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# Understanding inconsistencies in risk attitude elicitation games: Evidence from smallholder farmers in five African countries

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ABSTRACT

Recent empirical studies eliciting farmers' risk attitudes through lab-in-the-field experiments have reported high levels of inconsistency in responses. We investigate inconsistencies in risk attitudes elicitation games using data from incentivized lotteries involving 2,319 smallholder farmers from Eastern Africa (Kenya, Uganda, Tanzania) and Northern Africa (Tunisia, Morocco). Our sample demonstrates high levels of inconsistent behavior, with 48 % of the farmers exhibiting some type of inconsistency. Depending on the country, inconsistencies are explained by poverty, gender, and/or the interaction of gender and level of education. We find no significant impact (negative or positive) of education alone in all but one country model. Furthermore, we find session fixed effects to significantly explain inconsistencies in many cases, suggesting that session-specific circumstances, including inconsistencies across enumerators, play a crucial role in the successful implementation of these experiments. Our findings suggest that using risk attitude parameters without accounting for the presence and the potential causes of inconsistency may lead to unreliable results. This study may guide practitioners in identifying farmer typologies more prone to inconsistent decisions and inform policymakers about factors influencing operators' choices.

## 1. Introduction

Understanding farmers' risk preferences in developing countries is crucial for both research and policymaking. For instance, risk preferences significantly influence the adoption of agricultural innovation (Wong et al., 2020; Love et al., 2014; Karlan et al., 2014; Cole et al., 2013). Risk-averse farmers may avoid or delay the adoption of new technologies due to financial risks and other concerns, such as those related to climate change (Holden, 2015; Liu, 2013; Ross, 2012).

Due to their crucial role in farmers' investment decisions, risk preferences have been extensively studied by economists, using various elicitation methods, spanning from survey questions related to risk-taking (He et al., 2018; Chuang & Schechter, 2015; Coppola, 2014; Dohmen et al., 2011; Anderson & Mellor, 2009), whereby participants report their willingness to take risks or their self-reported risk perception across several domains, to incentivized lottery choice experimental designs, such as binary choice lists or multiple price lists (Holt & Laury, 2002). The latter consist in ordered arrays of binary lottery choices presenting different levels of risk and expected outcomes, and have become the most popular risk elicitation technique in recent years (Bruns et al., 2022; Friedman et al., 2022; Engel & Kirchkamp, 2019; Charness et al., 2018; Brauw & Eozenou, 2014; Louis et al., 2012; Booth & Katic, 2013; Jacobson & Petrie, 2009; Andersen et al., 2008).

Economic theory suggests that, in lottery experiments, rational individuals with a concave utility function should switch to riskier options as the expected payoff increases compared to the payoff of less risky

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ones, and should not switch back again (He et al, 2018; Jacobson and Petrie, 2009; Laurent et al, 2007; Holt and Laury, 2002).[a] However, such experiments often produce responses that are inconsistent with theory (see, among others, Estepa-Mohedano & Espinosa, 2023; Brunette & Ngouhouo-Poufoun, 2022; Finger et al., 2022; Bruns et al., 2022; Charness et al., 2018; Gary et al., 2018; Chuang & Schechter, 2015; Hirschauer et al., 2014). Inconsistent choices are particularly common in experiments conducted in the field with non-standard subjects (Jacobson & Petrie, 2009), and even more in developing countries (see, for instance, Bejarano & Galarza, 2016; Charness & Viceisza, 2011). The traditional approach has involved removing inconsistent individuals from the sample or making additional assumptions to replace their choices with consistent values (Engel & Kirchkamp, 2019). However, identifying the reasons behind such inconsistencies would help prevent them, enhancing the reliability of experimental results and improving outcomes for the subjects making inconsistent decisions (Prasad & Salmon, 2013).

Despite the high incidence of inconsistent choices, only a few studies have investigated their determinants. Many of these studies are conducted in developed countries, commonly in a laboratory setting with students (namely, Gary et al., 2018; Charness et al., 2018; Bejarano & Galarza, 2016; Hirschauer et al., 2014), raising concerns about external validity (Gary et al., 2020). And although some field-experimental studies have been conducted with rural dwellers in developing countries (for instance, Estepa-Mohedano & Espinosa, 2023; Bruns et al., 2022; He et al., 2018; Ihli et al., 2016; Jacobson & Petrie, 2009), they focus on a single country case, limiting the generalizability of their findings across different contexts and larger populations.

Our study contributes to the literature on inconsistent responses in risk elicitation games by investigating their determinants among smallholder farmers from three Eastern (Kenya, Uganda, Tanzania) and two Northern African countries (Tunisia, Morocco). We rely on data from incentivized field experiments with 2319 smallholders. Our research goal is twofold:

i. investigating the presence of different types of inconsistencies and how it differs across countries,
ii. identifying the factors potentially linked to these inconsistencies.

Pursuing these two objectives will further help us understand, from an operational perspective, how these inconsistencies and their determinants can be addressed to improve the validity of field experiments.

We build on a strand of the literature that links inconsistent choices to the lack of cognitive abilities as well as poverty. The lack of cognitive abilities, inversely related to the level of education (Van Hootegem et al., 2023; Carlsson et al., 2015; Barone & Van de Werfhorst, 2009; Kerckhoff et al., 2001), can cause difficulties in information processing, logical reasoning, and problem-solving (Adam et al., 2022; Amador-Hidalgo et al., 2021; Andersson et al., 2016; Baldi et al., 2013; Cook et al., 2013). Individuals with lower levels of education may not grasp complex lottery tasks well, opposite to those with higher education, leading to our first hypothesis:

**H1**. *The level of education is a significant negative predictor of inconsistent choices.*

Poverty generates stress and consumes mental resources due to the difficult task of surviving and dealing with multiple, very concrete issues (Kaur et al., 2021; Mani et al., 2013; Banerjee & Duflo, 2007, 2011; Spears, 2011). In turn, stress may negatively affect attention and patience in completing tasks, including complex experimental tasks (Bruns et al., 2022; Franco, 2015; Haushofer & Fehr, 2014; Cook et al. 2013). Poor individuals can be identified through the share of money spent on food (Deaton, 2006; Duflo, 2006). Thus, our second hypothesis is:

**H2**. *Poverty, measured as the share of income spent on food, is a significant positive predictor of inconsistent choices.*

In addition to education and poverty, we explore the impact on inconsistent behaviors of gender and the implementation context, which includes the country and the experimental session (i.e., the specific data collection occurrence, with its climate, room setting, experimental team, etc.). First, there is evidence that women are more prone to inconsistencies (Charness et al., 2018; Charness & Viceisza, 2011; Jacobson & Petrie, 2009). Second, while poverty affects all household members, it may particularly impact the stress levels of household heads and main caregivers, which are often women (Hjelm et al., 2017; May & Norton, 1997). For these reasons, we not only investigate the impact of gender per se but also its interaction with poverty and, as a more exploratory analysis, education levels.

Concerning the context, studies conducted in different countries have highlighted different levels of inconsistencies, from 41 % among South African fishing communities (Brick et al., 2012) to 75 % in rural Senegal (Charness & Viceisza, 2011), suggesting that we must control for country effects in our cross-country sample. Instead, to the best of our knowledge, the effect of the session has not been explicitly investigated.

Our analysis reveals two types of inconsistencies, which are not mutually exclusive: "*multiple switches*", which consists in switching more than once between riskier and less risky options, contradicting the economic theory on concave utility functions, and "*primitive choice*", which consists in selecting the less risky option even when selecting the other one would maximize the payoff with certainty, which contradicts the hypothesis of rationality of economic agents.[b] The former is committed by around one third of the sample, the latter by one quarter, resulting in 48 % of our sample committing some types of inconsistencies, with much higher incidence in Eastern Africa. While we find no relationship between education or poverty and inconsistencies in the cross-country sample, these variables, as well as gender and the interaction of gender and level of education, significantly explain inconsistencies in specific countries. For instance, poverty is positively related to inconsistencies in Kenya, women are more prone to inconsistencies in Uganda, and the interaction between education and gender yields non-trivial effects. Besides identifying significant cross-country differences, we find that in each country sample as well as in the pooled dataset, session-fixed effects significantly explain inconsistencies, pointing to the role of the context (which could have resulted in different levels of attention), including the enumerators, in properly explaining the experiment.

The rest of the paper is structured as follows. Section 2 describes our sampling strategy, experimental interventions, and empirical approaches. Section 3 presents and discusses descriptive statistics and the results of the multivariate analysis. Section 4 summarizes and concludes.

## 2. Material and methods

### 2.1. Sampling strategy

Our data were collected from specific rural regions in five African countries (Kenya, Morocco, Tanzania, Tunisia, Uganda), as part of an international research and innovation project.[c] The regions and their geographical sizes were purposively selected by local partners based on

[a] Extremely risk-loving individuals may choose the riskier option from the start.

[b] These as well as other types of inconsistencies are explained more in detail in Section ↱↱2.2 as well as Appendix 2.

[c] EU Horizon 2020 FoodLAND "FOOD and Local, Agricultural and Nutritional Diversity" (2020-2025).

the characteristics of the local agriculture, and its suitability for the innovations being developed within the project. In each region, the project aimed to establish so-called "Food Hubs," where farmers and local stakeholders (i.e., researchers, processors, associations, and NGOs) collaborated to create organizational and operational conditions favorable to the adoption of innovations. Therefore, the goal was not to achieve representativeness at the country level, and our results should not be used to make inference on the composition or behaviors of the entire country's population. Nevertheless, the relationship *between* variables that we detect may well extend beyond the sampling regions.

Each Food Hub has different geographical characteristics. One consists of a single village (Ndole, Mvomero district, Tanzania); three of different villages within a single district (districts of Meknès, Morocco; Mukurweini, Kenya; and Jendouba, Tunisia); and one includes various villages from different districts (districts of Kamuli, Lwengo, Masaka, Mukono, Nakaseke and Wakiso, Uganda).[d] The focus was on crop farmers, except in Uganda, where fish farmers were involved instead. As a preliminary step in the project, surveys and economic experiments were conducted to assess farmers' socio-demographic, economic, and behavioral characteristics, which could impact their willingness to uptake innovations – whose deriving data are used in this paper. It is important to emphasize that the farmers in the Food Hubs had not been systematically involved in previous research projects and they had not been testing the project's innovations before the survey. Moreover, they had never been involved in behavioral experiments of the type discussed in this paper.

