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Improving the Use of Experimental Auctions in Africa: Theory and Evidence

Ulrich B. Morawetz, Hugo De Groote, and Simon Chege Kimenju

Experimental auctions have not been widely used in Africa. However, auctions are important tools for evaluating new products and technologies. To increase the quality of these experiments, we explore an alternative first-price bidding mechanism that is more similar to African market exchanges and we analyze factors likely to affect bidding. Experiments with African consumers show that the proposed first-price mechanism has no advantage over conventional second-price mechanisms. Results show high and significant cash-in-hand, experimenter, and time of day effects in main rounds, and significant ordering effects in test rounds. These effects need to be carefully considered when applying the Becker-DeGroot-Marschak mechanism in Africa.

Key words: Africa, BDM mechanism, experimenter effect, first-price auction, income effect, order effect, time of day effect

Introduction

Aid to developing economies is often offered in the form of new technologies–such as functional food for better nutrition, treated mosquito nets, or water pumps–that are intended to improve living conditions for recipients. Unfamiliar technologies may cause intended beneficiaries to view improvements with mistrust or suspicion. *Ex ante* target beneficial valuations of these technologies are important for gauging acceptance and guiding research efforts. For example, crop scientists have developed varieties of maize, sweet potato, and rice fortified with increased provitamin A content to combat worldwide vitamin A deficiency. Enhanced provitamin A levels in crops result from high levels of beta carotene, which gives some foods an unfamiliar yellow or orange color. New varieties of crops with unusual characteristics should be tested for acceptance among target populations to determine if they will be adopted.

Stated preference methods, such as contingent valuation (Kimenju and De Groote, 2008) or choice experiments (Naico and Lusk, 2010), are generally used to determine preferences for new food products. However, unless it is possible to combine stated preferences with revealed preferences (Jayne et al., 1996), the hypothetical nature of these methods is a drawback. To elicit consumer preferences *ex ante* while providing actual incentives, researchers in Western countries often use experimental auctions (Lusk and Shogren, 2007). Applications of experimental auctions in Africa are relatively new, but growing in number. Most have examined food preferences using choice experiments, experimental group auctions. or the auction-like Becker-DeGroot-Marschak (BDM) mechanisms (Becker, DeGroot, and Marschak, 1964). Masters and Sanogo (2002) studied infant

Ulrich B. Morawetz is a doctoral candidate at the University of Natural Resources and Life Sciences (BOKU) in Vienna, Austria; Hugo De Groote is principal economist and Simon Chege Kimenju is an agricultural economist at the International Maize and Wheat Improvement Centre (CIMMYT) in Nairobi, Kenya. This research was made possible through the financial support of the Theodor-Körner-Fonds. The authors received valuable help from two anonymous reviewers, the editor Gary W. Brester, Markus F. Hofreither, Amy Johnson, Carolyne Khalayi, Susanna M. Morawetz, Steve Muasya, Chris Musyoki, Emmanuel Ngumbau, Emmanuel Ngwaa, Peter Nzuki, D. Elisabeth Schwab, Kathleen Sinclair, Stefan Trautmann, Allan Wekesa, and Christoph Weiss. All errors are the responsibility of the authors. A data appendix to replicate the results is available at http://www.wiso.boku.ac.at/ulrichmorawetz.html

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food in Mali using a choice experiment; Rutsaert et al. studied imported rice and local improved rice in Senegal using group auctions; and Kiria, Vermeulen, and De Groote studied quality protein maize in Tanzania using the BDM mechanism. Several other studies analyzed consumer interest in orange maize biofortified with provitamin A. For example, De Groote, Kimenju, and Morawetz (2011) used a BDM mechanism in Kenya, and De Groote et al. used the BDM mechanism, group auctions, and choice experiments to perform a similar study in Ghana.

These studies of consumer preferences have for the most part simply copied methods used successfully in the West without exploring the theoretical and practical ramifications of their application in the context of rural African consumers. Significant differences between Western and African participants have been documented in other research areas using economic experiments: students in Niger were less risk averse but had a higher discount rate than students in China, the United States, and France (Ehmke, Lusk, and Tyner, 2010); farmers in Ethiopia were more risk averse than students in the Netherlands (Akay et al., forthcoming); and inhabitants from small-scale societies with a higher degree of market integration were more cooperative in economic experiments (Henrich et al., 2001). Economic experiments in developing countries are considered a useful tool for understanding how people react to proposed solutions to environmental and development problems (Ehmke and Shogren, 2009). However, the effect of situations specific to rural, developing nations on the application of experimental auctions has not yet been studied. Many factors must be considered when conducting experimental auctions in rural Africa including differences in participants' market experience, income, exposure to games and mass communication, experimenter skills, and a lack of computer resources.

The BDM mechanism is used frequently in auctions in Western countries. In this scenario, a single participant bids against a random number generator and, when his or her bid is higher than the random number, he or she buys the good at a price equal to the randomly drawn number; this type of auction is equivalent to a second-price or Vickrey auction with two participants (Vickrey, 1961).

Our experience with the BDM mechanism and other types of auctions in Africa (specifically Kenya, Ghana, and Tanzania) has led to several concerns. One concern is experimenters often find it difficult to explain differences in paying a random price rather than a bid price to auction participants. African consumers have more experience with first-price auctions in which the winner buys a good at their own (highest) bid price (Cox, Roberson, and Smith, 1982). Therefore, first-price auctions are more intuitive and easier to understand for participants relative to paying a random price that is used in a BDM mechanism. A second concern is the order of presentation of different products in the BDM mechanism. Less-skilled auction participants may be influenced by the order in which products are offered.

