify the maize varieties they grew in the previous season (2012–13) and what they were growing in the current season (2013–14). We present the 10 most common varieties that account for about 88% of the maize cultivars accessed by households across both seasons. Varieties from Seed Co, one of the oldest seed companies in Zimbabwe and in fact in southern Africa, were found to dominate. The Seed Co varieties were grown by close to 60% of the sample households. SC513 was the most commonly (34.1% in 2012–13 season and 31% in 2012–13 season) grown variety in both seasons and the most preferred maize variety in Zimbabwe (Chikobvu et al., 2010). Seed Co varieties of 500 series, 400 series, SC03, and SC401 were also found to be quite common in both seasons. PANNAR varieties PAN413 and PAN53 were also among the top ten varieties cultivated in both seasons (Table 4).

Table 3. *Major characteristics of the sample households*

	Mean/Freq (%)	Min.	Max	St.dev.
Gender of HH head				
Female	22.6			
Male	77.4			
Age of household head (in years)	37.95	12.00	94.00	15.81
Literacy of household head (in years)	8.83	.00	18.00	3.29
Total household size	5.72	1	36	2.72
Total number of females in the household	2.92	0	21	1.72
Total number of males in the household	2.80	0	18	1.67
Mainstay of HH livelihood				
Farming	75.7			
Petty trading or other own business	12.4			
Temporary or permanent employment	10.7			
Other sources of income	1.1			
Total farm land owned (acre)	6.97	.50	185.00	8.53
Land allocated to maize (% total land owned)	59.98	2.00	100.00	22.77

Table 4. *The ten most frequently grown maize varieties*

Rank	2012–13 season		2013–14 season	
	Variety	Growing HHs (%)	Variety	Growing HHs (%)
1	SC513	34.1	SC513	30.9
2	PANNAR	16.2	PANNAR	16.1
3	SC500 series	14.4	SC500 series	12.9
4	SC400 series	6.9	SC400 series	8.1
5	PIONEER	5.9	PIONEER	7.3
6	PAN413	4.1	PAN413	4.3
7	SC403	1.7	SC6 series	2.4
8	PAN53	1.6	SC403	2.1
9	Retained	1.5	PAN53	2.1
10	SC401	1.4	SC401	1.8
Total		87.8		88

(b) *Econometric framework*

Discrete choice models such as conditional logit and random parameters logit are commonly used to analyze consumer choice behavior based on the random utility theory (RUT (McFadden, 1974). In this theory, utility U is assumed to be latent, with only the choice Y of alternative j ($j = 0, 1, 2$) by individual i ($i = 1, \ldots, 1,400$) in choice situation t ($t = 1, 2, \ldots, 9$) observed. Given a choice set t with J alternatives, the utility function can generally be written as

$$U_{ijt} = \beta_i' x_{ijt} + \varepsilon_{ijt} \qquad (1)$$

where x_{ijt} is a vector of explanatory variables including traits of the maize variety profiles and interactions of traits and socioeconomic characteristics, and ε_{ijt} is unexplained utility assumed to be independently and identically distributed (iid) across individuals, alternatives and choice sets with extreme value type I distribution. β_i is a conformable vector of the unknown utility weights the respondent assigns to the explanatory variables.

Conditional logit (McFadden, 1974) and mixed (random parameters) logit (Hensher & Greene, 2003; McFadden & Train, 2000) models are employed to estimate the utility weights attached to the different traits. Conditional logit assumes that the idiosyncratic errors are iid extreme values and the tastes for observed attributes are homogeneous. The assumption about the errors gives rise to the more stringent independence of irrelevant alternatives (IIA) assumption.

The mixed logit model relaxes the IIA assumption by allowing heterogeneity of preferences for observed attributes. Hence, the utility weight (β_i) for a given attribute will be given as

$$\beta_i = \beta + \Gamma v_i \qquad (2)$$

where β is the vector of mean attribute utility weights in the population, Γ is a diagonal matrix which contains σ (the standard deviation of the distribution of the individual taste parameters (β_i) around the population mean taste parameter (β)) on its diagonal, and v is the individual and choice-specific unobserved random disturbances with mean 0 and standard deviation 1.