In Kenya, Tunisia, and Uganda, a two-stage sampling strategy was adopted. First, villages were randomly selected, followed by the random selection of farmers within each village. However, in Morocco (where only two villages were involved in the study) and in Tanzania (one village) the random selection of villages was not necessary. National researchers obtained lists of farming households operating in the selected villages from either local administrations or farmer associations, and allocated them to strata based on age, gender, and farm size (large or small according to local thresholds). If one gender represented less than one third of the farming population, the underrepresented gender (generally women) was oversampled to obtain better insights into gender-specific conditions, in line with the requirements of the funder.

Farmers were randomly sampled within each stratum by contacting them by phone and inviting them to the venue where the survey and the experimental sessions were to take place. This operation was repeated until all the strata were filled. We use the term "session" to refer to an event in a specific day when a group of smallholder farmers participated simultaneously in the games under the guidance of the same enumerators. Each session included about 20 farmers, to allow for the creation of groups for a public good game, and lasted approximately three hours. Transport and refreshments were provided.

The target sample size was 500 farmers in each Food Hub. The final sample sizes were 500 in both Morocco and Tunisia, 504 in Kenya, 482 in Tanzania, and 406 in Uganda, resulting in a total of 2393 observations. After removing 74 observations for which the level of education was missing or classified as "other", making categorization difficult, the final sample size was reduced to 2319.

### 2.2. Surveys and experimental interventions

Standardized survey questionnaires and experimental protocols (instructions) were used in all countries. The questionnaire differed between crop and fish farmers to account for the different production practices; however, the socio-economic and demographic variables used in this paper were measured using the same questions. Overall, the crop farmers' questionnaire included 36 questions, while the fish farmers' questionnaire had 38 questions, covering topics such as farm production, willingness to uptake innovations, behaviors, preferences, past setbacks, and future worries. The experimental protocol included three behavioral games: a two-round Public Good Game (PGG) with country-specific treatments; a lottery game to elicit risk attitudes; and a game to elicit time preferences with respect to monetary returns. The PGG varied between countries due to different treatments, while the other two experiments followed the same instructions across all locations. To ensure a consistent implementation of the survey and economic experiments across countries, sessions, and enumerators, we developed a step-by-step implementation protocol.[e] The questionnaires and the experimental instructions were initially drafted in English, and then translated into local languages by local partners. The questionnaires were pilot-tested with farmers in each country, while the experimental protocols were tested with students from local universities with the involvement of prospective enumerators, and then with farmers.[f] Both the questionnaire and the experiments were administered using pen and paper, except in Morocco and Tanzania, where survey data were collected using tablets.[g] Given that a large share of farmers were expected to be illiterate or to have very low levels of education, all participants received one-to-one support from local enumerators in all sessions. Explicit consent was obtained from all the participants prior to the activities.

The data collection took place between March and December 2021,[h] concurrently with the Covid-19 pandemic. Although international researchers involved in co-developing the experimental protocol were unable to travel to the countries during data collection, local teams received remote training,[i] and the implementation proceeded without any reported irregularities.

The farmers who took part in the experiment received a show up fee and a payoff that depended on the results of the games.[j] During the sessions, the payoffs were expressed in tokens, which were converted at the end of the session at a rate that ensured the same average payoff at purchasing power parity across the five countries. The focus of this paper is on the lottery game used to elicit smallholder farmers' risk attitudes.

A first version of the risk elicitation game was based on Shupp and Williams (2008). However, this protocol was perceived as too complex by the local teams due to the double computation task it entails. Therefore, after extensive cross-country discussions, it was replaced with a multiple price elicitation task *à la* Holt and Laury (2002). A pilot

[d] Overall, the project established 14 Food Hubs; however, in this paper we only focus on the five Food Hubs where behavioral experiments were implemented alongside surveys.

[e] The introduction to the experimental session, the instructions of the risk attitude elicitation game, and the instructions for paying the participants are provided as Supplementary Material, with the instructions for the other experiments omitted for conciseness. The full experimental protocol is available online (Kuhfuss et al., 2022).

[f] The experiment was piloted with 20 farmers in Morocco, 20 in Tunisia, 18 in Uganda, 13 in Tanzania, and 14 in Kenya.

[g] Since tablets were used in all the sessions of two countries (Morocco and Tanzania), it is not possible to disentangle country and tablet effects. However, there were no constraints in the tablet version, so that, for instance, multiple switches were possible.

[h] Most of the effort was concentrated between May and July, when 90% of the observations were collected. Limited additional sampling took place in Uganda in December to achieve the required sample size.

[i] For instance, the pilot implementation of the experiments in the local universities was monitored online by international partners using a laptop with webcam.

[j] While there is an almost perfect correspondence between the farmers who completed the survey and those who took part in the experiments, some participants joined only one of the two activities and are not included in the sample. It is also worth noting that the show up fee and the payoff were only awarded to the farmers who took part in the experiments, while those who left before, or those in the Food Hubs where no experiments were organized (not discussed in this paper) received no compensation.

experiment implemented in Tunisia showed a good understanding of the multiple price list approach, which was then used in subsequent pilots with local smallholders in other countries. Nevertheless, while the selected approach seems to be well understood by a large majority of participants in Tunisia and Morocco, the levels of inconsistent choices were far higher in Kenya, Tanzania, and Uganda. This discrepancy motivates the current investigation.

The selected multiple price list game requires players to make ten choices between pairs of lotteries (A and B) with different odds of winning the higher stake. In lottery A, the lower stake is 0.8 times the higher one; in lottery B, the ratio between the stakes is 0.026, making it riskier. The odds of winning the higher stake increase for each choice, ranging from 0.1 to 1.0. A rational, risk-neutral player would always choose the lottery that maximizes the expected payoff, i.e., lottery A in choices 1 to 4, and lottery B in choices 5 to 10. The choice at which players switch from lottery A to lottery B serves as a proxy for their risk appetite: risk-averse farmers would continue choosing lottery A beyond choice 4, while risk-loving farmers would switch to B before choice 4. A value-added of our experiment is the inclusion of a comprehension check, namely choice 10, where the winning of the higher stake is certain and therefore, players would always maximize their payoff by selecting B; choosing A over B in this round implies a lack of understanding of the probability mechanism.

Accordingly, as anticipated in Section 1, our risk attitude elicitation game allows us to identify two basic types of inconsistencies: *multiple switches*, and *primitive choice*. The former identifies farmers who switched between options A and B more than once; the latter identifies those who selected option A in choice 10. These two inconsistencies are not mutually exclusive: their relationship, as well as other types of inconsistencies, are described and visualized in Appendix 2. In addition to the above types, and following Bruns et al. (2022), in Section 3 we also provide insights into monotonous choice patterns because of their salience and high incidence, namely "*monotonous A*", indicating the farmers who selected A in all the choices, which is inconsistent because it entails a *primitive choice*, and "*monotonous B*", indicating the farmers who selected B in all the choices, which is a consistent choice pattern.

While in the original version of the game (Holt & Laury, 2002) the stakes are expressed in USD. However, we expressed them in experimental tokens while maintaining the same ratios between and within lotteries and ensuring that the average payoff was salient compared to the payoffs in the other games. We also included drawings of white and red balls to visualize the probability in each lottery to win the lower or higher stakes (see Appendix 1 for the visualization of probabilities). The concept was further illustrated by an enumerator in front of all the participants by performing two ball extractions from an opaque box containing a set number of red and white ping-pong balls (contextual aid). Estepa-Mohedano and Espinosa (2023), who study the impact of visual and contextual aids on inconsistencies in risk elicitation lotteries of rural people in Honduras, found that visual aids have no impact, whereas contextual aids do, reducing risk aversion. While we cannot systematically assess the impact of these two methods, qualitative insights from the enumerators before and after pre-testing suggest that the ball extraction was particularly helpful in explaining the experiment to farmers.

### 2.3. Empirical approach

To investigate inconsistent responses in the risk attitude elicitation game, we use both descriptive statistics and regression analysis. The consistency of responses is recorded using binary variables, with one (1) indicating an inconsistent response and zero (0) indicating a consistent response (as in Bruns et al., 2022). We create dummy variables to indicate whether inconsistencies were committed by a given farmer. To estimate the effects of education levels and poverty on these inconsistencies, we use logit models, as presented below.

$$P\left(Inconsistent\_response\_a_{ijk}\right) = b_o + b_1 * Level\_of\_education_{ijk} + b_2 * Poverty_{ijk} + \mathbf{b_3} * Farmer\_characteristics_{ikj} + \mu_j + \upsilon_{jk} + e_{ijk} \tag{1}$$

Where $i$ represents the farmer, $j$ represents the country, and $k$ represents the experimental session. *P(Inconsistent response_a$_{ijk}$)* is the likelihood that farmer $i$ in country $j$ and session $k$ provides an inconsistent response of type $a$. For each type of inconsistency, the dependent variable $Inconsistent\_response\_a_{ijk}$ is a dummy that takes one (1) if the farmer gave that specific type $a$ of inconsistent response in the risk attitude experiment, and zero (0) if they provided a consistent response. We develop a dummy variable for each inconsistent pattern, as well as for "*any inconsistency*" (the union of *multiple switches* and *primitive choice*).

We include in the model a vector of $Farmer\_characteristics_{ijk}$ (gender and age) to increase the precision of our estimates. We also include session-fixed effects $\upsilon_{jk}$ and, in the pooled cross-country models, country-fixed effects $\mu_j$ to control for heterogeneity at country and sessions levels. Then, the estimates of $b_1$ and $b_2$ indicate whether educational levels and poverty affect the likelihood of committing inconsistencies, in line with our two hypotheses.

To investigate whether the effects of education and poverty levels vary by gender, we develop an additional set of models that include interaction effects between these variables.

$$P\left(Inconsistent\_response_{ijk}\right) = b_o + b_1 * Level\_of\_education_{ijk} + b_2 * Poverty_{ijk} + b_3 * Level\_of\_education_{ijk} * Gender_{ijk} + b_4 * Poverty_{ijk} * Gender_{ijk} + \boldsymbol{b_5} * Farmer\_characteristics_{ijk} + \mu_j + \upsilon_{jk} + e_{ijk} \tag{2}$$

In Section 3, we will present and discuss the models with interaction effects, while the models without interaction effects are provided as Supplementary Material.