A third concern of using the BDM mechanism in Africa relates to ethical issues. In experimental studies involving real money, researchers must avoid pressuring poor participants to buy products with their own money. Thus, researchers commonly pay consumers for their participation and provide them with enough funds to buy the offered products. Participants are often provided 50% to 100% more than a product's price to avoid truncation issues. Although these amounts can represent significant sums of money for poor participants, previous studies have not addressed whether these amounts influence bidding behavior in Africa. Studies in Western countries have found a positive effect of these wealth enhancements on willingness to pay (WTP) for various food products (Rutström, 1998; Loureiro, Umberger, and Hine, 2003; Corrigan and Rousu, 2006). In addition, positive effects have generally been larger than can be reasonably explained by income effects alone.

A fourth concern is that experimenters may influence bidding behavior. Rural African consumers have limited computer experience and access, which often forces researchers to use people to run experiments. The effect of experimenter behavior in developed countries has been documented in laboratory experiments (Venkatesan, 1967) as well as in experimental auctions (Hoffman et al., 1993). In one experiment, the physical attractiveness of a solicitor collecting for a charity influenced willingness to donate (Landry et al., 2006). Experimenters also have crucial influence

Table 1. First- and Second-price Sealed-bid Auction Variants

Price winner pays	Sealed-bid group auctions	Individual auctions
Highest bid	First-price auction	First-price BDM mechanism
Second highest bid	Second-price auction	Second-price BDM mechanism

in hypothetical contingent valuation studies in developing countries (Köhlin, 2001; Whittington, 2002). For experimental auctions in rural Africa where experimenters and participants often have limited experience, the experimenter is even more likely to influence the bidding process. Finally, participants' WTP for food products in rural areas, where many people often do not have enough food, is also more likely to be influenced by the time of day. Rutsaert et al. found that Senegalese rice buyers' WTP declined by more than 50% if auctions occurred following a lunch meal.

Because of these concerns, we analyze the design aspects of experimental auctions that are likely to affect bidding by rural African consumers. We test if a new, first-price variant of the BDM mechanism would change bid averages and variances relative to the conventional, second-price BDM mechanism. We also evaluate product ordering effects and experimenter effects on bids. We test cash-in-hand effects by varying the levels of cash available to participants. Finally, we analyze the effect of the time of day the auction was held.

To our knowledge, this is the first study that focuses exclusively on methodological issues of experimental auctions in Africa and stresses the importance of local circumstances for unbiased measurements of WTP. It contributes to experimental auction theory by introducing a new auction variant, which is useful for comparing behavior in first- and second-price auctions.

Analytical Framework for Auction Design and WTP Elicitation

In Western countries, economists have validated results from experimental auctions by comparing outcomes to results obtained from other elicitation mechanisms, predictions from economic theory, and observed behavior (Lusk and Shogren, 2007). While we assume that the general principles of experimental auctions are universal, consumers in developing countries might face different economic conditions and cultural practices that could, in theory, affect the choice of experimental design and procedures used when conducting these experiments.

Principles and Types of Experimental Auctions

First-price and second-price sealed-bid auctions are conducted with a group of participants who bid against each other for desired goods. In both scenarios, participants' bids are collectively revealed, and the participant with the highest bid wins the auction. In a first-price auction, however, the winner buys the good based on the highest (his or her own) bid; in a second-price auction, the winner buys the good for the second highest bid. This approach is used to elicit a bidder's true WTP. Table 1 illustrates variants of the first- and second-price sealed-bid auction. The BDM mechanism is methodologically equivalent to a second-price auction and is the only common experimental auction mechanism that can be used with individual participants. Rather than competing against other bidders, participants' bids are compared to a random number; if a bid is higher, the participant buys the good at the random number price. To analyze the effect of the second-price procedure in individual auction mechanisms, we developed and tested a first-price BDM mechanism that compares to a conventional BDM mechanism as a first-price sealed-bid group auction compares to a second-price sealed-bid group auction.

Optimal Bidding in Experimental Auctions

The most common and best-known auction is the English auction: bidders sequentially offer ascending bids and the participant who offers the last and, therefore, highest bid wins. The winner buys the good for the last bid offered. On the other hand, sealed-bid auctions require participants to submit sealed bids simultaneously or, at least, bids are revealed simultaneously. In a first-price sealed-bid auction, the participant who submits the highest bid wins the auction and buys the good for an amount equal to his or her bid. English and first-price sealed-bid auctions are both common in Africa. English auctions were introduced by colonial authorities to help market export commodities such as tea, coffee, and tobacco (Houtkamp and van der Laan, 1993). Tea auctions began in 1956 in Nairobi, Kenya, and moved to Mombassa in 1969, where auctions are still held weekly at the Mombasa Tea Center. Coffee auctions in Kenya began in 1934; most Kenyan coffee is still sold at weekly auctions at the Nairobi Coffee Exchange. In addition to export commodities, English auctions are also popular with the Kenyan public as a way to raise funds for charities through selling a wide range of items.

First-price sealed-bid auctions were probably brought to Africa by international organizations. The United Nations, for example, has standard procedures for these auctions in which bids for sales are invited in sealed envelopes. Generally, the highest bid wins the auction, although some restrictions apply (United Nations, 2010). In Kenya, first-price sealed-bid auctions are common in government and non-government organizations for procurement and to dispose of obsolete equipment.

Economists frequently use auctions to determine WTP for goods (v). Experimental auction participants are usually provided with cash-in-hand, e, such that $e > v$ for all participants. However, first-price sealed-bid auctions are rarely used in economic experiments because rational and risk-neutral participants will often bid less than their maximum WTP (Cox, Roberson, and Smith, 1982). Intuitively, the optimal strategy is not to bid one's maximum WTP as gains occur if a participant can pay less than the maximum WTP. However, offering lower bids reduces the chances of winning. Optimal bids also depend on the number of participants and their maximum WTP.