Another improvement over the conditional logit model is the scaled multinomial logit (S-MNL) model. The S-MNL formulation allows the model to accommodate scale heterogeneity; i.e., variance in utility across individuals. The added advantage of S-MNL can easily be seen for the fact that in the simple multinomial (MNL) and mixed or random parameters (MIXL) logit specifications, there is a scale or variance

that has been implicitly normalized (to that of the standard extreme value distribution) to achieve identification (Fiebig et al., 2010). In S-MNL, the utility weights are given as

$$\beta_i = \beta \sigma_i \qquad (3)$$

The scaling factor, σ_i differs across individuals, but not across choices. This also implies that the vector of utility weights β is scaled up or down proportionately across consumers by the scaling factor σ_i.

Recent developments have shown that MIXL and S-MNL can be nested to avoid the limitations observed on MIXL in particular (Louviere et al., 2008). Fiebig et al. (2010) and Greene (2012) have developed a generalized multinomial logit model (G-MNL) that nests MIXL and S-MNL. In G-MNL, the utility weights are estimated as

$$\beta_i = \beta \sigma_i + \gamma \Gamma v_i + (1 - \gamma) \sigma_i \Gamma v_i \qquad (4)$$

The generalized mixed logit model embodies several forms of heterogeneity in the random parameters and random scaling, as well as the distribution parameter (γ), which ranges between 0 and 1. The effect of scale on the individual idiosyncratic component of taste can be separated in two parts—unscaled idiosyncratic effect ($\gamma \Gamma v_i$) and scaled by $(1 - \gamma) \sigma_i \Gamma v_i$ where γ allocates the influence of the parameter heterogeneity and the scaling heterogeneity. The parameter γ also determines how the variance of residual taste heterogeneity varies with scale in a model that includes both (Fiebig et al., 2010).

Several interesting model forms are produced by different restrictions on the parameters. For example, if we set the scale parameter $\sigma_i = \sigma = 1$, the model becomes ordinary MIXL. If $\gamma = 0$ and $\Gamma = 0$, we obtain the scaled MNL model. Two unique forms of G-MNL are also presented by Fiebig et al. (2010). By simply combining 2 (MIXL) and 3 (S-MNL), G-MNL-I is formed whereby the utility weight is given as:

$$\beta_i = \beta \sigma_i + \Gamma v_i \qquad (5)$$

The other form is called G-MNL-II developed based on MIXL and explicit specification of the scale parameter to yield

$$\beta_i = \sigma_i(\beta + \Gamma v_i) \qquad (6)$$

where σ_i captures the scale heterogeneity and $\sigma_i \Gamma v_i$ captures residual taste heterogeneity. The difference between G-MNL-I and G-MNL-II is that in G-MNL-I, the standard deviation of Γv_i is independent of the scaling of β, whereas in G-MNL-II, it is proportional to the scale heterogeneity (σ_i). G-MNL approaches G-MNL-I as γ approaches 1, and it approaches G-MNL-II as γ approaches 0. In the full G-MNL model, $\gamma \in [0,1]$ (Fiebig et al., 2010).

In this study, the general estimation framework developed by Train (2003), Hensher and Greene (2003), Greene and Hensher (2010) and Fiebig *et al.* (2010) is employed. We have, however, taken into consideration some of the appealing modifications and extensions of the framework presented by Greene (2012). Greene's specification of the utility weight explicitly shows how heterogeneities are accommodated:

$$\beta_i = \sigma_i[\beta + \Delta z_i] + [\gamma + \sigma_i(1 - \gamma)]\Gamma v_i \tag{7}$$

Observed heterogeneity (explained by observed sources of variation 'z_i') is reflected in the term Δz_i, while the unobserved heterogeneity is embodied in Γv_i. $\sigma_i = \exp[\bar{\sigma} + \delta\prime h_i + \tau w_i]$ is the individual-specific standard deviation of the idiosyncratic error term, h_i denotes a set of M characteristics of individual i that may overlap with z_i, δ denotes parameters in the observed heterogeneity in the scale term, w_i is the unobserved heterogeneity (standard normally distributed), $\bar{\sigma}$ is a mean parameter in the variance, τ is the coefficient on the unobserved scale heterogeneity.