In this study, we consider two key explanatory variables related to our two hypotheses. The first one is the educational level (**H1**). Individuals with higher levels of education are predicted to have greater cognitive ability to comprehend complex lotteries, which lowers the probability of providing inconsistent responses. After considering the distribution of education levels in our sample,[k] we developed a dummy that takes value one (1) if the individual's education is equal to or higher than primary, and zero (0) otherwise (i.e., illiterate, or literate with no qualification). The cutoff between "illiterate or literate with no qualification" and *any* qualification, is not affected by the specific school systems of the countries considered, and thus a more objective threshold. This approach also ensures a sufficiently large number of farmers fall

[k] In our survey questionnaire, education was assessed along a five-point scale: 1 = Illiterate; 2 = Without any qualifications but literate; 3 = Primary; 4 = Secondary; 5 = More than secondary; in addition to the category "other," which in most instances could not be recategorized, leading to the removal of those observations.

into each category, as the distribution of farmers holding primary education and beyond differs significantly between countries, as shown in Supplementary Material.

The second explanatory variable is poverty (**H2**). We define poor smallholders as those whose households spend a large percentage of their income on food. Through the survey questionnaire, we gathered self-assessed data on the percentage of household income spent on food using a five-point scale.[l] We developed a dummy variable for poverty that takes value one (1) if more than half of the household income is spent on food, and zero (0) otherwise. The fact that this percentage is assessed relative to one's household income reduces the bias due to variability of incomes between households and countries. We also argue that one's perception is more relevant for one's stress level than the absolute income. The threshold at 50 % of income is a salient and reliable cutoff point, resulting in a more balanced partition of the farmers compared to the five-level categorical variable. The full distribution of food expenditure levels by country, as well as models using the scaled variable, are provided as Supplementary Material, 4, 5, and 6.[m]

The survey also collected information about income levels (ranges). However, incomes tend to be underreported compared to consumption, which is generally preferred for calculating poverty headcounts (World Bank, 2020). For instance, Jacobson and Petrie (2009) used monthly expenses as an explanatory variable of inconsistent risk choices in Rwanda. Moreover, we lack income data for hundreds of farmers in at least three countries. This is another reason we prefer to use the share of income spent on food as a proxy for poverty. Nevertheless, as a robustness check, we plotted the distribution of this proxy variable along household income ranges to visualize the trend and assess the robustness of our proxy. Fig. 1 shows the distribution of the farmers' food expenditure by income levels. Farming households with lower income levels are more likely to spend larger shares of their income on food, and this share decreases as we move up the income scale. A Wilcoxon rank-sum test (Wilcoxon, 1945) confirms that income levels differ significantly across the food expenditure dummy ($p = 0.000$).

Since education and poverty may be correlated, we cross-tabulate the two dummy variables and calculate Chi-square tests, whose results are reported in Supplementary Material. The tests suggest that the two variables are significantly correlated in the overall sample and in the samples for Uganda, Tanzania, and Tunisia. Nevertheless, pairwise correlation coefficients are small (the largest being $-0.200$ for Tanzania), and the direction of the correlation is not consistent between countries. Furthermore, none of our models shows problems of collinearity between the two variables and removing one of them from the models presented in Section 3 does not affect the direction or the significance of the respective coefficients.

Finally, it is relevant to note that while education, and participants' characteristics in general, are measured at the individual level, poverty is measured at the household level. However, responsibilities for resources management, and associated stress likely vary between households. Participants were selected to be the household members with responsibility for managing the farm, regardless of their caregiving duties within the household.[n] Due to the likely gender imbalance in sharing caregiving responsibilities within households (Hjelm et al., 2017; May & Norton, 1997), controlling for gender is essential to capture the effect of poverty, as a source of stress, on inconsistencies.

An additional set of explanatory variables is represented by the experimental sessions. Session-specific effects are plausible, especially in the context of lab-in-the-field experiments, due to time- and location-specific circumstances that cannot be fully controlled by the experimenters (such as the venue, weather conditions, enumerators' behavior, etc.), even when protocols are strictly followed. Accordingly, we created dummy variables for each session in each country to control for session-fixed effects.

In Section 3, we present estimates relative to the logit models for *any inconsistency, multiple switches*, and *primitive choice*.[o] Additionally, to maintain the same baseline for all the models (i.e., the farmers who behaved consistently), when estimating the models for specific inconsistencies, we exclude from the sample farmers who committed other inconsistencies but not the one being considered.[p] Using a single multinomial logistic model is not possible because the inconsistencies are not mutually exclusive. Nevertheless, as a robustness check, for *multiple switches* and *primitive choice* we estimate multinomial logistic models where the dependent variable takes the value zero (0) for consistent choices, one (1) for the inconsistency considered, and two (2) for any other inconsistency *but not* the one considered. These models are provided in Appendix 4, and in Supplementary Material with a scaled variable for food expenditure.

All the models were preliminary tested for collinearity, which led to the removal of the interaction between gender and age that was included in an initial version.

Given the relevance of session-specific events beyond the control of the experimental teams, in addition to including session-fixed effects in our models, we also test if the share of inconsistent choices in each session differs significantly from the country-level average. We replicate this test on the residuals of country-level OLS models without session-fixed effects. Unlike reporting the coefficients of the session-fixed effects in the logit models, this approach avoids the bias from selecting a specific session as a baseline. Finally, we show that session-fixed effects explain a significant share of the variance in most countries.

## 3. Results and discussion

### 3.1. Descriptive statistics and identification of inconsistency types

As mentioned above, our sample includes 2319 smallholder farmers from five African countries. Summary statistics for the pooled cross-country sample are shown in Table 1, while Table 2 provides summary statistics for the same variables at the country level. In the pooled sample (top panel of Table 1), the average age of the farmers is 46 years,

[l] The levels were: 1 = A very limited part (<25%); 2 = Less than half (from 25% to 50%); 3 = About half (50%); 4 = More than half (from 50% to 75%); 5 = Almost all (from 75% to 100%). Household income refers to both farm and non-farm cash income. While farming households may self-provide a large share of their food, thus reducing their cash expenditure on food, our approach is supported by Engel's law (Browning, 2008), a well-established empirical regularity according to which the income elasticity of food is less than one, as well as by the extant literature (Deaton, 2006; Duflo, 2006).

[m] The smaller share of respondents spending over 50% of their income on food observed in Uganda (16%), relative to other countries, might be because these are fish farmers, and the income from fish farming is higher than from crop farming, and thus the probability of being poor is lower.

[n] As specified earlier, when the recruitment of 30% of women farmers was challenging, both husband and wife (or both partners) of the household were invited to participate, but in different sessions. In some countries (Primarily Morocco), even this second option turned out to be challenging and fewer women that the 30% target were able to participate.

[o] Model estimates for other types of inconsistencies such as *monotonous A* and *monotonous B* are provided in Appendix 3. The number of farmers committing *monotonous A* is also relatively large, but we do not include this inconsistency in Section 3 given that it is a specific case of *primitive choice*.

[p] As a result, the dependent variable assumes value one (1) if the inconsistency considered was committed, and zero (0) if no inconsistency was committed. For this reason, the sample sizes differ for different models, being smaller than the overall sample size, except for *any inconsistency*, which does not present this issue.

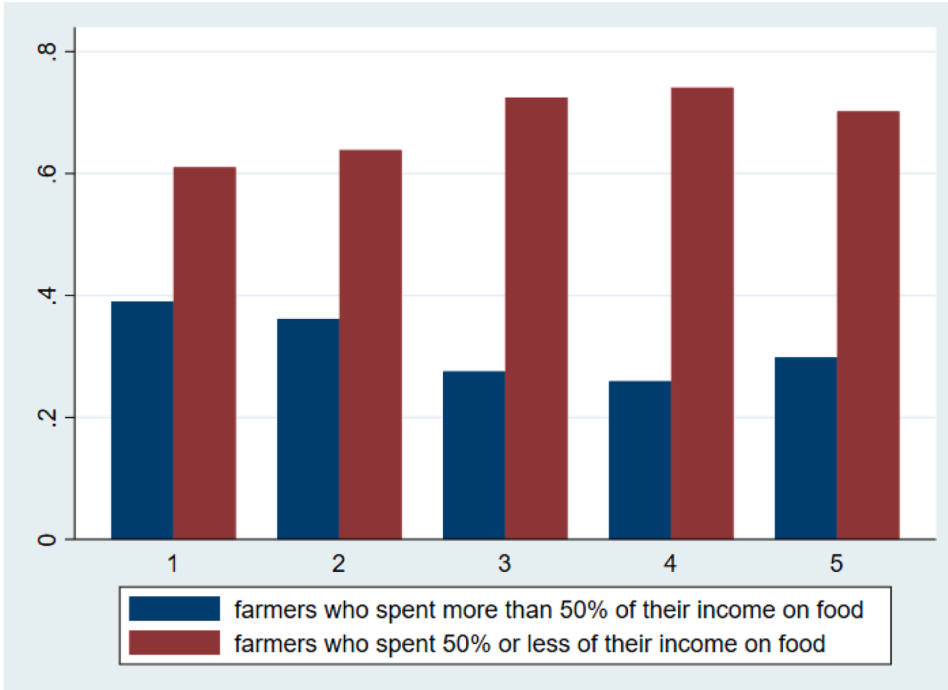


**Fig. 1.** Share of farmers by percentage of income spent on food, by level of income.
*Note*: The horizontal axis reports household income on a 1-to-5 scale (1 being lowest and 5 highest).

35 % are female, and most of them completed primary education. Nearly 48 % of the farmers exhibited some type of inconsistent behavior.

As shown in the top panel of Table 2, the socio-demographic characteristics of the farmers vary significantly between different country samples. Kenyan farmers are the oldest, Tanzanian farmers the youngest. The lowest percentage of female farmers is in Morocco and Uganda, while the Tunisian sample is the most balanced. In Morocco and Tunisia, around two fifths of the farmers declared to spend over half of their household income on food, whilst the smallest proportion of farmers spending this much on food is in Uganda—probably because in Uganda the focus was on fish farming, an activity that requires larger investments and thus a better financial situation.

