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Farmer preferences for adopting drought-tolerant maize varieties: evidence from a choice experiment in Nigeria

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Abstract

Drought is a major challenge to maize-producing households in sub-Saharan Africa (SSA) impacting productivity, food security, and rural farm household welfare. Drought-tolerant maize varieties (DTMVs) are improved yield-enhancing technologies that can build resilience to climate change in the majority of SSA, but they are poorly adopted. This study assesses farmers' preferences for various attributes of DTMVs and the implicit value they are willing to place on them based on a discrete choice experiment using primary data consisting of 320 maize farm households in northern Nigeria. We estimate farmers' preference heterogeneity using maximum simulated likelihood of a mixed logit model in preference and price space. The results show common preferences for drought tolerance, nitrogen use efficiency, and yield attributes. It further shows strong disutility for non-resistance to Striga attribute. We also find the role of gender, institutional and social influence significant in valuing DTMVs attributes. Understanding the market-preferred attributes of DTMVs can provide guidance on policies to promote adoption of DTMVs.

Introduction

Drought-tolerant maize varieties (DTMVs) are low-cost initiatives introduced under the Drought-Tolerant Maize for Africa (DTMA) project across 13 sub-Saharan African (SSA) countries, including Nigeria, to provide resilience to drought and climate variation (Kostandini, La Rovere and Abdoulaye, 2013). These varieties aim to increase the average productivity of smallholder farmers under drought conditions by 20–30% (Fisher et al., 2015). The adoption of DTMVs has been found to significantly contribute to food security, increase productivity, and enhance household welfare (Bezu et al., 2014; Wossen et al., 2017; Abdoulaye, Wossen and Awotide, 2018; Kassie et al., 2018). To highlight, in Nigeria, the adoption of DTMVs increased maize yields by 13.3%, reduced yield variance by 53%, and decreased downside risk exposure by 81% among adopters (Wossen et al., 2017). Despite the significant impact of DTMVs, low and slow uptake of this agricultural technology is evident in various contexts across the SSA that have received DTMV interventions (Abebe et al., 2013; Kagoya, Paudel and Daniel, 2018; Ward et al., 2018).

The poor adoption of DTMVs is concerning, given the prevailing drought and desertification issues in agricultural drylands (Medugu, Majid and Choji, 2008; Eze, 2018; Hassan, Fullen and Oloke, 2019), including growing concerns about projected losses of maize yield by 20% or more by 2050 due to climate risk (Lobell et al., 2011). This situation is particularly unsettling in the context of the SSA, where agricultural productivity is crucial for addressing poverty and hunger. Nigeria's food insecurity situation is concerning, the country was ranked 109th out of 125 countries in the 2023 Global Hunger Index, and listed among countries experiencing severe hunger with the highest level of concern and expected worsening situations (GHI, 2023). Enhancing rapid technology adoption among farm households is critical for achieving global sustainable development goals, particularly in addressing interconnected challenges of poor agricultural productivity, food insecurity, and rural economic welfare (Asfaw et al., 2012; Mathenge, Smale and Olwande, 2014; Awotide et al., 2015; Abdoulaye, Wossen and Awotide, 2018).

In past studies, poor adoption of DTMVs has been attributed to observable factors of farm households (Fisher and Carr, 2015; Holden and Fisher, 2015; Katengeza, Holden and Lunduka, 2019). However, this explanation may not be sufficient, as several underlying behavioral attributes and perceptions of innovations may have been overlooked. For example, improved seed varieties have varying traits that enable them to withstand targeted climate risks. DTMVs, besides their drought-tolerant attributes, include other traits such as duration (early or extra-early maturity), resistance to diseases and weeds, and varying ear sizes, all of which can inform farmers' decisions to adopt or not. This suggests that it is not enough to evaluate the adoption of DTMVs solely on observable households' characteristics, it is also crucial to consider farmers' preferences for specific DTMV attributes that maximize their utility. Based on this background, this study addresses this shortcoming through the following research questions: (1) What attributes of DTMVs do farmers prefer? (2) How does attribute preferences vary across farmers socioeconomic characteristics? and given that the price effect may play a role in the demand for improved maize varieties, we explore the implicit price they are willing to pay for defined attributes through the research question—(3) Will farmers be willing to pay for preferred DTMV attributes?.

A discrete choice experiment (DCE) is a popular approach to eliciting preference information and has been applied in various contexts in behavioral studies in fields such as management, hospitality, health, and transport (Jagger and Jumbe, 2016; Alemu and Olsen, 2018; Hu et al., 2021; Penn and Hu, 2020; Potoglou et al., 2020; Chen, 2021; Nthambi, Markova-Nenova and Wätzold, 2021), inclusive of a broad presence in agriculture and natural resources management (Ward et al., 2014; Ward and Singh, 2015; Owusu Coffie et al., 2016; Ward et al., 2016; Joshi, Khan and Kishore, 2019; Krah et al., 2019; Oyinbo et al., 2019; Shee, Turvey and Marr, 2020; Teferi, Kassie, et al., 2020). Attempts to elicit information on trait preferences in DTMVs are still quite scarce, similar research studies elicit trait preferences in improved seeds, such as drought-tolerant rice varieties and improved wheat varieties (Ward et al., 2014; Teferi, et al., 2020). In this study, we comparatively employed both the classical mixed logit and Bayesian approaches to elicit preference and willingness-to-pay (WTP) to estimate preferences that are valuable to farmers to guide plant breeders and policymakers in the design and promotion of DTMVs in Nigeria. The next section provides background information on maize production in Nigeria, improved seed varieties such as DTMVs, and their attributes in Nigeria. Data and empirical framework are presented in the third section, while the results and discussion are presented in section four, and the last section concludes the paper.

Study context: maize production in Nigeria and DTMV attributes

In Nigeria, maize is the second most widely grown crop after cassava based on the land areas covered and production indices (FAOSTAT, 2020). Maize, as a staple food crop, is consumed in many forms as a main dish, infant foods and snacks, and as a core ingredient in animal feed (Ekpa et al., 2018; Adewopo, 2019). Despite its importance, a major concern is that maize production has not kept pace with population needs (FAOSTAT, 2020) due to low productivity issues. Like most countries in the SSA, agricultural production is still largely rainfed, crop failure is inevitable due to prevalent extreme conditions such as drought. In maize production, drought stress attacks the most critical stages of growth which include, early in the growing season, flowering stage, and the mid to late grain filling, and drought stress during the silking and grain filling stages can impact yields losses of 50 and 20%, respectively (Liang et al., 2020). Extreme cases of drought stress in Nigeria have led to famine in the past (Mortimore, 1989), for example, drought in the periods of 1971–1972 exacerbated existing poverty and starvation and significantly reduced agricultural contribution to the GDP from 18.4 to 7.3% (Abubakar and Yamusa, 2013). DTMVs are means to mitigating climate risks at important growth stages and can increase the productivity of farm households by 20–30% (Genti et al., 2004).

