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Effect of decision rules in choice experiments on hunting and bushmeat trade

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Abstract: Providing insight on decisions to hunt and trade bushmeat can facilitate improved management interventions that typically include enforcement, alternative employment, and donation of livestock. Conservation interventions to regulate bushmeat hunting and trade have hitherto been based on assumptions of utility- (i.e., personal benefits) maximizing behavior, which influences the types of incentives designed. However, if individuals instead strive to minimize regret, interventions may be misguided. We tested support for 3 hypotheses regarding decision rules through a choice experiment in Tanzania. We estimated models based on the assumptions of random utility maximization (RUM) and pure random regret maximization (P-RRM) and combinations thereof. One of these models had an attribute-specific decision rule and another had a class-specific decision rule. The RUM model outperformed the P-RRM model, but the attribute-specific model performed better. Allowing respondents with different decision rules and preference heterogeneity within each decision rule in a class-specific model performed best, revealing that 55% of the sample used a P-RRM decision rule. Individuals using a P-RRM decision rule responded less to enforcement, salary, and livestock donation than did individuals using the RUM decision rule. Hence, 3 common strategies, enforcement, alternative income-generating activities, and providing livestock as a substitute protein, are likely less effective in changing the behavior of more than half of respondents. Only salary elicited a large (i.e. elastic) response, and only for one RUM class. Policies to regulate the bushmeat trade based solely on the assumption of individuals maximizing utility, may fail for a significant proportion of the sample. Despite the superior performance of models that allow both RUM and P-RRM decision rules there are drawbacks that must be considered before use in the Global South, where very little is known about the social–psychology of decision making.

Keywords: latent class model, poaching, regret, Tanzania, wild meat

Efecto de las Reglas de Decisión en los Experimentos de Selección sobre la Cacería y el Mercado de la Carne de Animales Silvestres

Resumen: La obtención de conocimiento del porqué se elige cazar o comerciar con carne de animales silvestres puede facilitar mejoras en el manejo de las intervenciones que típicamente incluyen el cumplimiento de leyes, el empleo alternativo y la donación de ganado. Las intervenciones de conservación para regular la cacería y el comercio hasta ahora han estado basadas en suposiciones de comportamiento de maximización de la utilidad (es decir, los beneficios personales), las cuales influyen sobre los tipos de incentivos que son diseñados. Sin embargo, si los individuos en lugar de eso buscan minimizar el arrepentimiento, las intervenciones pueden ser erróneas. Evaluamos el apoyo para tres hipótesis con respecto a las reglas de decisión mediante un experimento de selección en Tanzania. Estimamos los modelos con base en las suposiciones de la maximización aleatoria de la utilidad (MAU) y la maximización aleatoria pura del arrepentimiento (MAPA) y las combinaciones de estas. Uno de estos modelos tuvo una regla de decisión específica de atributo y otro modelo tuvo una regla de decisión específica de clase. El modelo MAU tuvo un mucho mejor desempeño que el modelo MAPA, pero el modelo específico de atributo fue el

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que tuvo el mejor desempeño de todos. El mejor desempeño se observó cuando permitimos a los respondientes con diferentes reglas de decisión y con heterogeneidad de preferencia dentro de cada regla de decisión en un modelo específico de clase, lo que revela que el 55% de las muestras usaron una regla de decisión MAPA. Los individuos que usaron una regla de decisión MAPA respondieron menos al cumplimiento de leyes, el salario y la donación de ganado que aquellos individuos que usaron la regla de decisión MAU. Por esto, las tres estrategias comunes (cumplimiento de leyes, actividades alternativas generadoras de ingresos y el sustento de ganado como sustituto de la proteína) probablemente sean menos efectivas en el cambio del comportamiento de más de la mitad de los respondientes. Solamente el salario provocó una respuesta elástica, y solamente fue para una clase MAU. Las políticas que regulan el mercado de la carne de animales silvstres basadas solamente en la suposición de que los individuos maximizan la utilidad pueden fallar para una proporción significativa de la muestra. A pesar del desempeño superior de los modelos que permiten las reglas de decisión MAU y MAPA, existen desventajas que deben ser consideradas antes del uso de los modelos en el hemisferio sur, en donde se conoce muy poco sobre la psicología social de las decisiones.