An alternative procedure is a second-price auction in which the optimal bid equals true WTP. In this type of auction, a participant with the highest bid still wins the auction, but buys the good at the second highest bid. The optimal strategy in a second-price auction is to bid one's maximum WTP independent of risk aversion (Cox, Roberson, and Smith, 1982). Second-price auctions are, therefore, incentive compatible (Cox, Roberson, and Smith, 1982).

Standard first- and second-price auctions are group exercises because they require at least two bidders. In areas with dispersed populations, group exercises can be difficult and expensive to organize particularly if stratified sampling requires gathering participants with predefined characteristics. To mitigate these difficulties, a procedure developed by Becker, DeGroot, and Marschak (1964) is particularly suitable for studying rural consumers in areas with dispersed populations. This BDM procedure allows individual participants to bid against a random distribution rather than real opponents.

The BDM mechanism is technically a variant of the second-price auction; the only difference is that the rival bid, r, is drawn from a random distribution rather than from other participants. If a participant's bid, b, is higher than or equal to the randomly drawn bid, r, then the participant wins the auction and buys the good at price r. If a participant's bid is lower than the randomly drawn number, then the participant cannot buy the good and no exchange takes place. The BDM mechanism, like the second-price group auction, is incentive compatible.

First-Price BDM Mechanism, a Variant Closer to Market Bargaining

Estimators that substantially reduce estimation variances can be preferable even if they are biased. For example, farmers may display bias in estimating crop areas. However, asking farmers to estimate crop acres may be more cost-effective than performing an expensive, but unbiased, land survey (De Groote and Traoré, 2005). For this experiment we compare a bidding mechanism that may have a slight bias and lower variance (first-price BDM mechanism) with a mechanism that may have a higher variance but no bias (second-price BDM mechanism).

Bias and variance could potentially differ among countries and cultures. Rural African participants are generally less-educated than participants in Western countries; they have less access to mass communication media, less exposure to a wide range of games, and interact with different market mechanisms. Different cultural contexts might influence behavior in unfamiliar bidding situations. Most Africans, however, have experience negotiating prices in market settings where buyers always pay their highest offer–essentially a first-price mechanism–and many are familiar with English or first-price sealed-bid auctions. We hypothesize that a first-price mechanism reduces bid variance.

The conventional BDM mechanism is a second-price mechanism because winning participants pay the second-highest bid (the random bid). We now consider an alternative BDM mechanism, in which a winning participant pays his own bid, *b*, instead of the randomly determined bid, *r*. This variant can be called a first-price BDM mechanism because it is an individual auction mechanism where the highest price (rather than the second highest price) is paid. As with the first-price sealed-bid group auction, the first-price BDM mechanism is not incentive compatible because participants have an incentive to bid less than their true WTP. The difference between the optimal bid of the first- and second-price BDM mechanisms depends on maximum WTP for the good, the distribution from which participants assume a random bid is drawn, risk aversion levels, income, and cash provided in the experiment.

To date, no studies have compared bidding behavior in first-price and second-price BDM mechanisms, but five studies have compared bidding behavior between first- and second-price group auctions. Two studies found that bids from a first-price auction were higher than those from a second-price auction (Coppinger, Smith, and Titus, 1980; Cox, Roberson, and Smith, 1982). These results might be explained by the limited options of the experimental design (Kagel, Harstad, and Levin, 1987), by heterogeneous risk aversion among participants (Cox, Roberson, and Smith, 1982), or by poor incentives for truthful value revelation (Harrison, 1989). Two later studies found bids from a second-price auction to be higher than those from a first-price auction (Kagel, Harstad, and Levin, 1987; Kagel and Levin, 1993). These studies all used hypothetical products with pre-assigned values.

The only study comparing first- and second-price group auctions in which participants are allowed to present their bids for an auctioned product without interference from an experimenter (home-grown values) did not find a significant difference between first- and second-price auctions (Lusk et al., 2001). This outcome had been predicted for group auctions with many rational, independent, homogeneous, and risk neutral participants using values drawn from a known uniform distribution (Vickrey, 1961). In home-grown value auctions, some participants' maximum WTP can be far from the market-clearing price. These participants can be difficult to engage in sincere bidding in group auctions (Shogren et al., 2001), which affects the elicited mean bids and makes comparison between first- and second-price bidding difficult. The individual first- and second-price BDM mechanisms make it easier to engage participants with a WTP substantially lower than the market-clearing price and might, therefore, create an advantage for comparing first- and second-price bidding. Our experience supports this idea, but we are unaware of any empirical studies comparing participants' sincerity during the BDM mechanism versus second-price group auctions.

Even if bids from a first-price BDM mechanism exhibit a slight bias, the mechanism might still be advantageous if its variance is lower than the variance of a second-price BDM mechanism. Participants in an auction with unfamiliar rules or procedures might potentially continue to act according to rules with which they are more familiar (Plott and Zeiler, 2005). Hence, even if participants are told it is in their best interest to bid their maximum WTP, limited understanding about how the elicitation mechanism works might trigger participants to default to strategies best suited to more familiar first-price auctions. We assume that this hypothesis holds true for some, but not all, participants. In a conventional second-price BDM mechanism, participants who do not grasp the concept might continue to act as if they were participating in a first-price auction. In a first-price BDM mechanism, however, all participants would bid using the same, more familiar strategy. This would then lead to a higher variance in the second-price BDM mechanism provided a substantial difference exists in the first- and second-price BDM mechanism bids as well as equal risk aversion, income and cash-in-hand among participants.