DTMVs, compared to traditional varieties exhibits trait features that manifest in the early stage seedling vigor and leaf rolling, in this case, leaf rolling takes longer under early-season drought stress and the flowering stage has shorter or narrower anthesis silking interval, also crop show stay-green attributes under moisture stress (Kassie et al., 2017). Besides, some cultivars of the DTMVs have traits that are resistant to diseases such as the maize streak virus and enhance better tolerance to low soil nitrogen (Fisher et al., 2015). Plant breeders have also made efforts to incorporate some DTMVs with strains that are resistant to parasitic weed problems such as *Striga hermonthica* infestations, which is highly endemic in the northern region of Nigeria and constitutes one of the most severe constraints to production (Dugje, Kamara and Omoigui, 2006; Kamara et al., 2020a, 2020b). Striga infestations can affect as high as 100% of the farmlands and can force farmers to abandon their farmlands (Ekeleme, Jibrin, et al., 2014). Some other DTMV features include extra-early maturing features (less than 90 days), increasing values in the number of ears per plant, and the number of kernels per ear (Kassie et al., 2017). With the aforementioned, DTMVs provide several features beyond mitigating drought, however, poorly demanded. As such, an adequate understanding of DTMVs preferred attributes will support plant breeders to integrate this into product profiles which will help to increase adoption of DTMVs, meet the food needs of the populace, and improve farm households' welfare.

Empirical methodology

In this study, the choice of the DCE over other elicitation method such as revealed preferences is due to its ability to model actual consumer purchasing scenarios and it is also less prone to hypothetical bias in estimation of WTP (Lusk and Schroeder, 2004). The design of this study choice experiment follows a five-stage approach which includes identification of attributes, identification of levels, experimental design, data collection, and analysis of data (Kjær, 2005), described as follows.

Design of DCE

DTMV attributes selection

Attributes selection process involved various consultations and collaborations with stakeholders such as the International Institute of Tropical Agriculture (IITA) responsible for the deployment of DTMA intervention specifically in Kano State, Nigeria where the study took place. Within the team, we consulted with the plant breeders in the IITA under the DTMA Nigeria team to understand existing varieties and attributes in the study location. The collaborative effort also includes discussing with team leads at the forefront of DTMV interventions, this includes extension workers, key farmers working with a network of farmers, and seed dealers in the regions under study. An additional effort was exploring a database of existing maize varieties that are drought tolerant and have been deployed for farmers on the Nigeria seed portal database. The attributes (yield, maturity/duration, resistance to Striga, nitrogen use efficiency, cob size, grain size, price, and tolerance to drought) and their levels are illustrated in Table 1.

Yield, from as early as the green revolution era is important for food availability and overall farm households' welfare (Evenson and Gollin, 2003; Golin et al., 2005). To design yield attributes and levels, we considered potential yield attainable under

Table 1. DCE attributes and corresponding levels

Attributes	Description	Levels
Yield	Grain yield (t ha^{-1})	3.0 t ha^{-1}, 6.0 t ha^{-1}, 8.5 t ha^{-1}, 9.0 t ha^{-1}
Maturity/duration	Measured by the time from planting to maturity of maize crop. Less than 90 days is early maturing; between 90 and 120 days is medium maturing; and more than 120 days are late maturing.	Early maturing, medium maturing, and late maturing
Resistance to Striga	The ability of maize variety to resist parasitism by *S. hermonthica*; a popular parasitic weed in cereal production	Yes, No
Nitrogen use efficiency	The ability of maize variety to efficiently take up nitrogen in the soil	Low, medium, high
Cob size	Observation is jointly based on the maize length and diameter	Small, medium, and large
Grain size	Observation based on the relative kernel size	Small, large
Price of maize seed per kg (Nigerian Naira)	Maize seed price in Nigerian naira kg^{-1}	200, 250, 300, 400
Tolerant to drought	The ability of maize variety to have high seedling vigor, shorter/narrower anthesis silking interval, and a stay-green attributes under moisture stress	Low, medium, high

favorable conditions as designed by plant breeders for varieties of drought-tolerant maize, ranging from a lower to a higher rank—3.0, 6.0, 8.5, and 9.0 t ha^{-1}. Studies have shown potential yield as high as 10 t ha^{-1} in drought-prone zones, provided conditions are favorable (African Centre for Biodiversity (ACB), 2017).

Duration or maturity periods are also significant attributes of improved maize seeds. For example, late maize varieties when sown earlier can utilize the longer period of grain filling which helps to gain more yield than early maturing varieties (O. B. et al., 2012). At the same time, late maize varieties tend to have high plant height which makes them susceptible to lodging, in contrast, early varieties are shorter, high yielding, have better nitrogen use efficiency, and agronomic performance (Liu and Wiatrak, 2011). In our experimental choice survey, we designed three levels for duration/maturity attributes: this includes early for varieties that mature within 90 days; medium for varieties that mature between 90 and 120 days; and late for varieties that mature after 120 days.

Nitrogen is one of the yield-limiting nutrients in maize production in Nigeria (Kamara, Ewansiha and Menkir, 2014). It is highly mobile and subject to excessive loss in the soil (Pasley et al., 2020). Among the existing varieties deployed are maize cultivars that perform well under low nitrogen conditions (Bänziger and Lafitte, 1997; Kamara et al., 2005; Badu-Apraku et al., 2019). Also, cultivars that are tolerant to drought are efficient in the uptake of nitrogen suggesting that such cultivars require less investment in nitrogen fertilizer application (Kamara, Ewansiha and Tofa, 2019). Based on this, in our experimental study, we incorporated three levels of nitrogen use efficiency: low, medium, and high.

Cob size and grain size are common attributes in maize cultivars (Abate et al., 2013; Buah et al., 2013; Tadesse, Medhin and Ayalew, 2014) and their sizes have a lot to do with the potential yield and marketability of outputs (Kassie et al., 2017). In our experimental design, cob-size levels include small, medium, and large, while grain size levels are small and large. We varied drought-tolerant levels into low, medium, and high to assess households' perception of their degree of preference for drought-tolerance attributes in maize. The price attribute represents the common cost of a kg of DTMVs seed farm households ever purchased.