Palabras Clave: arrepentimiento, cacería furtiva, carne de animales silvestres, modelo de clase latente, Tanzania

摘要: 深入理解狩猎和野味交易的决策将有助于改进管理干预措施, 这些措施通常包括执法、替代性就业和牲畜捐赠。迄今为止, 管理野生动物狩猎和野味交易的保护干预措施一直以效用 (即个体利益) 最大化行为的假设为基础, 这会影响设计激励措施的类型。然而, 如果个人反而致力于减少遗憾, 干预措施则可能会被误导。我们通过在坦桑尼亚进行选择实验, 测试了三个决策规则假设的支持情况。本研究基于随机效用最大化 (RUM) 和纯粹随机遗憾最大化 (P-RRM) 的假设及二者的组合来对模型进行了估计。其中一个模型包含属性特异的决策规则, 另一个模型包含了类别特异的决策规则。 RUM 模型的表现优于 P-RRM模型, 而属性特异模型的表现甚至更好。允许受访者采用不同决策规则, 且每个决策规则中存在偏好异质性的类别特异模型表现得最好, 表明了样本中55%的受访者使用了P-RRM决策规则。与使用 RUM 决策规则的受访者相比, 使用P-RRM决策规则的个体对法规执行、工资水平和牲畜捐赠的反应程度更低。因此, 三种常见的策略——法规执行、替代性创收活动以及提供牲畜作为替代蛋白质, 或许不能有效地改变半数以上受访者的行为。只有工资水平会引起人们很大的 (即弹性的) 反应, 且只对一种 RUM 决策类型的人群起到作用。因此, 仅基于个体效用最大化的假设来管理野味交易的政策在很大一部分人群中都可能会失败。尽管允许 RUM 和 P-RRM 决策规则的模型表现优越, 但在南半球使用这些模型之前必须考虑到一些缺陷, 因为在发展中国家, 人们对决策的社会心理学仍知之甚少。**【翻译: 胡怡思; 审校: 聂永刚】**

关键词: 野味, 偷猎, 坦桑尼亚, 遗憾, 潜在类别模型

Introduction

Biodiversity conservation is primarily about understanding and managing human behavior (Schultz 2011). The evolving field of conservation psychology addresses human behavior toward nature. It attempts to identify strategies producing individual behavioral change (Saunders 2003) and in doing so should prioritize high-impact biological targets and behavior (Schultz 2011). Bushmeat hunting and the bushmeat trade constitutes one such high-impact activity considered a significant threat to conservation efforts in tropical and subtropical countries (Ripple et al. 2016). Simultaneously, bushmeat is a source of protein and micronutrients to more than 150 million households in the Global South (Nielsen et al. 2018) and important to cash-income-constrained communities in remote locations with few domestic animals (Nielsen et al. 2017). Regulating the bushmeat trade is a significant challenge, and information about the psychological and behavioral determinants of individual decisions to engage in this trade is essential for making informed decisions about the design of management interventions. Obtaining reliable information is complicated due to the illegal nature of bushmeat hunting, which makes actors in the bushmeat trade reluctant to share information. Behavioral studies in the bushmeat literature have been limited, and the few that exist mainly use correlational survey data to evaluate socioeconomic determinants of hunting effort or its importance (e.g., Kümpel et al. 2009). However, recent advances have seen the use of indirect-questioning techniques to quantify the prevalence and examine preferences and trade-offs in the choice to participate in this illegal activity (Nuno et al. 2013; Conteh et al. 2014). Other researchers have focused on identifying incentives motivating changes in behavior, generating information about what most efficiently may induce actors to shift to an alternative livelihood strategy (Nielsen et al. 2014) or reduce effort invested in hunting (Moro et al. 2013). Other applications of stated-preference methods have been used to evaluate the determinants of demand for bushmeat relative to other protein sources (Moro et al. 2015; Walelign et al. 2019a) and determine how road development will affect household labor allocation to the bushmeat trade (Walelign et al. 2019b). Choice experiments, in particular, can generate highly relevant information for designing management strategies when surveys target individuals involved in the bushmeat trade and produce information on actors' preferences and trade-offs between different attributes of the choice to engage in hunting. Choice experiments, described more fully below, involve presenting scenarios with choices described in terms of different levels of the attributes of a decision and asking respondents to choose serially between two or more alternative combinations of attribute levels. Relevant attributes are all those that shift the cost-benefit ratio of the decision to hunt or trade bushmeat and can be influenced by policies. These attributes could include donations or programs promoting livestock husbandry as alternative sources of protein and income. Nielsen et al. (2014) provide an example of a choice experiment in the context of the bushmeat trade. They found that a salary paying US$3.37/day in a hypothetically available alternative income-generating activity would induce 90% of actors in a bushmeat market in Tanzania to shift occupation. In contrast, law-enforcement patrol frequency and magnitude of sanctions had a negligible effect. Despite the benefits of choice experiments, minimal effort has gone into examining the psychological process underlying choices (i.e., how decisions to engage in the bushmeat trade are reached). This is the topic of the present paper.