If we assume that v represents maximum WTP for the product among the population and that d is the difference between WTP for the first- and the second- price BDM mechanism, then expected bids from the first-price BDM mechanism are $E(v) + E(d)$. The variance of first-price BDM mechanism is defined as:

$$\text{Var}(b^{1st}) = \sigma. \tag{1}$$

In the second-price BDM mechanism, w is the share of participants bidding as in a first-price BDM mechanism, so the expected bid of the second-price BDM mechanism is $E(v) + wE(d)$. Assuming that N participants bid in the second-price BDM mechanism and the variance within each group is the same, then the total variance is:

$$\text{Var}(b^{2nd}) = \sigma + (1 - w)(-wE(d))^2 + w((1 - w)E(d))^2. \tag{2}$$

If at least one participant bids "incorrectly" in the second-price BDM mechanism ($w > 0$), Var(b^{2nd}) is greater than Var(b^{1st}).

However, this difference is reduced if participants have heterogeneous risk aversion levels, incomes or cash-in-hand. The variance of the first-price BDM mechanism is susceptible to these characteristics while the variance of the second-price BDM mechanism is not. Without further assumptions about consumer preferences, it is impossible to tell whether Var(b^{2nd}) is actually larger than Var(b^{1st}). We address this question empirically after clarifying the role of experimental design variables.

WTP as a Function of Experimental Design Variables

Order Effects

In the previous section we assumed maximum WTP, v, to be independent of experimental design variables. That is, v is determined only by consumer characteristics, z, and characteristics of the good, x; $v = v(x,z)$. This relation has been the subject of all other experimental auction studies in Africa. We extend this relation and allow for v to depend on experimental design variables as well.

All experimental auctions in Africa to date have used the "within participant" design, in which each participant bids for all (not just one) of the products included in the study. Order effects occur if the order of product presentation influences WTP. Lusk and Shogren (2007) suggest that order effect are influenced by learning while bidding and by participant fatigue. If WTP for a good depends on the order of presentation, WTP becomes $v = v(x,z,o)$, where o represents order as a number between 1 and the total number of possible orders of presentation.

Cash-in-Hand Effects

In the theoretical optimal bidding model, personal income and money provided in the experiment do not play a role in optimizing the second-price BDM mechanism (Irwin et al., 1998). However, several authors have shown that maximum WTP depends on income and, thus, on cash-in-hand (e.g., Hanemann, 1991).

In high-income countries, researchers have found that differences in participation payments resulted in differences in WTP for chocolates (Rutström, 1998), cookies (Loureiro, Umberger, and Hine, 2003), and chips and salsa (Corrigan and Rousu, 2006). However, the estimated effects were too large to be reasonably explained by income effects. In low-income countries, participation payments can create relatively large changes in income, making an income effect more plausible. Additionally, experiments often include a test round to familiarize participants with bidding procedures. If a participant wins and pays for the test round product, his or her cash-in-hand is reduced. This potential outcome can affect a participant's bid and resulting mean WTP. This situation can be modeled by making WTP for a good depend on income, y, and cash-in-hand, e; such that, $v = v(x, z, o, y, e)$.

Experimenter Bias Effects

Consumers estimate the value of a good based on, among other things, information available to them. In experimental auctions, participants have pre-existing information that comes from past personal experience represented by participant characteristics, z. Additional information is provided by the experimenter; this information, although usually standardized, will differ slightly from experimenter to experimenter, especially if the experimenter must rephrase instructions for participants. These differences have been called experimenter effects and can originate from both visual and verbal cues (Venkatesan, 1967). Experimenter effects have been documented in experimental auctions in the West (Hoffman et al., 1993) and contingent valuation studies in developing countries (Köhlin, 2001; Whittington, 2002). To analyze the experimenter effect in experimental auctions in Africa, we note that maximum WTP for a good depends on the experimenter, q, such that $v = v(x, z, o, y, e, q)$.

Time of Day Effects

Experimental auction bids can change throughout a day. For example, bids for vacuum-packaged beef in the United States were not the same at various times of the day (Hoffman et al., 1993), while bids for rice in Senegal were found to be higher in the morning (Rutsaert et al.). This phenomenon may reflect differences in participant samples, but could also reflect real differences in valuation that depend on time. Such differences could be related to unfulfilled shopping plans, hunger, fatigue, or schedule. Participants who intend to buy a product or a close substitute, as well as participants who are hungry, might value a food item more highly (Hoffman et al., 1993; Rutsaert et al.). Higher bids as a result of hunger are particularly plausible for ready-to-eat food. On the other hand, if the good auctioned is either non-food or food that cannot be eaten right away, a hungry participant might prefer to spend the money on a snack from a nearby shop and, therefore, bid lower. The influence of time of day on valuation as a result of unfulfilled shopping plans or hunger can be noted as $v = v(x, z, o, y, e, q, t)$, where t represents time of day.

An alternative explanation for the influence of hunger on bidding is the relationship between the metabolic state of a participant and decision-making under risk. Hungry participants are less risk averse (Symmonds et al., 2010), so they likely bid lower in a first-price BDM mechanism. Similarly, risk aversion could also be influenced by other stress-generating circumstances such as tiredness or discomfort.

Experimental Design

De Groote, Kimenju, and Morawetz (2011) estimated Kenyan consumers' WTP for yellow and fortified maize meal to better understand acceptance of new, vitamin fortified, maize varieties developed by the International Maize and Wheat Improvement Center (CIMMYT). We use data from this study to examine differences between first-price and second-price BDM mechanisms, as well as presentation ordering, cash-in-hand, experimenter, and time of day effects. Acceptance of new yellow maize varieties is of particular concern because white maize is the main food staple in most of Eastern and Southern Africa, and many consumers associate yellow maize with livestock feed and imported food aid for the poor. The quality of some of those varieties deteriorate after long storage and if improperly handled (Muzhingi et al., 2008). Nonetheless, new vitamin fortified varieties, although yellow in appearance, are more nutritious than traditional white varieties.