Table 2 (bottom panel) reports the incidence of various types of inconsistencies by country. The overall incidence of inconsistent choices differs significantly between countries, ranging from as many as 90 % in the Kenyan sample to only 18 % in the Moroccan one. The types of inconsistencies differ significantly between countries too, and we suggest that their source may also differ: they may indicate inattentive behavior, cognitive limitations, or lack of numeracy skills (Bruns et al., 2022; Cohen & Romm, 2022; Amador-Hidalgo et al., 2021; Andersson et al., 2016). Regardless of the type, the highest incidence is always observed in Kenya, and the lowest in either Morocco or Tunisia, despite Northern African samples presenting the highest shares of farmers with a low level of education (37 %) and spending more than half of their income on food (58 % and 60 %, respectively).

To visualize specific inconsistencies in more detail, Fig. 2 reports the switching pattern of all the farmers who took part in the experiment, likely the main indicator of how inconsistently they responded to the game.

The switching pattern exhibits a high degree of volatility and is quite inconsistent, as indicated by the bars from 5 to 12, or *multiple switches*, which account for 37 % of the sample. Additionally, a significant number of participants made no switches at all (*monotonous A* or *B*), as indicated by the first two bars, which accounts for almost 17 % of the farmers. The second (*monotonous B*) and third bars (single switch from A to B) represent the farmers who consistently expressed their preferences for risk, together accounting for around 52 % of the sample. Although *monotonous B* is consistent, the two monotonous patterns might identify farmers who, having not understood the task properly, stuck to their initial selection in all choices: unfortunately, we have no way to verify the underlying reason of their behavior.

The overall level of inconsistency in our sample (48 %) is comparable to those observed in Peru by Galarza (2009) (52 %), and in Rwanda by Jacobson and Petrie (2009) (55 %), and slightly higher than those discovered by Brick et al. (2012) among South African fishing communities (41 %). In turn, it is considerably lower than those detected by Charness and Viceisza (2011) in rural Senegal (75 %), or by Bruns et al. (2022) in rural Cambodia (70 %). These figures, including our own, suggest that multiple price listing experiments may result in a significant share of inconsistent responses, despite being praised as the gold standard for risk preference elicitation, and often used in related experimental studies.[q]

To conclude our overview of descriptive statistics, we focus on the relationship between inconsistencies and gender. In our sample, 35 % of the farmers are female, and of those female participants, nearly 52 % committed at least one type of inconsistency. In contrast, 45 % of the male participants behaved inconsistently. A Pearson Chi-square test of independence shows that there is a significant association between gender and inconsistency [$\chi^2$ ($N = 2319$) $= 8.937$, $p = 0.003$]: women are significantly more likely to provide inconsistent responses in our risk preference elicitation task. This finding is in line with Charness et al. (2018) and Jacobson and Petrie (2009).

[q] A notable exception is represented by Ihli et al. (2016), who recorded an overall inconsistency rate of 5.7% using a similar protocol among smallholders in Uganda, where we detect an inconsistency rate of 77.3% instead.

**Table 1**
Descriptive statistics for the pooled cross-country dataset ($N = 2319$).

| Variable | Variable type | Mean | S.D. | Min | Max |
|---|---|---|---|---|---|
| Level of education (five levels) | ordered categorical[a] | 2.92 | 1.19 | 1 | 5 |
| Education more than primary (dummy) | dummy[b] | 0.710 | 0.454 | 0 | 1 |
| Age (years) | count | 46.46 | 14.96 | 18 | 92 |
| Gender (female) | dummy[c] | 0.352 | 0.478 | 0 | 1 |
| Income spent on food (five levels) | ordered categorical[d] | 2.83 | 1.39 | 1 | 5 |
| Food expenditure >50 % (dummy) | dummy[e] | 0.326 | 0.469 | 0 | 1 |
| No. of switching & switching patterns in the lottery task | | | | | |
| Consistent switch | dummy[f] | 0.523 | 0.500 | 0 | 1 |
| Inconsistent switch | dummy[g] | 0.477 | 0.500 | 0 | 1 |
| Number of switches | count[h] | 2.24 | 2.27 | 0 | 9 |
| Primitive choice | dummy[i] | 0.266 | 0.442 | 0 | 1 |
| Multiple switches | dummy[j] | 0.369 | 0.483 | 0 | 1 |
| *Primitive choice – Multiple switches* | *dummy* | *0.108* | *0.311* | *0* | *1* |
| *Multiple switches – Primitive choice* | *dummy* | *0.210* | *0.408* | *0* | *1* |
| *Primitive choice ⋂ Multiple switches* | *dummy* | *0.158* | *0.365* | *0* | *1* |
| Monotonous A | dummy[k] | 0.101 | 0.302 | 0 | 1 |
| Monotonous B | dummy[l] | 0.065 | 0.247 | 0 | 1 |

*Notes: Primitive choice, multiple switches* and *monotonous A* sum up to more than *inconsistent switch* because several farmers committed more than one inconsistency..
[a] 1 = illiterate; 2 = without any qualifications but literate; 3 = primary; 4 = secondary; 5 = more than secondary.
[b] 1 = education equal to or greater than primary; 0 = no formal education.
[c] 1 = female; 0 = male.
[d] Share of household income spent on food: 1 = *A* very limited part (less than 25 %); 2 = Less than half (from 25 % to 50 %); 3 = About half (50 %); 4 = More than half (from 50 % to 75 %); 5 = Almost all (from 75 % to 100 %).
[e] 1 = spent >50 % of income on food; 0 = spent ≤50 % of income on food.
[f] 1 = switched only once from A to B or always chose B; 0 = committed at least one inconsistency.
[g] 1 = committed at least one inconsistency; 0 = switched only once from A to B or always chose B.
[h] Number of switches (takes 0 to 9).
[i] 1 = chose A in lottery task 10; 0 = otherwise.
[j] 1 = switched 2 or more times between A and B; 0 = otherwise.
[k] 1 = always chose A; 0 = otherwise.
[l] 1 = always chose B; 0 = otherwise

**Table 2**
Descriptive statistics by country.

| Variable | Variable type | Kenya | Uganda | Tanzania | Tunisia | Morocco |
|---|---|---|---|---|---|---|
| Level of education (five levels) | ordered categorical | 3.10 | 3.82 | 2.71 | 2.65 | 2.57 |
| Education more than primary (dummy) | dummy | 0.677 | 0.891 | 0.767 | 0.631 | 0.634 |
| Age (years) | count | 52.26 | 43.78 | 41.15 | 45.78 | 48.22 |
| Gender (female) | dummy | 0.430 | 0.294 | 0.415 | 0.471 | 0.142 |
| Income spent on food (five levels) | ordered categorical | 2.53 | 2.09 | 2.98 | 3.34 | 3.01 |
| Food expenditure >50 % (dummy) | dummy | 0.289 | 0.160 | 0.312 | 0.402 | 0.422 |
| No. of switching & switching patterns in the lottery task | | | | | | |
| Consistent switch | dummy | 0.101 | 0.227 | 0.633 | 0.765 | 0.824 |
| Inconsistent switch | dummy | 0.899 | 0.773 | 0.367 | 0.235 | 0.176 |
| Number of switches | count | 3.97 | 3.31 | 1.79 | 1.38 | 0.99 |
| Primitive choice | dummy | 0.521 | 0.398 | 0.197 | 0.098 | 0.144 |
| Multiple switches | dummy | 0.743 | 0.669 | 0.268 | 0.179 | 0.054 |
| *Primitive choice – Multiple switches* | *dummy* | *0.156* | *0.104* | *0.099* | *0.056* | *0.122* |
| *Multiple switches – Primitive choice* | *dummy* | *0.378* | *0.375* | *0.170* | *0.138* | *0.032* |
| *Primitive choice ⋂ Multiple switches* | *dummy* | *0.364* | *0.294* | *0.099* | *0.042* | *0.022* |
| Monotonous A | dummy | 0.150 | 0.092 | 0.090 | 0.056 | 0.112 |
| Monotonous B | dummy | 0.063 | 0.076 | 0.057 | 0.102 | 0.032 |
| N | | 505 | 357 | 477 | 480 | 500 |

*Notes*: See Notes to Table 1.

### 3.2. Determinants of inconsistencies

To identify the factors related to inconsistencies, we present three sets of logistic regression models (all including the same explanatory variables): one for *any inconsistency* (Table 3), and one for each of the two major inconsistency types of inconsistencies, *multiple switches* (Table 4), and *primitive choice* (Table 5).

When the logistic models are run using the cross-country sample (first result columns in Tables 3-5), controlling for farmer characteristics, country, and session-fixed effects, in most instances we find no significant correlation between inconsistencies and the level of education and poverty, nor with other explanatory variables. The same is true for the monotonous choice patterns (first result columns in Tables A1 and A2 in Appendix 3), as well as for the multinomial logistic models for