The full model (with no restriction on γ and τ) is estimated by maximum simulated likelihood (Greene, 2007). In order to impose the limits on γ, γ is re-parameterized in terms of α, where $\gamma = \exp(\alpha)/[1 + \exp(\alpha)]$ and α is unrestricted. Likewise, to ensure $\tau > 0$, the model is fit in terms of λ, where $\tau = \exp(\lambda)$ and λ is unrestricted. Combining all terms, the simulated log likelihood function for the sample of data is specified as:

$$\log L = \sum_{i=1}^{N} \log \left\{ \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_i} \prod_{j=1}^{J_{it}} P(j, X_{it}, \beta_{ir})^{d_{itj}} \right\} \tag{8}$$

where $\beta_{ir} = \sigma_{ir}[\beta + \Delta z_i] + [\gamma + \sigma_{ir}(1 - \gamma)]\Gamma v_{ir}$, $\sigma_{ir} = \exp\left[\frac{-\tau^2}{2} + \delta\prime h_i + \tau w_i\right]$, v_{ir} and w_{ir} are the R simulated draws on v_i and w_i, $d_{itj} = 1$ if individual i makes choice j in choice set t and 0 otherwise, and $P(j, X_{it}, \beta_{ir}) = \frac{exp(x'_{itj}\beta_{ir})}{\sum_{j=1}^{J_{it}} exp(x'_{itj}\beta_{ir})}$.

(c) *Estimating willingness to pay for maize traits and trait levels*

This generalized mixed model also provides a straightforward method of re-parameterizing the model to estimate the taste parameters in willingness to pay (WTP) space, which has recently become a behaviorally appealing alternative way of directly obtaining an estimate of WTP (Fiebig *et al.*, 2010; Fosgerau, 2007; Greene, 2012; Hensher & Greene, 2011; Scarpa, Thiene, & Train, 2008; Train & Weeks, 2005). If $\gamma = 0$, $\Delta = 0$ and the element of β corresponding to the price or cost variable is normalized to 1 while a nonzero constant is moved outside the brackets, the following re-parameterized model emerges:

$$\beta_i = \sigma_i \beta_c \left[\begin{array}{c} 1 \\ \left(\frac{1}{\beta_c}\right)(\beta + \Gamma v_i) \end{array} \right] = \sigma_i \beta_c \left[\begin{array}{c} 1 \\ (\theta_c + \Gamma v_i) \end{array} \right] \tag{9}$$

This model produces generally much more reasonable estimates of willingness to pay for individuals in the sample than the model in the original form in which WTP is computed using ratios of parameters (Greene & Hensher, 2010; Hensher & Greene, 2011; Train & Weeks, 2005).

Four of the formulations discussed above were used in estimating the choice models and their derivatives—heterogeneity in mean and willingness to pay models. The first specification was without any control on the key parameters γ and τ resulting in the generalized mixed logit model (Eq. (4)). The second specification fixed γ at zero resulting in the type II generalized multinomial logit model (G-MNL-II) of (Fiebig *et al.*, 2010),

which is also known as scaled random parameters logit model (Greene, 2012) (Eqn. (6)). The third specification fixed γ at 1 generating the type I generalized multinomial logit (G-MNL-I) (Fiebig *et al.*, 2010) or the hybrid model (Greene, 2012) (Eqn. (5)). The fourth specification fixed τ at one (Eqn. (7) at $\tau = 1$). The model quality indicators did not show any considerable difference across the four models for all estimations. Therefore, the results of the four choice models will be presented, but in the interest of brevity, only the results of the unrestricted model (Eqn. (4)) will be presented for the discussion on willingness to pay and heterogeneity in mean.

4. EMPIRICAL RESULTS AND DISCUSSION

In this section, we present the empirical results that include the G-MNL model results, the heterogeneity in mean parameters, as well as the WTP estimates. The different formulations of the G-MNL model resulted in very similar results except the G-MNL with $\tau = 1$. In both choice decision and heterogeneity in mean estimations G-MNL ($\tau = 1$) has the lowest values for all model selection criteria. Among the choice models G-MNL-II specification performs best whereas G-MNL-I specification performed best among the heterogeneity in mean models. In the case of WTP in WTP space estimation, however, the G-MNL ($\tau = 1$), despite the less sensible coefficient estimates, performs slightly better than the other formulations which have identical results.

(a) *G-MNL model results*

Results of the full G-MNL model (Eqn. (4)) show that drought tolerance, yield, semi-flint texture, covered cob tip (husk), and cob size (in that order) are the traits that have a strong and positive effect on choice of a maize variety. Flint texture (compared to dent) was found to be significantly and negatively related to the likelihood of choosing a given maize variety. Unobserved heterogeneities were also evident around mean taste parameters for yield, grain size, drought tolerance, tip cover and price (Table 5).