Survey Tools and Sampling Design

We conducted a series of first- and second-price BDM mechanism experiments using the "within participant" design to study Kenyan consumers' bidding behavior. Participants were assigned in alternating order to first-price and second-price BDM mechanisms; half of the participants were assigned to each group. We explained the procedure to participants and emphasized that transactions would be executed if a participant's bid was higher than the random number. To help participants understand the procedure, we organized a test round using cupcakes. Each participant was provided with 25 Kenyan Shillings (KShs) (US$1=KShs75 in 2009) and asked to bid for three types of cupcakes, one at a time, with information about the flavor of each cupcake provided before bidding.

Participants stated their bids for the first type of cupcake and the procedure was repeated for the other two types. One of the three rounds was randomly assigned to be binding, and the bid for this round was compared to a number that was randomly drawn from a normal distribution with a mean of 10 and a standard deviation of 3, N(10, 3). When the bid was higher than the randomly drawn number, the participant bought the cupcake. For the first-price BDM mechanism, the purchase price was the same as the bid he or she had offered. For the second-price BDM mechanism, the purchase price was the randomly drawn number. Participants kept the remainder of the money that they did not spend and time was provided for answering questions.

During the actual auction, participants were provided with KShs105 and then presented with three types of maize meal: plain white, fortified white, and plain yellow. Plain white meal is ordinary meal without added nutrients. Fortified white meal is an industrial meal nutritionally enhanced with vitamins A and B, zinc, and iron, and was purchased at a local market. Plain yellow meal is milled from yellow maize and is not locally available to participants. All three meal products were presented as two-kilogram packages in plain brown paper bags.

The three products were presented in random order to participants who were educated about their characteristics and allowed to inspect the meal. We offered the different meal types in alternate order to test for order effects. However, fortified white meal was never offered before plain white; this allowed us to first measure the valuation of plain white maize meal as a benchmark. Participants were asked to bid for the first product, which the experimenter recorded, and the procedure was repeated for the other two products. To reduce costs and avoid the effects of reduced marginal utility over the rounds, only one of the rounds, randomly assigned, was binding. The bid from that round was compared to a number drawn randomly from a normal distribution N(86,25). If the participant's bid was higher than the random number, the participant bought the maize meal and paid either his or her bid (first-price BDM mechanism) or the randomly drawn number (second-price BDM mechanism).

Date, Location and Sampling

The experiments were conducted in Machakos Town in the Eastern Province of Kenya. We approached 151 consumers from local maize mills, shops, and supermarkets; approximately equal numbers of participants came from each location. In each selected outlet, we approached every third consumer and asked them for an interview. When they agreed (almost always), the interview was conducted on the spot. The interviews took place between August 28 and September 1, 2009, and were conducted by six experimenters who were trained to administer the questionnaire and implement the BDM mechanism. The experimenters were supervised by the authors.

The Empirical Model

Each participant submitted one bid for each type of meal. When more than one observation per participant is recorded, the individual specific error needs to be incorporated in the error term of a regression model. Fixed and random effects estimators are commonly used for such models. For orthogonal experimental designs like ours, the estimated coefficients for ordinary least square, fixed effects, and random effects regression models are the same, but standard errors do not represent the error structure correctly in the ordinary least squares regression (Oaxaca and Dickinson). We prefer the random effects model because, unlike the fixed effects model, it allows estimation of coefficients for variables that do not change between rounds.

In experimental auctions, the lowest possible bid is zero although some participants may prefer to bid a negative value. Thus, bids are censored at zero. Similarly, if participants do not bid more than the market price for the good, even though they may value it more highly, bids are censored from above. Estimated parameters will be biased in the random effects model if censored and uncensored observations are treated identically. The Tobit model (Tobin, 1958) is the standard method for analyzing censored data and can also be combined with the random effects model.

The observed bid by participant i for maize meal j, $b_{i,j}$, can be explained by a participant's WTP for the meal and by a strategic reduction of the bid (in the case of a first-price BDM mechanism). Participants' WTP are modeled as a function of maize meal characteristics (plain white, fortified white or plain yellow), represented as two dummy variables in vector $\boldsymbol{x}_j$, which represents either plain yellow or fortified white meal. The experimental design variables are bundled in a vector, $\boldsymbol{k}_j$, which consists of one binary variable for the BDM mechanism (first- or second-price), two binary variables for the order of presentation, one continuous variable for cash-in-hand (in KShs), five binary variables for the different experimenters, one continuous variable for the time of day, and one binary variable for time of day to control for the lunch time effect. The "short" model is specified as:

$$b_{i,j} = \alpha + \boldsymbol{\beta}'\boldsymbol{x}_j + \boldsymbol{\gamma}'\boldsymbol{k}_i + \mu_i + \varepsilon_{i,j}, \quad \text{for all } i \text{ and } j, \tag{3}$$

where α is a constant, $\boldsymbol{\beta}$ is the vector of the coefficients for the product characteristics, and $\boldsymbol{\gamma}$ is the vector of the coefficients for variables of the experimental design. The overall error is split into the participant specific part, μ_i, which captures those participant characteristics that influence value, and the idiosyncratic part, $\varepsilon_{i,j}$.