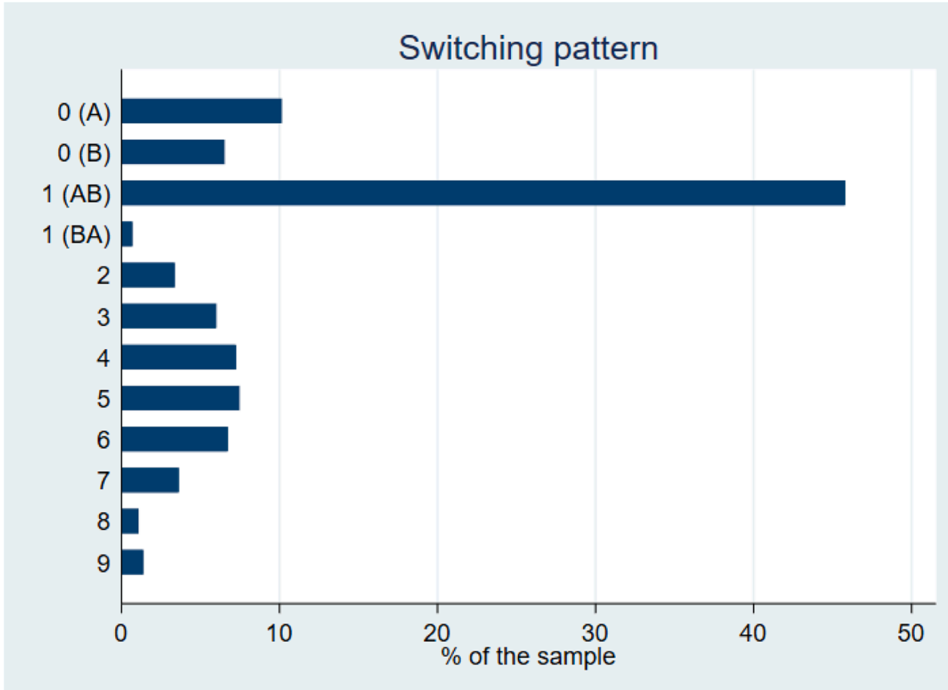


**Fig. 2.** Switching pattern (number of switches and direction) in the lottery task (pooled data, $N = 2319$).

**Table 3**
Results of logit regression for *any inconsistency* vs *consistent switch*.

| | Pooled data | Kenya | Uganda | Tanzania | Tunisia | Morocco |
|---|---|---|---|---|---|---|
| Education more than primary (dummy) | 0.032 | 0.153 | 0.619 | −0.126 | 0.383 | −0.144 |
| | (0.183) | (0.439) | (0.496) | (0.436) | (0.404) | (0.300) |
| Interaction of education and gender (female) | 0.096 | **−1.373*** | −0.908 | −0.271 | 0.827 | −0.664 |
| | (0.264) | (0.728) | (0.846) | (0.606) | (0.561) | (1.142) |
| Food expenditure >50 % (dummy) | 0.143 | **1.162**** | 0.628 | −0.006 | 0.166 | −0.297 |
| | (0.153) | (0.573) | (0.492) | (0.360) | (0.313) | (0.286) |
| Interaction of food expenditure and gender | −0.098 | −0.475 | −0.477 | −0.103 | 0.607 | −0.583 |
| | (0.257) | (0.819) | (0.862) | (0.515) | (0.580) | (0.874) |
| Age (years) | 0.005 | −0.015 | 0.010 | −0.003 | 0.007 | 0.015 |
| | (0.004) | (0.011) | (0.009) | (0.008) | (0.011) | (0.010) |
| Gender (female) | 0.020 | 1.045 | 1.162 | 0.501 | −0.606 | −0.577 |
| | (0.260) | (0.682) | (0.811) | (0.596) | (0.630) | (0.641) |
| Country fixed effects | Yes | No | No | No | No | No |
| Session fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations[1] | 2232 | 505 | 357 | 438 | 450 | 482 |
| Pseudo R square | 0.339 | 0.062 | 0.072 | 0.211 | 0.124 | 0.059 |

*Notes*: The farmers who committed *monotonous B* are included among consistent farmers here. The sample sizes (pooled data, Tanzania, Tunisia, and Morocco) are smaller than those reported in Table 2 because four sessions predict failure perfectly, thus the resulting observations are dropped. Robust standard errors in parentheses. Significant coefficients are marked in **bold**.

* $p < 0.1$,
** $p < 0.05$,
*** $p < 0.01$.

*multiple switches* and *primitive choice* (first result columns in Tables A3 and A4 in Appendix 4), and for the models without interaction effects (in Supplementary Material). In turn, the country-specific models yield mixed results, as discussed below.

For what concerns education, this variable alone yields no significant coefficient, except in Tunisia where, counterintuitively, higher education is marginally (10 %) positively correlated with *multiple switches* and its interaction with gender is positively related to *primitive choice*. However, the Kenyan models for *any inconsistency, multiple switches* and *primitive choice* provide marginally significant evidence (10 %) that more educated women commit less inconsistencies than the baseline group (lowly educated men), with the effect being larger for *primitive choice*.[r] Since Charness et al. (2018) and Jacobson and Petrie (2009) find that women are more prone to inconsistencies, our results suggests that education might have a stronger positive effect on women in this country, opposite to Tunisia where education seems to be less “effective” among

[r] This effect is robust to the inclusion of enumerator-fixed effects, only possible in Kenya, as reported in Supplementary Material.

**Table 4**
Results of logit regression on *multiple switches* vs *consistent switch*.

| | Pooled data | Kenya | Uganda | Tanzania | Tunisia | Morocco |
|---|---|---|---|---|---|---|
| Education more than primary (dummy) | 0.361 | 0.023 | 0.650 | −0.002 | **1.069*** | 0.109 |
| | (0.222) | (0.452) | (0.516) | (0.551) | (0.553) | (0.549) |
| Interaction of education and gender (female) | −0.376 | **−1.250*** | −0.796 | −0.514 | 0.084 | −0.730 |
| | (0.311) | (0.744) | (0.864) | (0.696) | (0.677) | (1.286) |
| Food expenditure >50 % (dummy) | 0.158 | **1.164**** | 0.616 | −0.174 | 0.360 | **−1.039**** |
| | (0.180) | (0.578) | (0.499) | (0.436) | (0.346) | (0.520) |
| Interaction of food expenditure and gender | 0.006 | −0.644 | −0.482 | 0.064 | 0.684 | −0.179 |
| | (0.302) | (0.836) | (0.892) | (0.592) | (0.625) | (1.068) |
| Age (years) | 0.001 | −0.018 | 0.014 | −0.002 | −0.001 | −0.004 |
| | (0.005) | (0.011) | (0.009) | (0.009) | (0.013) | (0.018) |
| Gender (female) | 0.502 | 1.019 | 1.038 | 0.799 | −0.001 | 0.784 |
| | (0.308) | (0.702) | (0.826) | (0.682) | (0.747) | (0.865) |
| Country fixed effects | Yes | No | No | No | No | No |
| Session fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1861 | 426 | 320 | 374 | 404 | 337 |
| Pseudo R square | 0.394 | 0.061 | 0.076 | 0.229 | 0.138 | 0.126 |

*Notes*: The sample only includes the farmers who committed *multiple switches* or behaved consistently; those committing other types of inconsistencies are not included. Robust standard errors in parentheses. Significant coefficients are marked in **bold**.

* $p < 0.1$,.

** $p < 0.05$,

*** $p < 0.01$.

**Table 5**
Results of logit regression on *primitive choice* vs *consistent switch*.

| | Pooled data | Kenya | Uganda | Tanzania | Tunisia | Morocco |
|---|---|---|---|---|---|---|
| Education more than primary (dummy) | −0.141 | 0.238 | 0.701 | −0.217 | −0.394 | −0.136 |
| | (0.206) | (0.450) | (0.542) | (0.528) | (0.540) | (0.316) |
| Interaction of education and gender (female) | 0.237 | **−1.433*** | −1.500 | 0.011 | **1.644**** | (omitted)[a] |
| | (0.316) | (0.770) | (0.919) | (0.767) | (0.814) | |
| Food expenditure >50 % (dummy) | 0.279 | **1.266**** | 0.429 | 0.172 | 0.185 | −0.117 |
| | (0.181) | (0.611) | (0.582) | (0.421) | (0.434) | (0.302) |
| Interaction of food expenditure and gender | −0.456 | −0.792 | −0.193 | −0.262 | −0.444 | −0.333 |
| | (0.308) | (0.859) | (1.010) | (0.649) | (0.844) | (1.560) |
| Age (years) | 0.006 | −0.017 | 0.009 | −0.010 | **0.036**** | 0.017 |
| | (0.005) | (0.013) | (0.012) | (0.009) | (0.015) | (0.011) |
| Gender (female) | −0.024 | 1.037 | **1.793**** | 0.364 | −0.674 | −1.781 |
| | (0.301) | (0.705) | (0.855) | (0.763) | (0.888) | (1.163) |
| Country fixed effects | Yes | No | No | No | No | No |
| Session fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1631 | 314 | 223 | 340 | 316 | 416 |
| Pseudo R square | 0.316 | 0.057 | 0.111 | 0.187 | 0.152 | 0.058 |

*Notes*: The sample only includes the farmers who committed *primitive choice* or behaved consistently; those committing other types of inconsistencies are not included. Robust standard errors in parentheses. Significant coefficients are marked in **bold**.

* $p < 0.1$,.

** $p < 0.05$,

$p < 0.01$.

[a] The variable was omitted since it predicted failure perfectly.

women than it is for men.[5] Such dynamics allow us to derive our first result:

**R1**. *Education alone is not related to inconsistencies at cross-country level, while its interaction with gender yields a marginally significant impact in specific country settings.*

While our hypothesis is not supported, the absence of a significant correlation between inconsistencies and education as a proxy of cognitive abilities aligns with previous studies conducted in developing countries, for instance Jacobson and Petrie (2009) in Rwanda, He et al. (2018) in rural China, Bruns et al. (2022) in rural Cambodia, or Estepa-Mohedano and Espinosa (2023) in Honduras. Tunisia represents an exception for which we lack previous studies for comparison. Additionally, Bruns et al. (2022) identify an interaction between gender and cognitive abilities, but in that case, the (positive) relationship holds only for male participants.

[5] The models in Appendix 3 show similar behaviors for *monotonous A* and, interestingly, that more educated smallholders are less likely to choose *monotonous B* in Tanzania. The models in Supplementary Material and in Appendix 4, confirm the above dynamics, and highlight a strong negative impact of education on the probability for women to commit *primitive choice* in Morocco. This result must be considered cautiously due to the small number of female farmers in the Moroccan sample.

Concerning poverty, the Kenyan models for *any inconsistency, multiple switches* and *primitive choice* confirm (5 %) the positive impact of this variable, though the effect is larger for the latter type of inconsistencies.[t] Instead, opposite to expectations, poorer smallholders in Morocco are relatively less prone to *multiple switches* (5 %). Finally, the interaction between poverty and gender yields no significant coefficient, suggesting that stress (and consequent erratic behavior) does not affect women relatively more, despite their more prevalent role as caregivers in the households (Hjelm et al., 2017; May & Norton, 1997).[u] Based on these findings, we can sustain the following result, which only partially supports our hypothesis:

**R2**. *Poverty is not related to inconsistencies at cross-country level, its impact being country-specific, and more often positive.*

While the literature highlights the negative relationship between poverty and the ability of completing complex tasks (see, among others, Banerjee & Duflo, 2007, 2011; Spears, 2011; Mani et al., 2013; Haushofer & Fehr, 2014), previous studies on inconsistencies in risk elicitation tasks have rarely investigated the impact of this variable. Exceptions are Jacobson and Petri (2009), who find a non-significant impact using food expenditure levels in Rwanda, and Franco (2015), who run their experiment in a Colombian university and only find an impact under a saliency treatment. Thus, our partially positive result calls for further research on this aspect.