The model with gamma fixed at zero (G-MNL-II/S-RPL: $\gamma = 0$) generated comparable results to that of the unrestricted model (full G-MNL). The only difference is that flint texture (cp. to dent) did not appear to be significantly affecting the likelihood of choosing a given maize variety. This model showed more pronounced unobserved heterogeneities in grain size and semi-flint texture and less so in large cob size traits. In addition to those observed in full G-MNL, unobserved heterogeneities were found to be significant around the mean taste parameters for medium cob size and the two levels of texture (semi-flint and flint).

Medium cob size (cp. to small) and covered tip (cp. to open) attributes were found to be not significantly affecting maize variety choice in the model with $\gamma = 1$ (G-MNL-I/Hybrid model). This model resulted in very similar unobserved heterogeneity coefficients (standard deviations of the random taste coefficients) with G-MNL II ($\gamma = 0$). The fourth model with the restriction $\tau = 1$ [G-MNL ($\tau = 1$)] resulted in slightly different coefficients both for mean taste parameters and standard deviations of random taste parameters compared to the other three models. Coefficients are much heavier than in the other models and the medium cob size, flint texture, and covered tip trait levels were insignificant. Unobserved heterogeneity was also evident across the means of taste parameters of most traits including price.

Importance of drought tolerance was revealed in all but G-MNL ($\tau = 0$) formulations even compared to the ultimate

Table 5. *G-MNL model results of variety choice model*

Taste parameters	Full G-MNL		G-MNL-II ($\gamma = 0$)		G-MNL-I ($\gamma = 1$)		G-MNL ($\tau = 1$)	
	β.	St. err.	β.	St. err.	β.	St. err.	β.	St. err.
Yield	1.416‡	0.060	1.330‡	0.058	1.394‡	0.059	2.280‡	0.117
Medium size cob	0.081‡	0.030	0.062†	0.031	0.048	0.031	−0.099	0.052
Large size cob	0.086‡	0.026	0.098‡	0.026	0.107‡	0.026	0.189‡	0.049
Grain size	0.054	0.047	0.029	0.047	0.053	0.049	0.200†	0.097
Drought tolerant	1.502‡	0.067	1.484‡	0.066	1.473‡	0.064	2.196‡	0.131
Semi-flint texture	0.150‡	0.034	0.099‡	0.034	0.149‡	0.035	0.219‡	0.050
Flint texture	−0.120‡	0.045	−0.021	0.044	−0.091†	0.045	0.092	0.068
Covered tip	0.145†	0.057	−0.045	0.056	0.073	0.057	−0.040	0.103
Price	−3.812‡	0.772	−3.733‡	0.743	−3.796‡	0.857	−6.165‡	0.712
Constant	3.634‡	0.130	4.013‡	0.128	3.517‡	0.137	4.212‡	0.149
Heterogeneity in mean								
Yield	1.231‡	0.074	1.201‡	0.074	1.224‡	0.074	1.066‡	0.137
Medium size cob	0.004	0.226	0.105	0.120	0.010	0.207	0.005	0.200
Large size cob	0.133†	0.059	0.109	0.074	0.095	0.076	0.261‡	0.054
Grain size	0.166	0.165	0.278†	0.116	0.364‡	0.099	0.560‡	0.117
Drought tolerant	1.290‡	0.073	1.267‡	0.069	1.239‡	0.071	1.449‡	0.111
Semi-flint texture	0.113	0.097	0.157†	0.078	0.178†	0.074	0.067	0.126
Flint texture	0.261‡	0.072	0.225‡	0.082	0.279‡	0.076	0.407‡	0.076
Covered tip	0.019	0.248	0.085	0.233	0.011	0.234	0.202	0.194
Price	0.037	1.803	0.073	2.045	0.319	1.313	0.711†	0.306
Tau	0.188	0.656	0.053	0.199	0.163	0.510	1.066	3.191
Gamma	0.091	0.318	0.000		1.224	3.822	0.508	1.520
Sigma(i)	0.015	29.982	0.105	0.817	0.144	0.372	0.481	1.571
N	12,600		12,600		12,600		12,600	
LL Function	−6,729.4		−6,727.3		−6,729.5		−6,746.6	
McFadden Pseudo R^2	0.514		0.514		0.514		0.513	
AIC/N	1.071		1.071		1.071		1.074	

Note: ‡, †, * imply significance at 1%, 5%, 10% level, respectively.

measure of performance of a variety; i.e., yield (Table 5). The temporal dimension of traits being considered is crucially important in understanding the relative importance of the traits from farmers' point of view. Although farmers normally consider productivity of crop varieties when making adoption decisions, they also take into consideration the suitability of such varieties to the conditions of the local environment, particularly when they live in drought-prone environments. The fact that a variety has drought tolerance trait can therefore be more convincing to the farmers in selecting a variety than mere exposition of the potential yield of the variety in question.