D-optimal choice set design

In designing choice sets, it is important to control for the non-dominance of one attribute over the other. The D-optimal design approach takes this into account by explicitly considering the importance of attribute levels and at the same time ensuring that the alternatives in the choice set provide more information about the trade-off between the different attributes (Carlsson and Martinsson, 2003). We specified the D-optimality criterion using a modified Federov search algorithm based on calculating the determinants of the variance–covariance matrix of the parameters from a non-linear logit model as applied in similar contexts (Shee, Turvey and Marr, 2020). From the eight attributes, we generated varying choices using JMP software. In the design process, we considered varying four key attributes while four remain fixed. This is to give the respondents a clearer view of choices and to understand the changes appropriately. The fixed attribute in the sample choice card includes yield, maturity/duration, price of maize grain per kg, and tolerant to drought, while others vary. The result generated a set of 50 unique choice sets which were assigned to five different blocks, such that each respondent was required to respond to 10 choice sets. The choice set was constructed with three alternatives including an opt-out option (see Fig. 1). In the case of this study, the opt-out option is necessary as it represents real-life situation and reflects existing preferences for non-drought tolerant or traditional varieties. Overlooking the effect of opt-out effect in DCE simply infer that participants' preferences are not adequately considered and could lead to inaccurate measurement of attribute preferences and error in policy recommendation (Boxall, Adamowicz and Moon, 2009; Campbell and Erdem, 2019). Also, the DCE is highly susceptible to hypothetical bias (Usk and Chroeder, 2009; Moser, Raffaelli and Notaro, 2014). However, an unforced situation such as the use of the opt-out option does not completely exclude errors in estimation, the common bias in the experimental process is the omission and avoiding choice which may include opting for the opt-out option which is simpler to understand (Boxall, Adamowicz and Moon, 2009). To control for this, participants are repeatedly reminded of the free will to choose between the designed drought-tolerant varieties. Such an approach culminates into a repeated reminder of the opt-out approach which has been found to reduce or mitigate hypothetical bias (Ladenburg and

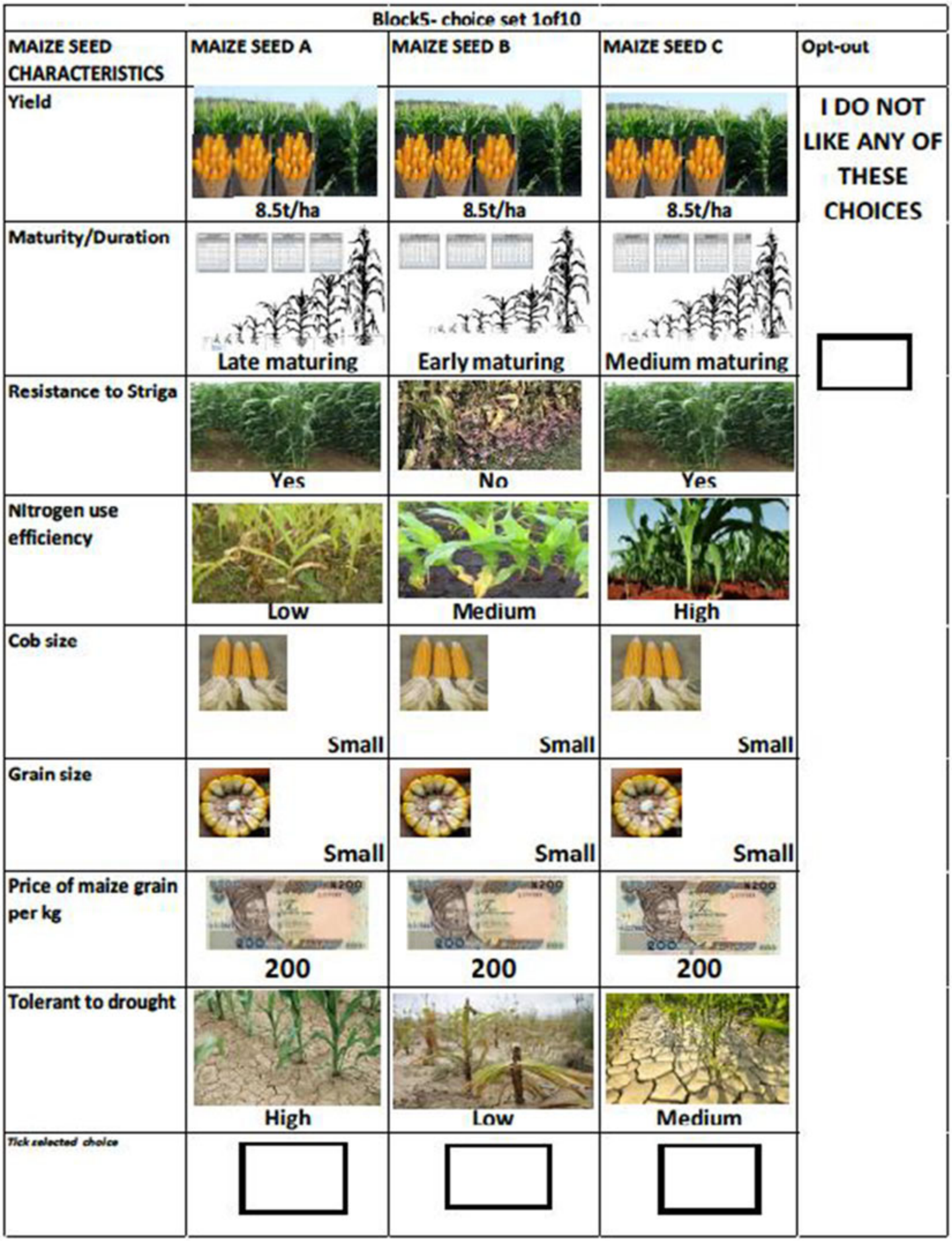

Figure 1. Sample choice card.

Olsen, 2014; Alemu and Olsen, 2018). In our experimental approach, the opt-out option is repeated in each choice card and participants are made to understand that opt-out options represent their non-interest in any of the drought-tolerant choices and indicate their preferences for the lowest levels in each attribute which are relatively close to attributes of traditional varieties and serves as the status quo for this study.

In the data collection stage, aside presentation of choice cards, a short survey was presented to households covering their respective socioeconomic characteristics.