Behavioral economics applying discrete choice models to examine stated preferences has been dominated by the random utility maximizing (RUM) theory, which is based on the assumption that decision makers strive to maximize utility. "Utility" is defined as the extent to which consuming a good is useful in satisfying the consumers want or need. In the context of a choice experiments, it is assumed that respondents chose the alternative that maximizes their utility. However, the characteristic of the utility maximization function may make it unrealistic in some situations. An example is choice sets in which 1 weak attribute of an alternative can be compensated by other strong attributes (Hess et al. 2013). Such choice sets may be particularly important in the context of decisions about illegal bushmeat hunting where sanctions can be severe and include shoot-on-sight policies (Messer 2010). The proposed alternative random regret minimization (RRM) decision rule (Chorus 2010) involves semicompensatory models extending from regret theory. Regret is a negative emotion with a powerful social and reputational component and is central to how humans learn from experience and to the psychology of risk aversion. Conscious anticipation of regret creates a feedback loop that elevates regret from the emotional realm into the realm of rational choice behavior, where it is postulated to be an important determinant of choices modeled in decision theory (Loomes & Sugden 1982). The RRM theory is also based on the assumption that choices may induce feelings of anticipated regret because the decision maker in most situations has to decide to live with a suboptimal performance on 1 or more attributes of the choice to achieve a more satisfactory outcome on other attributes and that one strives to reduce this regret (Hensher et al. 2013). However, RRM differs markedly from regret theory that focuses mainly on single-attribute risky choices. Random regret minimization was developed instead to capture semicompensatory choice behavior and choice-set composition effects (Chorus 2012). This semicompensatory aspect is important to capture because of the complexity of the bushmeat trade as a livelihood strategy. Contrary to regret theory, RRM does not encompass or enable testing of prospect theory in which loss and gain perspectives are assessed asymmetrically. Hence, our contribution here, concerned with the preferences of assumed rational economic agents in the market, occurs at the interface of an increasingly blurred distinction between social psychology and behavioral economics (Cialdini 2018).

Choice situations can induce feelings of anticipated regret when the decision is difficult and important (including to others in the decision makers' social network who are important to them) or when the decision maker expects to receive feedback about chosen and nonchosen options in the short term (Zeelenberg & Pieters 2007). These are characteristics that apply to engaging in bushmeat trade because household welfare depends on the outcome and both hunters and traders will be held accountable for their actions if apprehended. Hence, actors in the bushmeat trade may aim to minimize anticipated regret rather than maximizing utility. If so, this may lead to a systematically different pattern of choices than if it is assumed that decision makers only follow a utility-maximization strategy. This may have implications for the optimal design of management interventions.

We examined this question by applying models specifying different options of choice behavior to choices made by actor groups in a bushmeat market in Tanzania. These choices involved trade-offs between scenarios with varying effort invested in hunting or trading bushmeat under different conditions of wage in an alternative salary-paying income-generating activity; enforcement effort; sanctions; and extension services promoting livestock as a substitute protein production and income-generation strategy. We tested three hypotheses about what decision rule actors use in their choice to participate in the bushmeat trade. Hypothesis 1 is the decision is made based on a regret-minimizing rather than a utility-maximizing decision rule. We tested hypothesis 1 by estimating and comparing the performance of separate RUM and P-RRM models following van Cranenburgh et al. (2015). Hypothesis 2 is the decision rule is attribute specific. We tested hypothesis 2 by specifying a hybrid RUM-RRM model that enabled utility-maximization behavior for some attributes and regret-minimization behavior for others, following Chorus et al. (2013). Hypothesis 3 is the decision rule is class specific. We tested hypothesis 3 by specifying a latent class model in which the utility in different latent classes is described as either random regret with a profound regret or random utility, following Hess & Stathopoulos (2013). Thus, respondents were sorted into classes, thereby allowing for different decision strategies among individuals. We tested hypotheses 2 and 3 by sequentially comparing model performance with the best performing model from the previous hypothesis.