Other traits are also important in maize variety choice decisions. For instance, cob tip cover (or husk cover) is an important attribute in rural Zimbabwe, given the challenges imposed by birds and other rodents. Similarly, the texture of the grain has an important implication in terms of expected grain yield per unit area, poundability, and flour yield per unit of grain. Farmers are aware that dent textured maize is softer and can easily be pounded compared to flint maize, and flint maize gives higher flour output per unit of grain. Maize varieties with medium and large sized cobs are preferred to those with small cobs as size of the cob has a lot to do with grain yield and marketability of the cobs.

(b) *Heterogeneity in maize trait preferences*

Estimates of preference heterogeneity are presented in Table 6. Unobserved heterogeneity around the mean of the taste parameters was quite consistently evident with respect to yield, drought tolerance, grain texture (flint and semi-flint), big cob size, and husk cover. Therefore, we

introduced some observed sources of variation to identify which factors are responsible for the heterogeneity. The heterogeneity-in-mean variables were selected after an iterative process of model estimation and comparison based on intuition and the conventional criteria of log likelihood, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) (Kadane & Lazar, 2004). The first three heterogeneity-in-mean model formulations [full G-MNL, G-MNL ($\gamma = 0$), and G-MNL ($\gamma = 1$)] generated highly comparable results (Table 6). The G-MNL ($\tau = 1$) model resulted in some implausible coefficient estimates. Our discussion will therefore be based on the unrestricted model (full G-MNL).

Gender of the household head, household size, and occupation of the household head were found to be the factors that best explain variation around the average level of taste preference for the traits. The preference for the grain yield trait was found to be different between farmers and respondents engaged in non-agricultural activities. Only 1.1% of the respondents are engaged in activities not related to farming, paid permanent and temporary employments, and trading. These respondents were categorized as households that depend on other sources of income. These households were found to have significantly less interest in the grain yield trait compared to those who depend on farming for a living.

Interest in drought tolerance was found to be negatively related to household size. This is unexpected, nonetheless, household size in communal areas of Zimbabwe is strongly related to income poverty (Kassie et al., 2012). These poorer households are considered more likely to be risk averse, and might have perceived DT maize as a new technology that will increase their vulnerability to farm production risk.