Econometric framework

Mixed logit and hierarchical Bayesian estimation model

To derive the marginal values for DTMV attributes (yield, maturity, resistance to Striga, nitrogen use efficiency, cob size, grain size, and price), we model farm household choices based on the behavioral framework of random utility theory (McFadden, 1974). For the choice scenarios presented to farmers (Maize seed A, Maize seed B, Maize Seed C, and Opt-Out—see Fig. 1), we assume that the indirect utility associated with maize farmer n choosing alternatives j in a choice set t is defined as follows:

$$u_{njt} = x'_{njt}\ \beta_n + \varepsilon_{njt} \tag{1}$$

where x'_{njt} represents the vector of choice attributes of alternatives j, β represents the preference parameters for each DTMV attributes, and ε_{njt} is the error components of utility independently and identically distributed across maize farmers and alternatives. The opt-out option takes similar modeling approach and, in this context, is represented by maize farmer non-interest in any of the DTMV options and it is indicative of the lowest level of attributes which are related to current traditional management practices. In a conditional or multinomial logit model, the random parameters ε_{njt} are Gumbel-distributed errors, and are specified to be the same for all choices made by individual maize farmers, and are illustrated as follows for a maize farmer n chooses alternatives i from among J alternatives:

$$P_{nit} = \frac{\exp\ (x'_{nit}\beta)}{\sum_{J=1}^{J} \exp(x'_{njt}\beta)} \tag{2}$$

There is however a shortcoming in the assumption of the independence of irrelevant alternatives property and inability to conduct random test variation. The mixed logit model also known as the random parameter logit overcomes this limitation by allowing random test variation and observing substitution patterns (McFadden and Train, 2000).

To account for preference heterogeneity, we interact farmers socioeconomic characteristics with attributes of DTMVs, and the researcher specified distribution for β_n, $f(\beta|\vartheta)$ where ϑ are the parameters of the distribution which has a mean vector b and covariance matrix S, $\beta_n \sim N(b,\ S)$. The unconditional probability of sequences of choices is defined as follows:

$$P_n(\vartheta) = \coprod_t \frac{\exp\ (x'_{nit}\beta_n)}{\sum_{j=1}^{J} \exp\ (x'_{njt}\beta_n)} f(\beta|\vartheta)d\beta \tag{3}$$

The mixed logit model presented can be estimated using the maximum simulated likelihood approach.

For robustness analysis, this study also employs the hierarchical Bayesian estimation procedure. The advantage of the hierarchical Bayesian procedures over the classical mixed logit method is that the common approach of using maximization of the likelihood function in classical methods is not required in the Bayesian procedure; this help to overcome the problems of convergence which can be due to poor starting values in the model or the inclusion of bounded distributions (Train, 2012). Also, the Bayesian procedure under more relaxed conditions attains desirable estimation properties such as consistency and efficiency (Train, 2012).

Following the standard procedure, we specified the prior beliefs about b and S are specified as $b \sim N(0,\ v)$, v is large, and $S \sim IG(v,\ 1)$ for $v \to 1$, where IG stands for inverted Gamma distribution. The parameters b and S are called population level parameters. We use Gibbs sampling to estimate three sets of parameters $b,\ S,\ and\ \ \beta_i \forall i$. The posterior for $b,\ S\ and\ \beta_i \forall i$ is

$$K(b,\ S, \beta_i|Y) \propto \coprod_i \frac{\exp\ (x'_{tin}\beta_i)}{\sum_{j=1}^{j} \exp\ (x'_{tin}\beta_i)}\ \emptyset(\beta_i|b,\ S)k(b, S) \tag{4}$$

The Gibbs sampling involves taking a sequence of draws in which each draw for a parameter is estimated conditional on the parameters in the model in a hierarchical procedure. During estimation, the algorithm starts with initial values of b^0, S^0, and β_i^0. The nth iteration of the Gibbs sampling can be estimated using the following steps (1) take a draw of b^n, from $f(\beta, S)$ where β is the mean conditional on S^0 and β_n^0; (2) take a draw of S^n conditional on b^n and β_i^0, and (3) take a draw of β_i^n conditional on b^n and S^n. These steps are repeated sequentially over many iterations until the values have converged to draws in the posterior. Several draws from the posterior are then used to calculate the required statistics.

Using Stata 16, we fit the Bayesian mixed logit model using '*bayesmixedlogit*' which uses the adaptive Markov chain Monte Carlo sampling from the posterior distribution of individual level coefficients and fixed coefficients (Baker, 2023).

WTP and WTP space estimations

Estimated parameters from the mixed logit model can be used to obtain WTP measures. The WTP is calculated as the change in price or premium to keep the same level of utility after an attribute change. The WTP for the nth attribute is calculated as

$$WTP_n = -\ \frac{2\beta_n}{\beta_p} \tag{5}$$

where β_n is the estimated parameter of the nth attribute and β_p is the estimated coefficient of seed price in the context of this study. Following similar studies (Lusk and Schroeder, 2004; Shee, Turvey and Marr, 2020), the WTP is harmlessly multiplied by 2 due to the use of effects coding. Estimated coefficients of WTP in preference space represent individual farm households' preferences or marginal utilities for various attributes of DTMVs. In the preference space, while the coefficients of other attributes are allowed to vary normally, the price coefficient is specified to be fixed across all observations. The implication of this is that attribute distribution in the WTP model will be the same as the distribution of random coefficient, at the same time, the mean and variance are scaled by the fixed price coefficient to provide a meaningful interpretation (Revelt and Train, 1998). The limitation of this approach is that it is not realistic since the price effect is not likely to be fixed across all attributes.

An alternative approach is called WTP space estimation of mixed logit, developed by (Train and Weeks, 2005) suggesting re-parameterizing the model in terms of WTP and estimating WTP directly. In estimating WTP in price-space, we re-specify the utility individual i derives from choosing t during choice task n is specified as a function of individual taste parameter x_{itn} and individual specific characteristics z'_i:

$$V_{tin} =\ x_{itn}\beta_i + z_{itn}\delta'_i + \varepsilon_{itn} \tag{6}$$

where β_i and δ_i are individual-specific coefficients for attributes and individual-specific characteristics. ε_{itn} is assumed to be an extreme value distributed with variance given by $\mu_i^2(\Pi^2/6\ )$, where μ_i is an individual-specific scale parameter. As shown by Train and Weeks (2005), dividing Equation (6) by μ_i does not affect behavior and result in a new error term which is independent and identically distributed extreme value with variance equal to $\Pi^2/6$:

$$V_{itn} =\ x_{itn}\lambda_i + z_{itn}c'_i + \varepsilon_{itn} \tag{7}$$

where $\lambda_i = \beta_i/\mu_i$ and $c_i =\ \delta_i/\mu_i$.