In addition to our key explanatory variables, we find that older farmers in Tunisia and women in Uganda are more prone to commit *primitive choice*. The latter result is again in line with the finding by Charness and Viceisza (2011) in rural Senegal and Jacobson and Petrie (2009) in Rwanda. Besides confirming these findings, the models in Appendices 3 and 4 also show that women are less likely to commit *any inconsistency*, particularly *primitive choice*, in Morocco,[v] while older farmers are more likely to commit *monotonous A* in Morocco and Tunisia. Interestingly, Bruns et al. (2022) find that in rural Cambodia older respondents are significantly more likely to commit other inconsistencies but not *monotonous A*.

To summarize, we find mixed evidence on both our hypotheses, suggesting that the impact of education and poverty on inconsistent behaviors in risk elicitation tasks follows country-specific patterns, and may have a strong gender component.

### 3.3. Country and session effects

Besides the sizeable variation in the level of inconsistencies between countries, in many instances, and in both the pooled and the country-specific samples, we found a statistically significant correlation between the sessions and the level of inconsistencies (not reported in Tables 3, 4 and 5). This result warrants further investigation.

In the models reported in Tables 3, 4, and 5, one session-fixed effect is omitted in each country for collinearity reasons, and the coefficients for the other sessions indicate deviations with respect to this baseline as well as other variables. To deal with this issue as well as with the risk of over-rejection due to multiple-hypothesis testing, we implement some additional checks. First, we test in how many sessions the share of inconsistent choices deviates from the country average when no other variables are included, and in how many sessions the residuals of a model not including the session-fixed effects deviate from the country average.[w] Then, we implement two-stage participant data meta-analysis[x] to assess the statistical significance and magnitude of heterogeneity across countries and sessions. Besides *any inconsistency, multiple switches* and *primitive choice*, we also apply these robustness checks on the models for *monotonous A* because of the salience and relatively large incidence of this pattern.[y]

Table 6 reports the results of the initial tests for each country and for the main types of inconsistencies in turn. The largest percentage of sessions where the share of inconsistent choices deviates from the country average is observed in Tanzania overall as well as for *multiple switches* and *primitive choice* separately, and in Tunisia for *monotonous A*. Limited to the sessions where the share of inconsistencies is significantly *larger* than the country average, Kenya stands out for *multiple switches* (followed by Tanzania) and for *monotonous A*, and Tanzania stands out overall, and for *primitive choice*. This suggests that the distribution of inconsistent choices by session is left-skewed (for instance, in Tunisia there are many sessions with no inconsistencies at all), with few sessions performing particularly poorly.[z] The sessions explain between 97 % and 86 % of the overall variance in the pooled sample, depending on the inconsistency; in the country specific samples, the share varies between 7.6 % in the model for *primitive choice* in Kenya, and 81 % in the model for *any inconsistency* in Tanzania.[aa]

The Cochran's Q statistics obtained through the two-stage participant data meta-analysis are reported in Table 7.[ab] They suggests that the residual (net of other explanatory variables) between-country heterogeneity is significant at 1 % for *multiple* switches ($p < 0.001$) and *primitive choice* ($p < 0.001$), and at 10 % ($p = 0.070$) for *monotonous A*, but not for *any inconsistencies*. The country-fixed effects from the full models (reported in Supplementary Material) suggest that this is driven by Kenya and Uganda. The residual within-country heterogeneity is significantly different from zero in Tunisia for *any inconsistency*, where it accounts for 97 % of the total residual heterogeneity, likely because of the left-skewedness highlighted above; in Tunisia (97 %) and Tanzania (94 %) for *multiple switches*; in all countries for *primitive choice*, where it ranges between 91 % and 98 %; and in no countries for *monotonous A*. Such results suggest that the source of inconsistencies may differ, and for instance, *primitive choice* may be avoided or favored by the session-specific context (possibly the ability of the experimental team), supporting our decision to include both country- and session-fixed controls in our models.

It is worth noting that the session-fixed effects are particularly large

[t] Furthermore, this effect is not robust to the inclusion of enumerator-fixed effects, as shown in Supplementary Material. However, differently from education and its interaction with gender, the poverty dummy and the enumerators are not independently distributed, making it difficult to disentangle the respective effects, and leaving open the question of how these two elements interact – a hypothesis we cannot test with our sample size.

[u] The estimates in Supplementary Material and in Appendices 3 and 4 confirm such dynamics, with the addition that in Tunisia, poverty is marginally (10%) positively related to *multiple switches* if no interaction effects are included, and negatively to *monotonous B* (not an inconsistency).

[v] This result must be considered cautiously due to the small number of female farmers in the Moroccan sample.

[w] While the standard assumption is that residuals are independents and identically distributed, if the session-fixed effects are omitted from the model, they are likely to capture the variability due to session-specific features, in addition to unobservable factors.

[x] We apply the Stata command ipdmetan (Fisher, 2015) to the logistic models in Tables 3, 4, 5, and A1. The results must be considered with care due to the omission of several sessions.

[y] As a further robustness check, we also run ANOVA tests, first with all the explanatory variables of the models in Tables 3, 4, 5, and A1, and then with session dummies only, to calculate the share of variance explained by session-fixed effects.

[z] These results should be considered carefully, because the number of farmers that implemented the game at the same time varies considerably between countries. In Kenya in particular, the day of implementation was recorded as a session, therefore not all the sampled farmers have implemented the game at the same time.

[aa] The full results, based on the ANOVA tests, are included in Supplementary Material.

[ab] Forest plots visualizing the between- and within-country heterogeneity for each type of inconsistency in turn are reported in Supplementary Material.

**Table 6**
Direction of session-fixed effects for different forms of inconsistences, by country.

| Country | | Kenya | Morocco | Tunisia | Tanzania | Uganda |
|---|---|---|---|---|---|---|
| Total number of sessions | | 5 | 13 | 24 | 24 | 16 |
| *Any inconsistency* | Positive[a] | 1 (1) | 0 (0) | 1 (1) | 6 (6) | 1 (1) |
| | Negative[b] | 0 (0) | 2 (2) | 4 (3) | 7 (6) | 1 (1) |
| *Multiple switches* | Positive[a] | 1 (1) | 1 (1) | 1 (0) | 3 (5) | 1 (1) |
| | Negative[b] | 0 (0) | 5 (5) | 5 (2) | 9 (7) | 0 (1) |
| *Primitive choice* | Positive[a] | 0 (1) | 0 (0) | 1 (1) | 5 (5) | 1 (1) |
| | Negative[b] | 0 (0) | 3 (2) | 5 (5) | 6 (5) | 0 (0) |
| *Monotonous A* | Positive[a] | 1 (1) | 0 (1) | 0 (0) | 0 (0) | 1 (1) |
| | Negative[b] | 0 (1) | 3 (2) | 10 (10) | 4 (4) | 4 (3) |

*Notes:* The cells report the number of sessions where the share of farmers committing that inconsistency differs significantly (5 %) based on a two-tailed *t*-test. In parentheses: number of sessions where the residuals of a country-level linear regression that uses the same explanatory variables of our models apart from the sessions differ significantly (5 %) from the average based on a two-tailed *t*-test. There are nine sessions with no cases of *multiple switches*, 19 with no cases of *monotonous A*, and 10 with no cases of *primitive choice*: these sessions are categorized as "negative" even if the *t*-test could not be implemented.
[a] Sessions with significantly more inconsistent choices than the country average.
[b] Sessions with significantly less inconsistent choices than the country average.

**Table 7**
Analysis of residual within and between country heterogeneity using two-stage participant meta-analysis (Cochran's Q statistics), by type of inconsistency.

| Measure | *Any inconsistency* | | *Multiple switches* | | *Primitive choice* | | *Monotonous A* | |
|---|---|---|---|---|---|---|---|---|
| | *p*-value | $I^2$ | *p*-value | $I^2$ | *p*-value | $I^2$ | *p*-value[a] | $I^2$[b] |
| Kenya | 0.681 | 0.0 % | 0.684 | 0.0 % | 0.000 | 94.6 % | 0.841 | 0.0 % |
| Uganda | 0.586 | 0.0 % | 0.617 | 0.0 % | 0.000 | 96.4 % | . | . |
| Tanzania | 0.814 | 0.0 % | 0.000 | 93.9 % | 0.000 | 98.0 % | 0.297 | 18.6 % |
| Tunisia | 0.000 | 96.8 % | 0.000 | 97.4 % | . | . | . | . |
| Morocco | 0.264 | 18.9 % | 0.469 | 0.0 % | 0.000 | 91.1 % | 0.537 | 0.0 % |
| Between countries | 0.105 | n/a | 0.000 | n/a | 0.000 | n/a | 0.070 | n/a |

*Notes*: Analysis implemented using the Stata command ipdmetan, applied to the pooled models in Tables 3, 4, 5, and A1. Some countries and sessions are omitted, or the *p*-value could not be calculated because of the lack of residual heterogeneity after considering the explanatory variables others than the country and sessions.
[a] Test of whether -within or between-country heterogeneity differs significantly from zero.
[b] Share of residual heterogeneity explained by the sessions (within-country).

despite the efforts to maintain consistent implementation of the experiment across sessions by: (i) using a standardized protocol with precise instructions for the enumerators, (ii) training the enumerators in all countries, and (iii) testing the experiment with students first, and then with farmers in all countries. Such results highlight the importance of contextual factors for achieving a consistent elicitation of risk preferences and, specifically, point to the role of the enumerators in properly explaining the task.

## 4. Conclusions

Our study contributes to the literature on inconsistencies in risk attitudes elicitation games by being one of the first to investigate the effects of poverty, education, gender, and situational characteristics on different types of inconsistent responses using data from five African countries comparatively. Overall, despite the inclusion of visual and contextual aids to improve understanding, our sample of smallholder farmers exhibit a high level of inconsistent behavior in a multiple price listing experiment. Specifically, we find that, in certain countries, poverty, gender, and the interaction of gender and education significantly explain farmers' inattentive and erroneous choices, though without a clear consistent pattern between and across countries, which results in no significant impacts at cross-country level.