Table 6. *Heterogeneity in mean taste parameters models*

	Full G-MNL		G-MNL-II ($\gamma = 0$)		G-MNL-I ($\gamma = 1$)		G-MNL ($\tau = 1$)	
	β.	St. err.	β.	St. err.	β.	St. err.	β.	St. err.
Taste parameters								
Yield	.870‡	0.123	.846‡	0.124	.817‡	0.125	−0.653*	0.393
Medium size cob	−.074†	0.030	−.072†	0.030	−0.032	0.030	−.287‡	0.056
Large size cob	.093*	0.054	.097*	0.053	.170‡	0.061	0.155	0.121
Grain size	.576‡	0.046	.592‡	0.046	.581‡	0.045	3.458‡	0.177
Drought tolerant	1.999‡	0.121	2.015‡	0.121	2.052‡	0.124	4.237‡	0.334
Semi-flint texture	.298‡	0.091	.295‡	0.091	.290‡	0.101	1.163‡	0.144
Flint texture	−0.254	0.103	−.259†	0.103	−.288‡	0.104	−.485†	0.205
Covered tip	.928‡	0.117	.942‡	0.118	.927‡	0.122	2.807‡	0.295
Price	−1.998	0.089	−2.00‡	0.088	−2.009‡	0.088	−.665‡	0.096
Constant								
Observed heterogeneity								
Yield*Gender	0.048	0.075	0.046	0.076	0.014	0.077	.855‡	0.211
Yield*HH size	0.000	0.014	0.001	0.014	0.022	0.014	.442‡	0.049
Yield*Petty trader	0.012	0.103	0.016	0.104	0.099	0.108	−0.243	0.349
Yield*Temporary	0.126	0.105	0.133	0.106	.203*	0.109	0.307	0.392
Yield*Other jobs	−.706‡	0.206	−.719‡	0.207	−.732‡	0.210	0.449	0.742
Big cob*Gender	0.007	0.039	0.005	0.038	0.009	0.045	−0.066	0.083
Big cob*HH size	0.001	0.008	0.000	0.008	−0.015*	0.009	.064‡	0.018
DT*Gender	0.011	0.076	0.011	0.076	0.089	0.078	−.936‡	0.180
DT*HH size	−.046‡	0.011	−.048‡	0.011	−.054‡	0.012	.435‡	0.040
DT*Petty trader	−0.044	0.093	−0.050	0.093	−0.003	0.095	0.088	0.236
DT*Temporary	.451‡	0.099	.470‡	0.099	.548‡	0.101	.782‡	0.269
DT*Other jobs	−.622‡	0.177	−.643‡	0.177	−.668‡	0.182	−1.046†	0.417
Semi flint*Gender	.315‡	0.067	.308‡	0.067	.236‡	0.073	.290‡	0.099
Semi flint*HH size	−.048‡	0.013	−.046‡	0.013	−.036†	0.014	−.141‡	0.023
Semi flint*Petty trader	−0.032	0.034	−0.029	0.034	0.011	0.040	0.053	0.048
Flint*Gender	−0.053	0.075	−0.058	0.075	−0.114	0.075	−0.079	0.153
Flint*HH size	.049‡	0.016	.051‡	0.016	.059‡	0.016	.069†	0.033
Covered tip*Gender	−.295‡	0.089	−.312‡	0.089	−.391‡	0.092	.787‡	0.181
Covered tip*HH size	−0.028	0.018	−0.028	0.018	−0.019	0.019	−0.034	0.040
Heterogeneity in mean								
Yield	.639‡	0.069	.661‡	0.069	.661‡	0.070	2.364‡	0.107
Medium size cob	0.008	0.221	0.005	0.218	0.001	0.189	0.094	0.077
Large size cob	0.099	0.070	0.054	0.113	.260‡	0.039	.599‡	0.047
Grain size	.461‡	0.083	.464‡	0.083	.400‡	0.091	.397‡	0.111
Drought tolerant	.738‡	0.049	.750‡	0.048	.787‡	0.050	1.090‡	0.088
Semi-flint texture	.332‡	0.051	.330‡	0.050	.463‡	0.049	.148†	0.060
Flint texture	0.087	0.148	0.071	0.157	0.125	0.132	.789‡	0.065
Covered tip	.262†	0.132	.273†	0.129	.340‡	0.112	1.653‡	0.104
Price	0.009	0.385	0.009	0.390	0.000	0.402	3.998‡	0.328
Tau	0.001	0.006	0.001	0.006	0.001	0.005	2.364	3.186
Gamma	0.064	3,924.044	0.000	6.179	0.661	4.612	1.523	11.456
Sigma(i)	0.008	3,896.122	0.005	60.294	0.003	56.226	0.735	2.805
N	12,600		12,600		12,600		12,600	
LL Function	−7,724.03		−7,720.9		−7,711.5		−8,608.34	
McFadden Pseudo R^2	0.442		0.442		0.443		0.38	
AIC/N	1.232		1.232		1.23		1.372	

Note: ‡, †, * imply significance at 1%, 5%, 10% level, respectively.

Households headed by those engaged in petty trading, since they are unlikely to be fully or even partially engaged in farming, are also less interested in the drought tolerance trait in maize compared to those headed by farmers. Their interest is expected to be in traits with direct implications on the marketability of the maize. Similarly, households headed by those engaged in other activities are less interested in drought tolerance compared to farmers. This is not unexpected, as this group of respondents are rarely engaged in farming and hence, like petty traders, are likely to be less interested in the challenges maize production is facing. Their interest would be more likely to lie in the consumption-related attributes of maize.

Households headed by those engaged in temporary employment are however more interested in drought tolerance in maize compared to those headed by farmers. These are people who do temporary employment mainly to supplement their livelihoods. These people might be expected to be very keen to try new technologies that could relieve them from some of the livelihood pressures they are currently living with.