Most applied research emphasizes estimating $\boldsymbol{\beta}$, which measures differences in WTP for each product characteristic. Our emphasis is on analyzing the effect of the experimental design included in the vector of design variables $\boldsymbol{k}_j$. In the short model, this effect is assumed to be identical for all product characteristics. However, if the influence of experimental design variables differs for particular product characteristics, the estimated model must include relevant cross terms. This "long" model is specified as:

$$b_{i,j} = \alpha + \boldsymbol{\beta}'\boldsymbol{x}_j + \boldsymbol{\gamma}'\boldsymbol{k}_i + \boldsymbol{k}_i'\boldsymbol{C}\boldsymbol{x}_j + \mu_i + \varepsilon_{i,j}, \quad \text{for all } i \text{ and } j, \tag{4}$$

where $\boldsymbol{C}$ is a matrix of the coefficients of the cross effects of design variables, $\boldsymbol{k}_i$, with product characteristics, $\boldsymbol{x}_i$.

To test the hypothesis that the variance of the first-price BDM mechanism is smaller than the variance of the second-price BDM mechanism, we apply the robust Brown-Forsythe test (Brown and Forsythe, 1974). The hypothesis is that the ratio of the variance of the bids from the second-price BDM mechanism to the variance of the bids from the first-price BDM mechanism is equal to

Table 2. Participant Characteristics (N=151)

	Mean	St. Dev.
Age (years)	35.5	12.7
Male (%)	35.1	47.9
Formal education (years)	11.1	3.5
Cattle owned (number)	2.8	5.3
Maize harvest per ha (t)	0.6	0.9
Has eaten yellow meal before (%)	92.7	26.1
Aware of night blindness (%)	86.1	34.7
Aware of vitamins (%)	95.4	21.1

one. Because a higher variance could be caused by nuisance effects of other variables, we apply the Brown-Forsythe test for the residuals, $\mu_i + \varepsilon_{i,j}$, obtained from an OLS regression of equation (4) that excludes dummy variables for the first-price BDM mechanism. The residuals can be interpreted as bids net of the explanatory variables and are, therefore, expected to contain smaller nuisance effects.

Tests of order effects were conducted for the test round, as well as for the main experiment. The means of the bids in different rounds were compared using Welch tests; for the main round, the joint significance of order was also tested with a robust F-test of the regression coefficients.

All data analysis was done in R (R Development Core Team, 2011). The random effects model was estimated with the package "plm" (Croissant and Millo, 2008) and the Tobit model with the package "censReg" (Henningsen, 2011). The statistical significance of the coefficients were tested with heteroskedasticity consistent t- and F-tests from the packages "lmtest" (Zeileis and Hothorn, 2002) and "sandwich" (Zeileis, 2004, 2006).

Results

Study Area and Participants

The Machakos district in eastern Kenya is located in a transitional zone between the highlands and the dry mid-altitude zone, an area that experiences low average rainfall with high variability. Poverty levels are estimated at 60% (Central Bureau of Statistics, 2003). The district capital, Machakos Town, is connected to Nairobi to its northwest by 60 kilometers of paved road. The exact number of inhabitants of the town is difficult to estimate, but the 2009 population census indicates that there are around 100,000 inhabitants in the urban center (Kenya National Bureau of Statistics, 2010). Machakos Town is an important administrative center and market for agricultural products.

Table 2 presents summary statistics for participants in the first- and second-price BDM mechanisms. Average age was thirty-six and approximately two-thirds were female. The high proportion of women is a result of the selection procedure: participants were chosen at the outlets where they shop for maize meal–a chore for which women are predominantly responsible. Participants had, on average, more than eleven years of formal education. Therefore, most participants were likely able to understand the BDM mechanism. On average, participants owned 2.8 head of cattle, an important wealth indicator, but this was highly variable. The most striking observation is the low average maize yield (0.6 metric tons/hectare), a result of the 2008/09 drought. Most participants were familiar with characteristics of the auctions goods: 93% had previously consumed yellow maize, 86% were aware of night blindness (which is caused by vitamin A deficiency), and 95% knew of the existence of vitamins.

Table 3. Participant Bids (All Numbers in KShs)

BDM mechanism variant	First-price (N=75)		Second-price (N=76)		Both (N=151)	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
Bids in 1st test round	10.7	3.5	11.3	3.1	11.0	3.3
Bids in 2nd test round	9.0	3.5	9.0	3.0	9.0	3.2
Bids in 3rd test round	7.6	3.1	7.5	3.3	7.6	3.2
Bids plain white 2 kg meal	76.0	15.2	77.2	13.6	76.6	14.4
Bids fortified white 2 kg meal	90.3	19.6	89.1	18.8	89.7	19.2
Bids plain yellow 2 kg meal	69.3	21.6	67.6	20.3	68.5	20.9

Test Rounds and Unconditional Bids

Table 3 presents the means and standard deviations of participants' bids in both the first-price and second-price BDM mechanism. No difference was found between the mean bids of the first- and second-price BDM mechanisms in either the test rounds or the main rounds; equality was not rejected at a 5% significance level. However, there was a clear order effect in the test round bids: average WTP decreased from the first type of cupcake offered to the last; these differences were all statistically significant. Conversely, we did not find that order of presentation had any influence on bid during the main round. Pair-wise Welch tests of equality of the means were not rejected on a 5% level for all meal types. Statistically significant differences were found for the mean bids for all three maize meal types. Mean bids for plain white meal (KShs76.6) were lower than those for fortified white meal (KShs89.7) but higher than those for plain yellow meal (KShs68.5).

Model Estimation

Conditional influence of the experimental design variables was tested using the regression results for equations (3) and (4). Table 4 shows the coefficients and robust standard errors for all experimental design variables and their cross terms estimated in the random effects model. Participants might be hesitant to offer bids much higher than market price, so we also estimated a Tobit model censored at the market price. The main findings remained the same (results are available from the authors on request). No participants offered zero bids, so there was no censoring at zero.