In Equation (7), V_{tin} is the utility associated with individual i, x_{tin} is a vector of the attributes for the nth alternative, β_i is a vector of individual taste parameters mapping these attributes into utility, z_i is a vector of terms defining individual-specific characteristics, and δ maps these characteristics into utility associated with the choice of a particular alternative.

The WTP for an attribute is noted as the ratio of the attribute coefficient to the price coefficient i.e. $w_i = \lambda_i/c_i = (\beta_i/\mu_i)/(\delta_i/\mu_i) = \beta_i/\delta_i$. The utility function in the WTP space (Train and Weeks, 2005) can thus be written as

$$V_{tin} = -c_i z_{itn} \ + (\ c_i \ w_i)^{'} \ x_{itn} + +\varepsilon_{itn} \tag{8}$$

For robustness analysis, we adopt the '*bayesmixedlogitwtp*' as an alternative approach to estimating WTP in preference space in Stata 16 (Baker, 2023).

Study area and sampling design

This study employs a multistage sampling procedure. The first stage includes randomly selecting a participating state out of the 18 states in the DTMA project in Nigeria. A substage to this was the consideration of states in the Savanna zones that are prone to drought and have had episodes of drought occurrences. Among these states, Kano State was randomly selected. Kano State is one of the largest agricultural-producing states in the north-west region and Sudan Savanna zone of Nigeria (Fig. 2). Due to the topographical location of Kano State in the Sudan Savanna zone, the state is prone to drought risks with an impact on local agricultural production (Achugbu and Anugwo, 2016). To highlight, an assessment of Kano State rainfall and temperature data between 1981 and 2014 indicated the presence of drought and its impact on locally produces staple food crops (Mohammed, 2017). With persisting climate variability and anomalies on poor productivity in Kano State and its environs, studies have recommended the need to encourage coping mechanisms for drought (Oladipo, 1993; Adamu et al., 2021).

Gwarzo and Rano Local Government Areas (LGAs) in Kano State were among the targeted LGAs for the DTMA interventions, however not all communities in both LGAs were implementation sites for the DTMA project. In the next stage of sampling, random selection was made among intervention and non-intervention communities. Within each LGA, eight communities were randomly selected (each consisting of four DTMA project intervention areas and four non-intervention areas). In total, sample selection was drawn from eight intervention and eight non-intervention areas, totaling 16 communities (Fig. 3). From each community, 20 maize-producing households were randomly selected using existing maize database listings from the IITA. The sample size consists of 320 maize farm households overall.

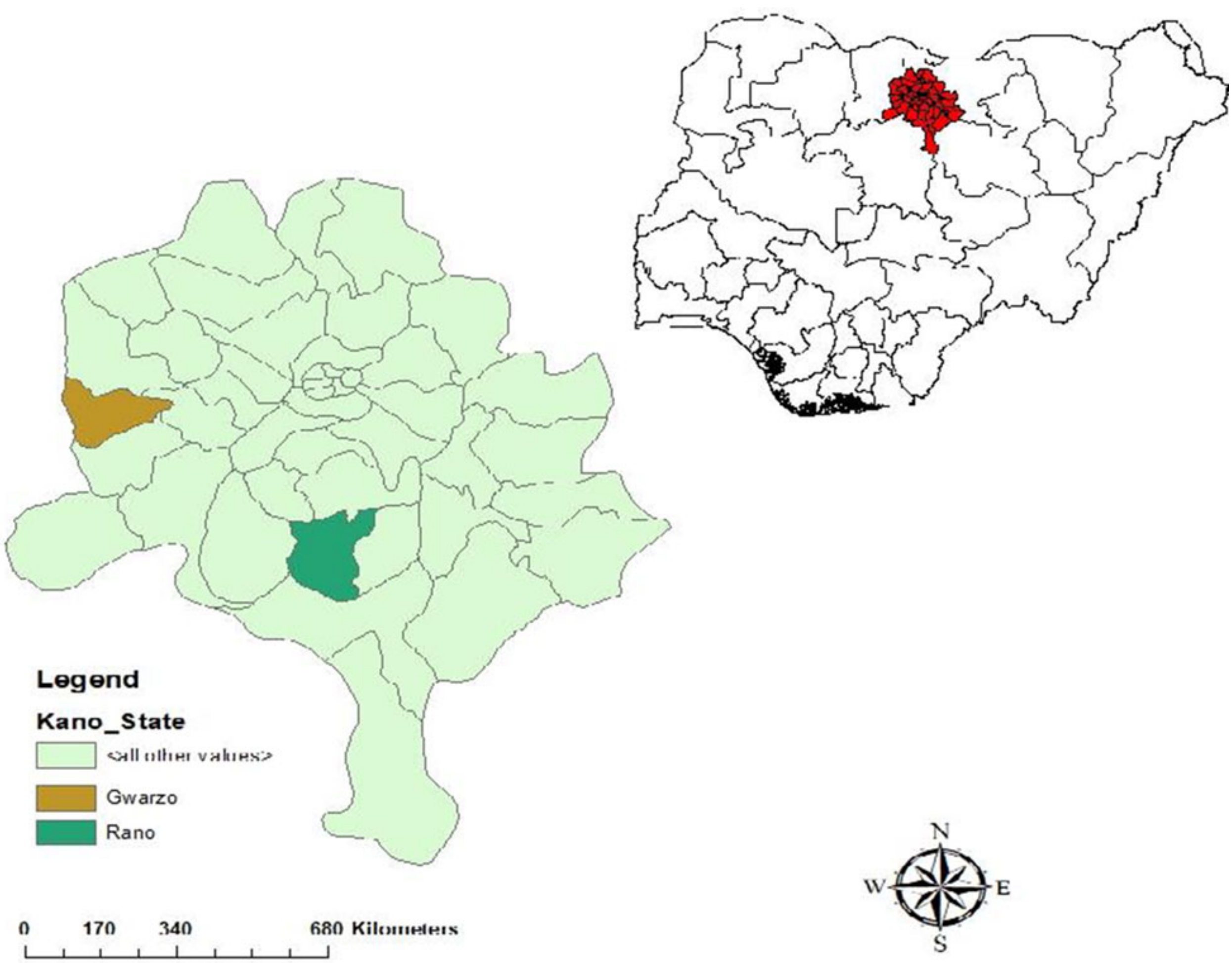

Figure 2. Geographical location of the study area.