Moreover, we obtain a noteworthy result on the effects of the sessions. Session effects significantly explain inconsistencies in all the country cases as well as in the pooled data. Therefore, in addition to individual conditions such as education, poverty and gender, risk elicitation studies should also pay attention to situational factors such as the location and the team managing the experimental sessions. Providing targeted training to the enumerators is essential to address the issue of inconsistencies effectively.

Overall, our findings warn researchers and policymakers of factors that might be related to inconsistent responses in risk elicitation tasks, calling for better tailoring of risk elicitation methods to people and their context (e.g., designing simpler games shaped by participants' life experiences). Indeed, due to the high degree of inconsistencies displayed by farmers in developing countries when completing risk elicitation tasks, the use of the resulting parameters (e.g., as an explanatory variable for the adoption of technology) without considering the existence and causes of inconsistency may lead to unreliable results and should be given serious consideration. The findings of this study can also inform policymakers about types of farmers who might be more prone to errors when answering survey questions that require computational skills, or context where inconsistent responses and behaviors are more likely, pointing out that the uptake of agricultural innovations in developing countries requires tailored extension services and dissemination strategies. Finally, our results for Kenya, where the level of inconsistencies is particularly high, provides tentative evidence that if poverty, and thus daily worries related to survival, are reduced, and equal opportunities for all genders to accessing education and training are provided, inconsistencies in decision-making might also reduce—although more research, possibly with a counterfactual approach, is needed to confirm these findings.

A possible limitation of our study is the concurrence of our fieldwork with the Covid-19 pandemic. The more experienced international researchers who had helped develop the experimental protocol could not travel to the countries during data collection. Consequently, the local teams, who had no previous experience of running lab-in-the-field experiments, were trained remotely and could not benefit from in-field support. Although no irregularities were reported during implementation and a record has been kept, the absence of more experienced researchers during the training of local enumerators and, possibly, limited awareness of the importance of details (e.g., tone of the voice, how specific participants' questions were answered, etc.) may have resulted in inconsistency in the enumerators' approaches. This could have led to varying levels of understanding by the participants, which are reflected in the session-fixed effects. Additionally, pandemic-related worries and the complex public health protocols may have reduced participants' attention. All the local teams reported that the sanitary protocols were strictly followed (including maintaining the required distance, wearing face masks, and using hand sanitizer) and that participants showed no anxiety. Nevertheless, at least one team highlighted that a few farmers did not show up due to sanitary concerns.

A second limitation of our study is that the identity of the enumerators assisting specific farmers was not recorded apart from Kenya. Hence, we cannot implement ex-post checks of enumerator-fixed effects. However, we developed step-by-step protocols to ensure quality, and careful attention was given to maintaining consistent implementation of the protocols across countries, sessions, and enumerators.

A further limitation of our study is that cognitive skills were not directly assessed, for instance through memory or attention tests. In the future, such measures could provide additional insights into the factors underlying inconsistent behaviors in risk elicitation experiments.

## CRediT authorship contribution statement

**Haftom Bayray Kahsay:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Simone Piras:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation. **Laure Kuhfuss:** Writing – review & editing, Project administration, Methodology, Investigation, Funding acquisition, Data curation. **Marco Setti:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization. **Valentino Marini Govigli:** Writing – review & editing, Writing – original draft, Data curation.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interest or personal relations that could have appeared to influence the work reported in this paper.

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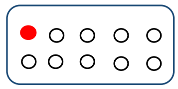
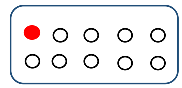
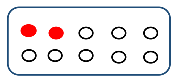
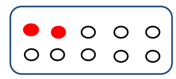
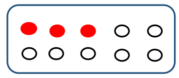
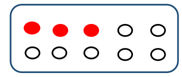
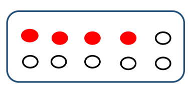
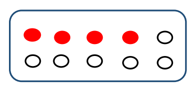
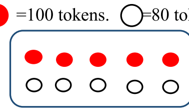
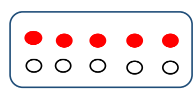
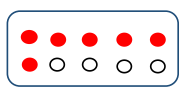
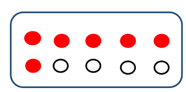
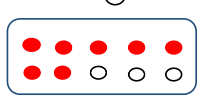
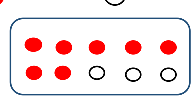
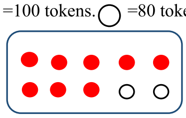
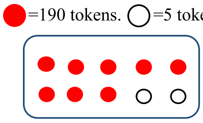
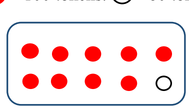
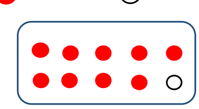
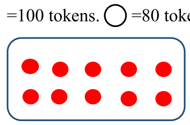
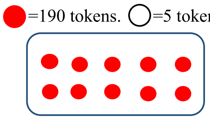
## Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.socec.2024.102307.

## Appendix 1. Risk attitude measurement experiment

Which lottery do you prefer to play – lottery A or lottery B? Please make 10 choices. Remember that only one of the decisions will be randomly selected for extraction. The red and white balls in the pictures symbolize your chance of randomly drawing the balls in each decision.

| No. | Lottery A | Lottery B | Your Choice (Lottery A or B?) |
|---|---|---|---|
| 1 | ● =100 tokens. ○=80 tokens  | ●=190 tokens. ○=5 tokens  | |
| 2 | ● =100 tokens. ○=80 tokens  | ●=190 tokens. ○=5 tokens  | |
| 3 | ● =100 tokens. ○=80 tokens  | ●=190 tokens. ○=5 tokens  | |
| 4 | ● =100 tokens. ○=80 tokens  | ●=190 tokens. ○=5 tokens  | |
| 5 | ● =100 tokens. ○=80 tokens  | ●=190 tokens. ○=5 tokens  | |
| 6 | ● =100 tokens. ○ =80 tokens  | ●=190 tokens. ○=5 tokens  | |
| 7 | ● =100 tokens. ○ =80 tokens  | ●=190 tokens. ○ =5 tokens  | |
| 8 | ● =100 tokens. ○ =80 tokens  | ●=190 tokens. ○=5 tokens  | |
| 9 | ● =100 tokens. ○ =80 tokens  | ●=190 tokens. ○=5 tokens  | |
| 10 | ● =100 tokens. ○ =80 tokens  | ●=190 tokens. ○=5 tokens  | |

## Appendix 2. Visual representation of the inconsistency types

Fig. A1 below illustrates the relationship between the basic inconsistencies *multiple switches* and *primitive choice*, and more specific inconsistent choice patterns that we have identified, in addition to *monotonous A* and *monotonous B*: (i) “*BA single switch*” (0.7 % of the pooled sample), which consists in switching only once but from B to A and also entails *primitive choice*; (ii) “*BAB two switches*” (1.3 % of the pooled sample), indicating the farmers who moved away from their initial selection (A) at a certain point but returned to it later, thus entailing *multiple switches* as well as *primitive choice*; and (iii) “*BAB two switches*” (2.1 % of the pooled sample), similar to the former but in the opposite direction and thus only entailing *multiple switches*.

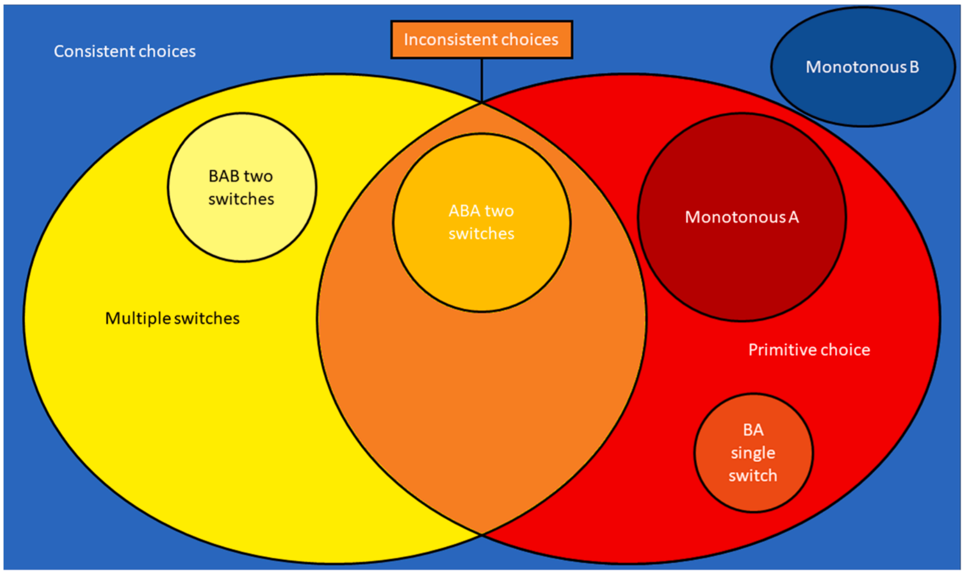



**Fig. A1.** Types of inconsistencies and their interrelationship.

## Appendix 3. Models for inconsistencies that are a specific case of other inconsistencies

Tables A1 and A2

**Table A1**
Results of logit regression for *monotonous A* vs *consistent switch*.

| | Pooled data | Kenya | Uganda | Tanzania | Tunisia | Morocco |
|---|---|---|---|---|---|---|
| Education more than primary (dummy) | −0.271 | 0.551 | 0.224 | −0.102 | −0.814 | −0.196 |
| | (0.236) | (0.583) | (0.855) | (0.573) | (0.655) | (0.351) |
| Interaction of education and gender (female) | 0.479 | **−2.336**** | −0.860 | 0.660 | **2.366**** | (omitted)[1] |
| | (0.399) | (0.943) | (1.360) | (1.109) | (1.049) | |
| Food expenditure >50 % (dummy) | 0.286 | **1.458**** | 1.353 | 0.078 | −0.121 | 0.031 |
| | (0.229) | (0.706) | (1.501) | (0.530) | (0.523) | (0.338) |
| Interaction of food expenditure and gender | −0.454 | 0.158 | −1.536 | −0.428 | −0.502 | −0.547 |
| | (0.388) | (1.020) | (1.807) | (0.883) | (1.041) | (1.595) |
| Age (years) | 0.010 | −0.006 | −0.037 | 0.004 | **0.042**** | **0.025*** |
| | (0.006) | (0.017) | (0.023) | (0.012) | (0.018) | (0.013) |
| Gender (female) | −0.258 | **1.604*** | 1.569 | −0.388 | −1.050 | −1.651 |
| | (0.372) | (0.848) | (1.100) | (1.104) | (1.084) | (1.158) |
| Country fixed effects | Yes | No | No | No | No | No |
| Session fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 1133 | 127 | 98 | 269 | 217 | 400 |
| Pseudo R-sq. | 0.185 | 0.155 | 0.180 | 0.105 | 0.125 | 0.088 |

*Notes*: Robust standard errors in parentheses. Significant coefficients are marked in **bold**.