Bidding Differences in First- and Second-Price BDM Mechanisms

The binary variables for the first-price BDM mechanism are not significantly different from zero for the short or long model. Therefore, we cannot reject the hypothesis that bids in a first- and second-price BDM mechanism are equal. The F-test on the common significance of all main and cross effects indicates that the hypothesis of equal bids in the first- and second-price BDM mechanism cannot be rejected ($F_{420;3}$-statistic of 0.96 and a p-value of 0.41).

Theoretical differences between first- and second-price BDM mechanism bids are needed to calculate type II errors. Theoretical differences can only be assumed because they depend on the unknown true WTP for the products, the unknown utility function, and the unknown assumptions of participants about the random distribution. If the theoretical bids from the first-price BDM mechanism were 10% lower than the mean of bids from the second-price BDM mechanism, the type II error would be 0.006 for the short model. For the long model, the type II error would be 0.09 for the main effect, 0.0004 for the cross effect with fortified white, and 0.014 for the cross effect with plain yellow. For the conventional significance level of 0.20 for type II errors, we conclude that there is no difference greater than 10% between bids from the first- and second-price BDM mechanism.

Table 4. Results of Random Effects Model Regression

	Short model		Long model	
	Coeff. Est.	**St. Error**	**Coeff. Est.**	**St. Error**
Intercept	20.18	29.36	64.84	35.04
fortified white	13.08	1.20***	−24.29	30.7
plain yellow	−8.13	1.54***	−104.73	37.84**
First-Price BDM mechanism (yes=1)	1.63	2.25	−0.80	2.31
x fortified white			2.70	2.31
x plain yellow			4.59	2.94
Order of presentation: W,Y, WF	1.75	2.39	2.75	2.58
x fortified white			4.43	2.79
x plain yellow			−7.45	3.84*
Order of presentation: Y, W, WF	0.51	2.80	−0.02	2.79
x fortified white			4.19	2.91
x plain yellow			−2.58	3.46
Cash at Maize BDM Mechanism (KShs)	0.60	0.23**	0.22	0.26
x fortified white			0.32	0.21
x plain yellow			0.84	0.26**
Experimenter 2	−8.99	3.81*	−7.32	4.08
x fortified white			2.78	3.89
x plain yellow			−7.79	4.35
Experimenter 3	11.32	3.11***	9.91	3.27***
x fortified white			1.42	3.37
x plain yellow			2.80	4.77
Experimenter 4	7.65	3.53*	4.89	3.53
x fortified white			8.74	2.93***
x plain yellow			−0.48	5.39
Experimenter 5	3.94	3.48	2.01	3.61
x fortified white			7.33	3.42*
x plain yellow			−1.54	3.74
Experimenter 6	1.91	2.95	0.26	3.01
x fortified white			−1.19	3.32
x plain yellow			6.14	3.72
Afternoon (yes=1)	14.35	4.93***	9.52	5.11
x fortified white			7.29	6.01
x plain yellow			7.19	6.63
Time of day (hours)	−2.29	1.02*	−1.65	1.02
x fortified white			−0.99	1.1
x plain yellow			−0.93	1.24
Share var.: idiosync.; individual	0.55	0.45	0.52	0.48
θ; Adj. R^2 (within)	0.46	0.36	0.49	0.41
Participants; Observations	453	151	453	151

Notes: *, **, and *** specify significance at the 10%, 5%, and 1% levels. Experimenter dummies: Experimenter 1 is reference. Auction Order dummies are "W"=plain white, "WF"=fortified white, and "Y"=plain yellow. Order "W, WF, Y" is reference.

If there is no difference between the bids in the first- and the second-price BDM mechanism, then the variance in the second-price BDM mechanism is not affected by limited understanding among some participants. The variance could be larger in the first-price auction if the participants have heterogeneous risk aversion, income or cash-in-hand. Table 5 compares the variances of the

Table 5. Comparison of Variances From First- and Second-price BDM Mechanism, Using Robust Brown-Forsythe Test (H_0: Ratio of Variance is One)

	Ratio of variances[a]	95% Confidence Interval	F-stat.	Degr. of Freed.	p-value
Bids	0.9	[0.69; 1.17]	0.38	451	0.54
Residuals[b]	0.95	[0.73; 1.24]	0.02	451	0.89

Notes: [a] Ratio of variances is calculated as the second- over the first-price BDM mechanism.
[b] Residuals are from a regression as in equation (4), but without a dummy for the first-price BDM mechanism. They can be interpreted as bids with netted out effect of the other experimental design variables.

first- and second-price BDM mechanism using a robust Brown-Forsyth test. The estimated ratio of the variance of the second-price BDM mechanism to the variance of the first-price BDM mechanism is 0.90. The F-test does not reject the hypothesis that the ratio of the variances is equal to one. For the residuals, we find a ratio of 0.95 and a p-value of 0.89, indicating that the difference in the variances is even smaller prior to netting out the influence of the experimental design variables.

The Effect of Product Ordering

For the short model, the dummy variables for order of presentation for each product type were individually insignificant at a 5% level. The dummy variables were also jointly insignificant as the $F_{441;2}$-statistic was be 0.30 (p-value of 0.74). For the long model, the $F_{423;6}$-statistic of joint significance is 2.10 (p-value of 0.06) and, therefore, is not significant at a 5% level. The individual dummy for plain yellow meal presented before fortified white was significant at the 10% level. The presence of order effects in the test round, but not in the main round, demonstrates the importance of conducting test rounds to familiarize participants with auction procedures.