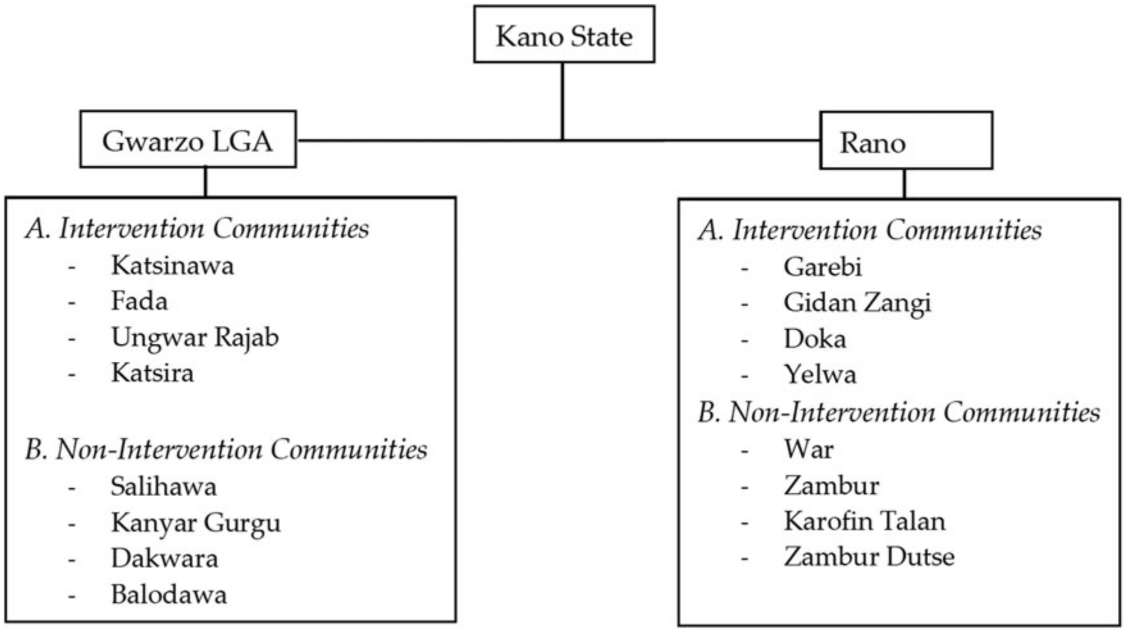

Figure 3. Illustrations of LGAs and communities from which samples were selected.

Results and discussion

Table 2 presents the descriptive statistics and statistical mean differences based on the adoption of DTMVs. The data show that average age of the household head is approximately 43 yr. Also, respondents' average years of education is 5.4 yr, and the maximum years of education on the average in the household is 9.56 yr. Small-holder farmers are located an average of 33.44 min away from the nearest seed market. Average years of experience in maize production in 15.52 yr and an average of 9.12 yr in the adoption of improved maize varieties.

In terms of institutional variables, 88% received one form of a loan or the other from local private agricultural firms, 34% belonged to credit institution groups and 61% were members of agricultural groups. The statistics on extension access shows that 58% of farm households had access to extension. Access to extension, in this context, includes farmers who visited an extension agent and/or were visited by an extension agent in the past agricultural season. The result further revealed that on average, the total land area allocated to maize production is 5.32 acres, out of which maize farm households averagely allocated 1.8 acres to the production of DTMVs.

Table 2 illustrates estimates of significant mean difference between adopters and non-adopters for some variables. For instance, adopters have higher total livestock units than non-adopters and 76% of adopters have ease availability of DTMVs in their community compared to 18% of non-adopters. Similarly, adopters significantly ($P < 0.01$) have more years of educations (6.16 yr) compared to non-adopters (4.58 yr). This difference also reflects in years of farming experience, access to extension information, and access to agricultural groups' platform.

Mixed logit estimation in preference and WTP price space

Table 3 presents the empirical results from the maximum simulated likelihood estimation of the mixed logit model. We compare results from mixed logit model estimation in preference space (M1) and price space (M3). Models M2 and M4 respectively controlled for respondents' socioeconomic characteristics in the preference and price space. Only significant socioeconomic terms are presented for discussions.

Across all models (M1–M4), the significance ($P < 0.01$) of the log-likelihood supports the presence of preference of heterogeneity for most of the attributes and justifies the use of a mixed logit model. Negative coefficients show disutility and farmers' lower preference and value for an attribute and vice versa. Across all models (M1–M4), we find similar and significant preferences ($P < 0.05$; $P < 0.01$) for nitrogen use efficiency (high and medium); tolerant to drought (high); and yield (very high) attributes. In a similar case study, drought-tolerant attributes is one of the most preferred traits among maize farm households in Zimbabwe (Kassie et al., 2017).

Farmers however show distaste and lower preference for non-resistance to Striga attributes across all models. Striga infestation is highly endemic in cereal cropping systems in Nigeria (Kamara et al., 2020a, 2020b); it is not surprising that farmers show lower preference for this attribute. Striga infestations is a pre-existing issue among maize farm households (Badu-Apraku et al., 2018), and quite prevalent in drought-prone areas with low soil fertility and soil organic carbon (Ekeleme et al., 2014).

The price attributes significantly differ in the preference (M1 and M2) and price space estimation (M3 and M4) models. While farmers show disutility for the price attributes in price space models (M3 and M4), they show preference for the price attribute in preference space models (M1 and M2).

Results of estimations with socioeconomic attributes in preference and price space are respectively presented in models M2 and M4. Male respondents significantly ($P < 0.1$) have less preference for early maturing attributes (M2). Also, farmers who had access to extension services and farmers who are member of agricultural groups preferred the large grain size attribute (M2). Also in M4, farmers significantly preferred early maturing attribute. The result is however quite mixed for farmers who accessed extensions services in the past agricultural season. While access to