Table 7. *Willingness to pay for maize traits in willingness to pay space*

	Full G-MNL		G-MNL ($\tau = 1$)	
	β.♣	St. err.	β.	St. err.
Taste parameters				
Yield	−2.478‡	0.499	−3.088‡	0.816
Medium size cob	.877‡	0.145	1.400‡	0.303
Large size cob	−.917‡	0.189	−1.580‡	0.376
Grain size	−1.979‡	0.326	−4.668‡	0.988
Drought tolerant	−6.354‡	0.911	−10.571‡	2.062
Semi-flint texture	−0.335	0.215	−1.662‡	0.434
Flint texture	−0.176	0.240	1.349‡	0.416
Covered tip	−1.270‡	0.365	−4.689‡	1.046
Price	1	Fixed	1	Fixed
Observed heterogeneity				
Yield*Gender	−1.164‡	0.300	−.702†	0.340
Yield*HH size	−0.071	0.051	−.160†	0.073
Yield*Petty trader	1.048‡	0.372	0.546	0.488
Yield*Temporary	−0.386	0.403	−0.816	0.566
Yield*Other jobs	−0.491	0.690	0.317	0.983
Big cob*Gender	.538‡	0.127	.551‡	0.180
Big cob*HH size	−0.014	0.020	−0.006	0.029
DT*Gender	0.355	0.264	1.366‡	0.423
DT*HH size	−0.024	0.054	0.061	0.062
DT*Petty trader	−0.032	0.361	−0.107	0.425
DT*Temporary	−0.528	0.431	−1.044*	0.580
DT*Other jobs	−0.263	0.722	1.322	0.933
Semi flint*Gender	−.430‡	0.160	−0.206	0.186
Semi flint*HH size	−0.006	0.031	.211‡	0.057
Semi flint*Petty trader	−0.126	0.085	−0.198*	0.102
Flint*Gender	0.257	0.182	.50*	0.260
Flint*HH size	−0.039	0.034	−.340†	0.082
Covered tip*Gender	−0.233	0.247	.666†	0.297
Covered tip*HH size	−0.065	0.049	0.016	0.056
Price*Gender	0.062	0.078	−0.120	0.102
Price*HH size	−.027†	0.013	−0.028	0.018
Price*Petty trader	−0.020	0.129	0.002	0.182
Price*Temporary	−.963‡	0.157	−.684‡	0.185
Price*Other jobs	1.420‡	0.228	.760†	0.366
Heterogeneity in mean				
Yield	2.20‡	0.372	1.240‡	0.394
Medium size cob	0.201	0.148	0.046	0.266
Large size cob	.445‡	0.106	.841‡	0.206
Grain size	1.946‡	0.329	.769‡	0.295
Drought tolerant	2.604‡	0.400	2.451‡	0.533
Semi−flint texture	.964‡	0.166	.367*	0.189
Flint texture	0.033	0.149	.559**	0.220
Covered tip	1.311‡	0.285	0.493	0.343
Price	0	Fixed	0	Fixed
Tau	1.964	10.850	1.240	7.889
Gamma	0.000	0.051	0.000	0.015
β_WTP	−0.162	1.293	−0.024	0.756
S_B0_WTP	0.224	24.584	0.015	9.041
Sigma(i)	0.287	16.398	0.056	5.978
N	12,600			12,600
LL Function	−7,242.8			−7,218.6
McFadden Pseudo R²	0.48			0.48
AIC/N	1.156			1.152

Note: ‡, †, * imply significance at 1%, 5%, 10% level, respectively. ♣Signs of coefficients need to be reversed as the coefficient of price was fixed to be 1.

Considering that drought has important implications for local livelihoods, it was anticipated that respondents with temporary employment would show a strong interest in drought tolerance.

The estimations also show that as household size increases interest in semi flint texture (cp. to dent) decreases and interest in flint texture (cp. to dent) increases. The declining interest in fully or partially dented maize varieties could be due to the

fact that varieties with such texture are susceptible to storage pests. The pressure on the household food economy due to the increasing size of the household is expected to make farmers more wary of potential post-harvest losses. Similarly, male farmers are more interested in semi-flint texture and less so in covered tip traits of maize compared to their female counterparts.