Cash-in-hand Effects

All participants were given KShs25 before the test round and KShs105 before the main round. Cash-in-hand at the beginning of the main round varied among participants because some had spent some money in the test round. The average expense in the test round was KShs3.6, leaving the average participant with KShs21.4 (standard deviation 5.5). Low average expenses are explained by the fact that only a third of participants won the test round and had to pay for their cupcakes. Among participants who won a test round, the mean expense was KShs11 (8.5% of the total participation payment).

The coefficient for cash-in hand was positive and significant on a 5% level in the short model (Table 4). In the long model, dummies for cash-in-hand were jointly significant, as the $F_{3;420}$-statistic was 6.7 (p-value less than 0.01). This result, however, is driven by the significant positive effect of the plain yellow meal. For every extra KShs1 available to participants at the beginning of the main experiment, the average bid for plain yellow meal increased by KShs0.84 (95% confidence interval of [0.33; 1.36]) compared to the average bid for plain white meal. This influence of cash-in-hand is important for interpreting the large and negative coefficient for plain yellow meal (KShs-104.73). Participants who spent all of their money in the test round were left with KShs105 for the actual round. Their cash-in-hand effect was KShs111.35. Participants who spent no money in the test round were left with KShs130 in the actual round, and the cash-in-hand effect was KShs137.87. In both cases WTP for yellow maize meal is positive. This result suggests that cash-in-hand can influence bidding for some products. In our case, cash-in-hand influenced bidding on the inferior plain yellow maize meal. Consequently, unconditional WTP estimates are susceptible to manipulation even in a "within participant" design.

Experimenter Bias Effect

Regression results show significant effects of different experimenters. F-tests for the experimenter variables reject the hypothesis of equal bids for different experimenters in both models (for the short model the $F_{444;6}$-statistic is 5.6 and for the long model the $F_{432;15}$-statistic is 4.90, with both p-values smaller than 0.01).

Coefficients in table 4 indicate substantial differences among bids collected by different experimenters. In both models the differences were largest between Experimenters 2 and 3, with differences of KShs20.31 (27% of the average bid) for plain white meal for the short model and KShs17.24 (22% of the average bid) for the long model. The cross effects show that Experimenters 4 and 5 collected significantly different bids (at a 5% level) for fortified white maize compared to plain white maize meal. For Experimenter 4 this difference was as high as KShs8.74 (11% of the average bid for plain white meal).

Because experimenters influence the bidding for different meal types in different ways, mean comparisons are suspect even for "within participant" designs. The unconditional average estimated WTP for product characteristics depends on the number of experiments that were executed by different experimenters.

Time of Day

We used two variables to measure the influence of time of day. We included a dummy variable for "afternoon" if the interview started after 1pm and a continuous variable giving the time when the interview started. The joint effect of these variables was significant in the short model ($F_{441;2}$-statistic was 4.58 with a p-value of 0.01) at a 5% level but not in the large model ($F_{423;6}$-statistic was 1.62 with a p-value of 0.14).

Conclusions

Researchers in rural Africa often encounter difficulties that their counterparts in Western countries do not. In this paper, we analyze the individual BDM mechanism, which is particularly easy to apply in these circumstances because of its flexibility.

Our comparison of two variants of the BDM mechanism revealed that differences in mean bids were no higher than 10%. We can interpret this in one of two ways: either participants bid their maximum WTP or they bid strategically lower. Which of the two is true does not matter for "within participant" design, since we did not find a difference in how auction type influences bidding for different meal types. Our new first-price BDM mechanism would be interesting to researchers if it had a substantially lower variance than the standard second-price BDM mechanism, but we found no such evidence. Consequently, bidding in our new first-price BDM mechanism does not only result in similar mean estimates, but also similar variances. We recommend using the usual second-price BDM mechanism as it has the additional advantage of being theoretically incentive compatible.

The circumstances in which experiments in rural Africa are conducted differ greatly from those in Western countries. Our evidence is mixed as to whether experimental design variables influence the bidding process under these circumstances and cause WTP estimates to be suspect. We found that order of presentation had no significant influence on WTP in the main rounds, but did have an influence in the test rounds. Thus, test rounds are crucial when using inexperienced participants in experimental auctions.

We also found that cash-in-hand increased WTP for plain yellow maize meal, but had no apparent effect on other products. This could be because consumers perceive plain yellow meal as an inferior good. The important conclusion is that cash-in-hand can matter and researchers should perform sensitivity analyses when conducting similar experimental auctions. Alternatively, if researchers conduct test rounds, they should make sure each participant has the same cash-in-hand for the main experiment. This could be achieved by not actually executing purchases in the test round. Alternatively, cash-in-hand amounts could be adjusted after the test round by compensating participants for money spent. Finally, care should be given to assure that amounts of cash distributed for the test round are small relative to cash distributed for the main experiment.

Experimenter effects clearly influence estimated WTP. In addition to intense training and translation of the questionnaires into local languages, we suggest that researchers include main and cross effect variables for experimenters in their regression models to reduce experimenter effects before making *ceteris paribus* conclusions.[1]

We also found evidence that time of day influenced bidding. Unlike other studies, we do not have a particular explanation for this effect. We consider it important for researchers to test and report these effects as a standard practice in the future.

Many issues still remain to be explored for developing best practices for experimental auctions. Researchers should document as many variables and circumstances as possible to evaluate possible effects and refine experimental procedures. Among issues yet to be explored are the size of the auction audience, storage of auctioned goods, or validity tests such as those developed by Corrigan and Rousu (2008). If researchers carefully record all potentially relevant circumstances, the BDM mechanism is a suitable and convenient method for *ex ante* valuations in poor countries.

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[1] See Whittington (2002) for further issues on training experimenters in developing countries.

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