Table 2. Mean difference between adopters and non-adopters of DTMVs

Socioeconomic characteristics	Mean values (standard deviation) Adopters of DTMVs ($n = 166$)	Non-adopters of DTMVs ($n = 154$)	Mean difference	Total
Gender (1 = male, 0 otherwise)	0.95	0.97	0.02	0.96
	(0.02)	(0.01)		
Age (yr)	43.61	42.77	−0.84	43.21
	(10.88)	(12.33)		
Maximum education (yr)	10.13	8.95	−1.18**	9.56
	(5.54)	(5.23)		
Household size	13.69**	15.29**	1.60**	14.46
	(7.57)	(6.29)		
Farm experience (yr)	25.43*	23.01*	−2.42*	24.26
	(12.20)	(11.91)		
Experience with improved maize varieties (yr)	9.77	8.42	−1.35	9.12
	(8.26)	(6.54)		
Maize land (acres)	5.16	5.48	0.32	5.32
	(4.04)	(3.97)		
Land own (acres)	8.76	9.77	1.01	9.24
	(7.23)	(9.61)		
Number DTMVs	2.25	0.33	−1.91***	1.32
	(4.02)	(1.37)		
DTMVs availability (1 = yes; 0 otherwise)	0.76	0.18	−0.58***	0.48
	(0.43)	(0.39)		
Distance to seed market (min)	29.76	37.52	7.76**	33.44
	(22.51)	(25.93)		
Total livestock units	3.19	2.40	−0.79**	2.81
	(3.69)	(3.08)		
Received loan (1 = yes; 0 otherwise)	0.84	0.92	0.07**	0.88
	(0.37)	(0.28)		
Credit group (1 = yes; 0 otherwise)	0.40	0.29	−0.11**	0.34
	(0.49)	(0.45)		
Member of agricultural group (1 = yes; 0 otherwise)	0.71	0.51	−0.20***	0.61
	(0.45)	(0.50)		
Receive temperature information (1 = yes; 0 otherwise)	0.84	0.92	0.08**	0.88
	(0.37)	(0.28)		
Access to extension (1 = yes; 0 otherwise)	0.58	0.77	−0.40***	0.38
	(0.45)	(0.46)		

*, **, *** represent significant levels at $P < 0.1$, $P < 0.05$, and $P < 0.01$, respectively.

extension services significantly influenced preference for high yielding attributes (M2), the effect shows distastes for attributes that have high tolerant to drought (M4) and not resistant to Striga (M2 and M4). These results are relevant for promotions of the adoption of DTMVs and suggest a focus on influencing adoption based on attributes of farm households that can likely promote adoption.

Table 4 presents the mean WTP estimates derived from the maximum simulated likelihood estimates models in M1 and M2. The coefficient estimates of attributes vary across models with positive coefficient showing WTP more and vice versa. For example, farmers are willing to pay NGN67.760 less for early maturing varieties, however in M2 model (which include socio-economic variables), farmers are willing to pay NGN267.859

Table 3. Estimates of mixed logit model in preference space and WTP space

	Preference space (M1)		Preference space with socioeconomic attributes (M2)		WTP space (M3)		WTP space with socioeconomic attributes (M4)	
Variables	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Mean coefficient								
Price	0.002***	0.001	0.002***	0.001	−6.182***	0.272	−6.119***	0.256
Maturity/duration (early)	0.111	0.086	−0.444	0.540	74.464	45.197	−146.405	253.018
Maturity/duration (late)	−0.059	0.080	−0.221	0.496	−2.916	39.797	−66.458	246.076
Resistant to Striga (no)	−1.586***	0.101	−1.558**	0.546	−770.003***	215.852	−858.469**	346.374
Nitrogen use efficiency (high)	1.770***	0.113	2.393***	0.699	902.022***	248.235	1242.756***	478.242
Nitrogen use efficiency (medium)	0.756***	0.108	1.504**	0.706	410.506***	125.474	794.943**	424.143
Cob size (large)	0.076	0.088	−0.198	0.583	45.670	44.199	−82.544	281.038
Cob size (medium)	−0.079	0.088	0.075	0.558	−35.357	43.688	9.419	279.382
Grain size (large)	0.091	0.072	0.091	0.439	64.988	36.634	110.702	217.114
Tolerant to drought (high)	2.118***	0.106	2.959***	0.741	1094.788***	297.376	1696.295***	623.602
Tolerant to drought (medium)	0.843***	0.104	1.458**	0.737	456.900***	140.229	872.104*	469.667
Yield (medium, 6.0 t ha^{-1})	0.278**	0.110	0.755	0.680	158.102***	77.926	470.584	352.444
Yield (8.5 t ha^{-1}, high)	0.841***	0.104	0.933	0.724	462.100***	134.864	571.687	381.719
Yield (9 t ha^{-1}, very high)	1.044 ***	0.115	2.145**	0.734	532.703***	165.676	1152.060**	500.036
Gender_Maturity/duration (early)			−1.105*	0.649				
Extension_yield (v.high)			0.007**	0.250				
Extension_resistance striga (no)			0.582***	0.202			326.665***	127.430
Extension_tolerant to drought (high)							−174.996*	103.116
Membership_Grain size (large)			0.421**	0.197				
Membership_duration (early)							207.879**	107.500
Standard deviation								
Price					0.460***	0.061	0.491***	0.061
Maturity/duration (early)	0.550***	0.134	0.522***	0.137	252.799	93.647	204.607	90.037
Maturity/duration (late)	−0.322**	0.165	0.334**	0.173	207.097	85.557	213.415	82.162
Resistant to Striga (no)	0.871***	0.121	0.793***	0.123	−336.520	110.442	−249.550	99.870
Nitrogen use efficiency (high)	0.799***	0.119	0.803***	0.116	277.671	122.805	−186.151	122.443
Nitrogen use efficiency (medium)	0.627***	0.226	0.333*	0.193	156.164	209.048	207.152	121.467
Cob size (large)	0.415***	0.165	0.452**	0.150	−175.762	90.131	−193.356	84.673
Cob size (medium)	0.110	0.250	−0.043	0.314	40.794	231.254	61.792	157.149

(*Continued*)

Table 3. (*Continued.*)

	Preference space (M1)		Preference space with socioeconomic attributes (M2)		WTP space (M3)		WTP space with socioeconomic attributes (M4)	
Variables	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.	Coef.	Std. err.
Grain size (large)	0.094	0.196	0.086	0.244	−102.348	82.468	−92.868	85.306
Tolerant to drought (high)	0.546***	0.128	0.498***	0.146	85.577	149.704	−134.523	100.577
Tolerant to drought (medium)	0.799***	0.155	−0.453***	0.165	−260.913	98.403	−239.181	88.760
Yield (medium, 6.0 t ha^{-1})	−0.269	0.243	−0.141	0.349	−157.465	112.886	−119.906	93.294
Yield (8.5 t ha^{-1}, high)	−0.375**	0.191	−0.367	0.185	−35.818	148.325	−6.427	97.261
Yield (9 t ha^{-1}, very high)	0.696***	0.161	0.710***	0.159	−339.159	118.536	−332.781	108.660
Mean price					−0.002***	0.001	−0.002***	0.001
SD price					0.001***	0.000	0.001***	0.000
Number of observations	12,800	12,800	12,800	12,800	12,800	12,800	12,800	12,800
Number of choices	3200	3200	3200	3200	3200	3200	3200	3200
Number of Halton draw	500	500	500	500	500	500	500	500
Simulated log-likelihood	−2792.700		−2771.162		−2783.296		−2753.833	
Wald χ^2	97.42***		79.10***		13,367.37***		12,853.54***	
Prob. > χ^2	0.000		0.000		0.000		0.000	

Notes: Among the interaction terms, only the terms with significant coefficients are presented in the table.
*, **, *** represent significant levels at $P < 0.1$, $P < 0.05$, and $P < 0.01$, respectively.