(c) *Willingness to pay for maize traits*

Willingness to pay (WTP) estimates are the derivation of the marginal rate of substitution between significant attributes and significant purchase prices. The WTP measures result from common choice-specific parameter estimates that are conditioned on the choices that are observed to have been made by an individual (Hensher & Greene, 2003). Negative WTP estimates are normally allowed to account for negative preferences related to disutility. Based on the full generalized multinomial logit (G-MNL) formulation, the WTP estimation done in WTP space resulted in coefficients in the realistic range given the price of maize seed in the market. The WTP values show that the implicit price of drought tolerance (DT) is way higher than all other traits. This is justified as drought is the most important challenge for maize production in communal areas of Zimbabwe (Chikobvu *et al.*, 2010). WTP for DT is followed by that of grain yield and grain size, in order (Table 7). The WTP for an increase or change in an attribute level is the price increase, which, combined with the attribute increase, leaves the deterministic part of the respondent's utility for a profile unchanged and hence the choice probability unchanged (Fiebig *et al.*, 2010).

Considering the mean WTP coefficients (disregarding the heterogeneity), sample farmers are willing to pay a premium for drought tolerance that is 2.56 times the amount they are willing to pay for an increase in grain yield of one ton/acre. The value farmers attach for a drought-tolerant maize variety over a non-tolerant one is 7 times the value they attach for a change from small to big cob size. Similarly, farmers value drought tolerance 3.2 times higher than the value they attach to changing a maize variety from small grain sized to large grain sized. The value farmers attach for drought tolerance is 5 times higher than the implicit price they attach to changing a variety from open tip cover to covered one.

Heterogeneity in the mean willingness to pay (WTP) estimates (full G-MNL) were evident with respect to grain yield, big cob size, grain size, drought tolerance, semi-flint texture, and tip cover. In line with the heterogeneity in mean results discussion above, male respondents seem to be willing to pay more for grain yield trait and semi-flint texture (cp. to dent) and less willing to pay for big (cp. to small) cob size. Petty traders are again less willing to pay for grain yield trait of maize compared to farmers.

5. CONCLUSION

Drought and the risk associated with it will continue to be formidable challenges for rain-fed maize production in the water-scarce communal areas of Zimbabwe. Therefore, the development and deployment of crop technologies that reduce the vulnerability of farming communities to dry spells and prolonged droughts is essential. In maize-based livelihood systems, along with water conservation and soil management, drought-tolerant maize is a key option available to farmers as a protection against drought.

Given the appropriateness of the technology, it is imperative to have considerable adoption of the DT maize varieties to bring about any impact at farm household level. Farmers' adoption decisions for improved maize varieties are essentially governed by their willingness to pay for the different traits. It was therefore important to elicit the preferences of farmers for the different traits of maize and estimate the implicit price they are willing to pay for the traits.

We employed a choice experiment approach to elicit preferences for traits of maize and used recent developments in discrete choice modeling to quantify the implicit prices farmers are willing to pay for the traits, with drought tolerance as a particular focus. All eight formulations of basic G-MNL and G-MNL-with-mean–heterogeneity models consistently showed that drought tolerance is the most important trait for farmers choosing a maize variety in communal areas.

If farmers in communal areas of Zimbabwe are to continue growing maize, maize breeding and variety dissemination efforts need to take into account the trait preferences of these farmers. The results of this study would apparently be useful for researchers to clearly set their criteria to prioritize variety development activities. Seed companies and extension agents will have varieties with traits preferred by farmers and concomitantly, farmers will have varieties that will help them cope with the different sources of agricultural risk they are living with.

The uncertainty about whether DT maize might fail to appeal to poor farmers (much as some other technologies, such as Bt cotton, have done) (Lybbert & Bell, 2010), will only be settled when the promotion of DT materials is targeted correctly. This study has shown that in communal areas of rural Zimbabwe, drought tolerance is the most important maize trait for local farmers. Farm households and households headed by people who supplement their livelihoods with temporary employment were found to be more interested in the DT trait. Marketing campaigns emphasizing the value which these new cultivars can add should be tailor-made with these interest groups in mind to enable faster dissemination of this new technology.

Innovative ways of promoting DT maize along with awareness-raising activities designed to enhance contextual understandings of drought and drought risk shall be employed to speed adoption of new DT maize varieties by risk-prone farming communities. Given the high level of rural literacy and the high rate of adoption of improved maize, trait-based promotion and marketing of varieties constitutes the right strategy. Yield and other traits, as important as they are, should be emphasized only when they need to be and not at the expense of the traits most preferred by farmers in their respective contexts.

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