* $p < 0.1$,.

** $p < 0.05$,

$p < 0.01$.

[1] The variable was omitted since it predicted failure perfectly.

**Table A2**
Result of logit regression for *monotonous B* vs *consistent switch*.

| | Pooled data | Kenya | Uganda | Tanzania | Tunisia | Morocco |
|---|---|---|---|---|---|---|
| Education more than primary (dummy) | −0.388 | 0.458 | −1.194 | **−1.608*** | −0.725 | 0.337 |
| | (0.334) | (0.820) | (0.917) | (0.875) | (0.630) | (0.658) |
| Interaction of education and gender (female) | 0.077 | −1.856 | −1.487 | 1.269 | 0.549 | (omitted)[1] |
| | (0.453) | (1.885) | (2.971) | (1.247) | (0.717) | |
| Food expenditure >50 % (dummy) | −0.051 | −0.336 | 0.334 | 0.305 | **−1.060**** | 0.597 |
| | (0.301) | (1.084) | (1.093) | (0.657) | (0.522) | (0.561) |
| Interaction of food expenditure and gender | 0.536 | 0.957 | (omitted)[1] | 0.886 | **2.114***** | (omitted)[1] |
| | (0.494) | (1.798) | | (1.095) | (0.748) | |
| Age (years) | 0.002 | −0.033 | **0.035*** | −0.033 | 0.001 | 0.022 |
| | (0.008) | (0.026) | (0.019) | (0.020) | (0.016) | (0.027) |
| Gender (female) | −0.279 | 1.239 | 1.180 | −1.280 | **−1.172*** | (omitted)[1] |
| | (0.455) | (1.639) | (2.761) | (1.268) | (0.675) | |
| Country fixed effects | Yes | No | No | No | No | No |
| Session fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 886 | 45 | 62 | 164 | 305 | 249 |
| Pseudo R-sq. | 0.181 | 0.070 | 0.160 | 0.139 | 0.089 | 0.047 |

*Notes*: Robust standard errors in parentheses. Significant coefficients are marked in **bold**.
* $p < 0.1$,.
** $p < 0.05$,.
*** $p < 0.01$.
[1] The variable was omitted since it predicted failure perfectly.

## Appendix 4. Multinomial logistic models for *primitive choice* and *multiple switches* (including a level for other inconsistencies only)

Tables A3 and A4

**Table A3**
Results of multinomial logistic regression for *primitive choice* vs *other inconsistencies* vs *consistent switch*.

| | Pooled data | Kenya | Uganda | Tanzania | Tunisia | Morocco |
|---|---|---|---|---|---|---|
| **Consistent (baseline)** | | | | | | |
| **Primitive choice** | | | | | | |
| Education more than primary (dummy) | −0.042 | 0.193 | 0.559 | −0.075 | −0.278 | −0.158 |
| | (0.195) | (0.452) | (0.552) | (0.502) | (0.511) | (0.318) |
| Interaction of education and gender (female) | 0.254 | **−1.281*** | −1.192 | −0.051 | **1.610**** | **−14.587***** |
| | (0.295) | (0.747) | (0.907) | (0.727) | (0.804) | (0.990) |
| Food expenditure >50 % (dummy) | 0.149 | **1.169**** | 0.414 | 0.092 | 0.010 | −0.126 |
| | (0.169) | (0.584) | (0.550) | (0.398) | (0.437) | (0.300) |
| Interaction of food expenditure and gender | −0.260 | −0.652 | −0.233 | −0.053 | −0.181 | −0.231 |
| | (0.288) | (0.838) | (0.933) | (0.595) | (0.811) | (1.555) |
| Age (years) | 0.005 | −0.013 | 0.007 | −0.008 | **0.037**** | 0.017 |
| | (0.005) | (0.011) | (0.010) | (0.009) | (0.015) | (0.011) |
| Gender (female) | −0.101 | 0.973 | **1.453*** | 0.220 | −0.687 | −1.867 |
| | (0.284) | (0.698) | (0.858) | (0.714) | (0.888) | (1.166) |
| **Other inconsistencies but not primitive choice** | | | | | | |
| Education more than primary (dummy) | 0.188 | 0.089 | 0.686 | −0.249 | **1.198*** | 0.005 |
| | (0.226) | (0.473) | (0.585) | (0.572) | (0.707) | (0.755) |
| Interaction of education and gender (female) | −0.128 | **−1.500*** | −0.386 | −0.371 | −0.069 | −0.539 |
| | (0.314) | (0.772) | (1.040) | (0.728) | (0.801) | (1.427) |
| Food expenditure >50 % (dummy) | 0.146 | **1.149*** | 0.788 | −0.173 | 0.390 | −1.164 |
| | (0.190) | (0.597) | (0.518) | (0.481) | (0.388) | (0.755) |
| Interaction of food expenditure and gender | 0.051 | −0.240 | −0.698 | −0.095 | 0.949 | −0.031 |
| | (0.302) | (0.855) | (0.952) | (0.654) | (0.692) | (1.149) |
| Age (years) | 0.004 | −0.018 | 0.012 | 0.005 | −0.016 | 0.001 |
| | (0.005) | (0.012) | (0.010) | (0.010) | (0.014) | (0.022) |
| Gender (female) | 0.211 | 1.146 | 0.640 | 0.688 | −0.050 | 1.224 |
| | (0.311) | (0.717) | (0.983) | (0.713) | (0.873) | (0.976) |
| Country fixed effects | Yes | No | No | No | No | No |
| Session fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2319 | 505 | 357 | 477 | 480 | 500 |
| Pseudo R-sq. | 0.281 | 0.032 | 0.067 | 0.228 | 0.194 | 0.133 |

*Notes*: Robust standard errors in parentheses. Significant coefficients are marked in **bold**.
* $p < 0.1$,.
** $p < 0.05$,.
*** $p < 0.01$.

**Table A4**
Results of multinomial logistic regression for *multiple switches* vs *other inconsistencies* vs *consistent switch*.

| | Pooled data[1] | Kenya | Uganda | Tanzania | Tunisia | Morocco |
|---|---|---|---|---|---|---|
| **Consistent (baseline)** | | | | | | |
| **Multiple switches** | | | | | | |
| Education more than primary (dummy) | 0.139 | 0.074 | 0.658 | −0.159 | **1.013*** | 0.167 |
| | (.) | (0.443) | (0.510) | (0.528) | (0.554) | (0.565) |
| Interaction of education and gender (female) | −0.076 | **−1.304*** | −0.831 | −0.494 | 0.134 | −0.748 |
| | (.) | (0.736) | (0.867) | (0.670) | (0.672) | (1.299) |
| Food expenditure >50 % (dummy) | 0.150 | **1.177**** | 0.640 | −0.100 | 0.357 | **−1.069**** |
| | (.) | (0.577) | (0.497) | (0.409) | (0.350) | (0.513) |
| Interaction of food expenditure and gender | −0.137 | −0.586 | −0.543 | −0.129 | 0.637 | −0.193 |
| | (.) | (0.825) | (0.874) | (0.574) | (0.623) | (1.058) |
| Age (years) | 0.002 | **−0.018*** | 0.014 | −0.006 | −0.003 | −0.004 |
| | (.) | (0.011) | (0.009) | (0.009) | (0.013) | (0.017) |
| Gender (female) | 0.200 | 1.019 | 1.095 | 0.774 | −0.018 | 0.793 |
| | (.) | (0.689) | (0.831) | (0.656) | (0.741) | (0.865) |
| **Other inconsistencies but not multiple switches** | | | | | | |
| Education more than primary (dummy) | −0.067 | 0.556 | 0.251 | −0.021 | −0.600 | −0.202 |
| | (.) | (0.553) | (0.867) | (0.541) | (0.595) | (0.344) |
| Interaction of education and gender (female) | 0.355 | **−1.767**** | −1.107 | 0.725 | **2.178**** | **−14.585***** [2] |
| | (.) | (0.853) | (1.267) | (1.040) | (1.004) | (1.029) |
| Food expenditure >50 % (dummy) | 0.134 | **1.098*** | 0.632 | 0.177 | −0.352 | 0.028 |
| | (.) | (0.645) | (0.765) | (0.486) | (0.535) | (0.324) |
| Interaction of food expenditure and gender | 0.005 | 0.045 | −0.321 | 0.021 | 0.154 | −0.383 |
| | (.) | (0.935) | (1.245) | (0.750) | (1.025) | (1.584) |
| Age (years) | 0.010 | −0.000 | −0.024 | 0.006 | **0.039**** | **0.021*** |
| | (.) | (0.014) | (0.015) | (0.011) | (0.018) | (0.012) |
| Gender (female) | −0.306 | 1.206 | 1.382 | −0.660 | −1.165 | −1.772 |
| | (.) | (0.788) | (1.159) | (1.065) | (1.099) | (1.168) |
| Country fixed effects | Yes | No | No | No | No | No |
| Session fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 2319 | 505 | 357 | 477 | 480 | 500 |
| Pseudo R-sq. | 0.321 | 0.047 | 0.092 | 0.227 | 0.201 | 0.157 |

*Notes*: Robust standard errors in parentheses. Significant coefficients are marked in **bold**.
* $p < 0.1$,.
** $p < 0.05$,.
*** $p < 0.01$.
[1] Robust standard errors could not be estimated for this model.
[2] The large coefficient is because none of the smallholders committed *other inconsistencies* but not *multiple switches*.

## Data availability

The code will be included as SM if the paper is published; the data have been published in the online repository Zenodo with one-year embargo from 28 February 2025.

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