Table 4. WTP estimate from the mixed logit without (M1) and with (M2) interactions

	WTP estimates from M1			WTP estimates from M2		
	WTP	LL	UL	WTP	LL	UL
Maturity/duration (early)	−67.760	−178.423	42.903	267.859	−394.300	930.018
Maturity/duration (medium)	35.883	−59.764	131.529	133.465	−457.660	724.590
Resistant to Striga (no)	965.142	340.058	1590.225	939.742	60.656	1818.828
Nitrogen use efficiency (high)	−1077.591	−1766.894	−388.288	−1443.433	−2673.318	−213.549
Nitrogen use efficiency (medium)	−460.098	−777.562	−142.634	−907.318	−1916.880	102.243
Cob size (large)	−46.533	−155.398	62.331	119.337	−573.409	812.082
Cob size (medium)	48.369	−54.163	150.901	−45.388	−706.856	616.081
Grain size (large)	−55.191	−141.640	31.257	−54.977	−574.031	464.078
Tolerant to drought (high)	−1289.419	−2103.963	−474.875	−879.620	−1919.479	160.239
Tolerant to drought (medium)	−513.342	−870.692	−155.992	−455.484	−1314.483	403.515
Yield (medium, 6.0 t ha^{-1})	−169.312	−361.093	22.469	−562.969	−1486.439	360.501
Yield (8.5 t ha^{-1}, high)	−511.645	−864.799	−158.492	−562.969	−1486.439	360.501
Yield (9 t ha^{-1}, very high)	−635.699	−1083.829	−187.570	−1293.960	−2488.505	−99.415

Notes: 95% confidence intervals (lower limit [LL] and upper limit [UL]).

more for early maturing attributes. In both models, farmers are willing to pay more for non-resistant to Striga attribute. In contrast, farmers are willing to pay less for yield, nitrogen use efficiency, cob size, and grain size attributes. The WTP estimates in this case (M1 and M2) is modeled over a fixed price which does not truly reflect farmers' perceived price effect for each attribute, this limitation is accounted for in the price model (M3 and M4).

Table 5. Estimates of hierarchical Bayesian model in preference and WTP space

	Preference (M5)		WTP space (M6)	
Mean coefficient	Coef.	Std. err.	Coef.	Std. err.
Price	3.644***	0.347	−6.959***	0.327
Early maturing	35,058.450	32,264.380	−0.048	0.095
Medium maturing	59,885.94	62,097.770	−0.254	0.100
Resistant to Striga (no)	−1408.026***	77.600	−1.223***	0.086
Nitrogen use efficiency (high)	72,131.660	103,291.600	1.592***	0.122
Nitrogen use efficiency (medium)	33,687.160	55,477.570	0.701***	0.082
Cob size (large)	112,757.400	140,799	−0.348***	0.108
Cob size (medium)	− 31,514.070	36,868.420	0.068	0.079
Grain size (large)	55,052.850	61,567.600	−0.010	0.108
Tolerant to drought (high)	108,173.900	148,511.100	1.741***	0.080
Tolerant to drought (medium)	98,746.450	112,722.900	0.673***	0.069
Yield (medium, 6.0 t ha^{-1})	−7444.947	39,591.580	0.593***	0.081
Yield (8.5 t ha^{-1}, high)	49,503.970	56,876.440	0.591***	0.069
Yield (9 t ha^{-1}, very high)	98,192.140	116,860.900	1.042***	0.071
Number of observations	12,800	12,800	12,800	12,800
Number of choices	3200	3200	3200	3200
Number of groups	320	320	320	320
Total draws	4000	4000	4000	4000
Burn-in-draws	1000	1000	1000	1000

*** represents significant level at $P < 0.01$.

Hierarchical Bayesian estimation in preference and price space

For robust analysis, Table 5 presents estimates of the hierarchical Bayesian model in preference (M5) and price space (M6). We compare estimates with mixed logit model in preference (M1 and M3). The Bayesian model estimates show similar low preference for non-resistant to Striga attribute, significant at $P < 0.01$. Comparing the estimates of mixed logit model and hierarchical Bayesian models in price space (M3 and M6), we find similar attribute preferences, except for large cob-size attribute in M3 model which was not significant. We find huge difference between models M1 and M5, except for coefficients of price and resistance to Striga (no) attributes.

Summary and conclusion

Drought remains one of the leading drawbacks to increasing maize productivity in the SSA, and despite the efforts put toward developing new seed varieties such as DTMVs, increasing the spread of adoption remains a challenge in several contexts. Low market demand for improved seed varieties such as DTMV challenges rapid adoption which has implication on productivity and welfare of the rural agricultural populace. Understanding and eliciting preferences for seed varieties can potentially influence approach to promoting and driving demand for adoption, thus, this study employs a discrete choice approach to elicit preference for DTMV attributes and the implicit price farm households are willing to pay for the attributes. We compare modeling in preference state and WTP space in two states: with and without household interactions using the maximum simulated likelihood estimations of mixed logit model. The hierarchical Bayesian model supports robust analysis of mixed logit model in preference states. Across all mixed logit model estimates (M1–M4), our result shows a common preference for tolerance to drought (high, medium), nitrogen use efficiency (high, medium), yield (very high, high, and medium), and disutility for non-resistance to Striga attribute. Our result recommends the need to consider maize farmers' trait preferences and adequate dissemination to encourage adoption. Streamlining designs of attributes and promotions to account for socioeconomic characteristics can further aid adoption as our study proves that preferences can be socially influenced and thus attributes should be inclined toward interest groups. For example, farm households that are members of agricultural groups prefer early maturing and large grain size attributes. Overall promotion and dissemination through marketing campaigns should be tailored toward incorporating different preferences according to various interest groups.

Data availability statement. The data that support the findings of this study are available on request from the author (Z. O.-U.).

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