Methods

Study Area

The study was conducted in the Kilombero Valley (6550 km^2), one of Africa's largest wetlands and part of the greater Selous–Niassa ecosystem, which encompasses the world-heritage-listed Selous Game Reserve to the south. To the north are the Udzungwa Mountains of the Eastern Afromontane Biodiversity Hotspot and to the northeast is Mikumi National Park. Data were collected in three anonymous villages in a project conducted under research clearance (number 2011-218-NA-2011-21) granted by the Tanzanian Commission for Science and Technology (COSTECH). The villages are known for unlicensed bushmeat trade and for ties to markets in urban centers and neighboring countries (Nielsen et al. 2016) that have resulted in marked declines of several species, including the near-endemic puku antelope (*Kubus vardoni*). The standard of material well-being in the area is extremely low (Starkey et al. 2002).

The bushmeat trade is clandestine. Hunters kill wildlife in the Kilombero Game Controlled Area or the Udzungwa Scarp and do the initial processing and potentially upgrading of the meat. Traders may also upgrade the meat, transport it to villages, and do the final processing and selling door-to-door to end consumers and to transport intermediaries. Local retailers sell the meat, primarily to end consumers (Nielsen et al. 2016). Village game scouts, Wildlife Division scouts, and foresters of the District Lands and Natural Resources Office occasionally conduct patrols. Still, patrol effort is low relative to the very large area (Nielsen & Meilby 2015). However, consequences, if caught, can be severe (Nielsen et al. 2016).

Data Collection

We conducted a survey from October through November 2011 in Swahili with individuals (80 hunters, 169 traders, and 76 local retailers) actively engaged in the bushmeat trade, identified using a snowball-sampling strategy and based on research assistant's local insight. We used a structured questionnaire to collect demographic and socioeconomic household information, including about respondents engagement in the bushmeat trade (questions provided in Supporting Information) (Nielsen et al. [2014, 2016] provides further details). After the initial questions, respondents were presented with the choice tasks.

Choice Experiment

We conducted focus group discussions to inform design of the choice experiment and to identify factors likely to affect individuals' choice of allocation of time to hunting or trading bushmeat. We conducted one focus group discussion in each village with 5–7 key informers involved in the bushmeat trade in June 2011. We selected 5 attributes influencing the choice: donation of dairy cows (a commonly suggested and pursued extension strategy); daily salary in an unspecified but hypothetically available alternative occupation of similar strenuousness; patrolling frequency by law enforcement staff and magnitude of the fine if caught; and number of trips undertaken by hunters (actor 1) and traders (actor 2) per month to hunt and purchase bushmeat for resale respectively (i.e., effort) (Table 1). For retailers (actor 3), this attribute was formulated as number of days spent per month selling bushmeat. See Supporting Information for details of attribute selection.

We made a fractional factorial design in which a subset of all possible combinations of attribute levels were selected while the ability to estimate main effects and some second-order effects was maintained (details in Supporting Information). We then grouped choice sets into three blocks. Each respondent was randomly presented with one block consisting of four choice sets each with tree alternatives (example in Supporting Information). We asked respondents first to select their most preferred alternative and subsequently the worst alternative in each choice set. (This was done to allow best- and worst-case choice modelling, but is not pursued further here). Choice sets contained no opt-out choice because all respondents were known to engage in the behavior as a livelihood strategy and because making a no-choice would be equivalent to choosing not to engage in making a livelihood. Qualitative and quantitative pretesting was conducted to establish the credibility and acceptance of the baseline condition, the mechanism of change, the change to be valued, and the payment vehicle by respondents through the focus group discussions (cf. above) and test implementation (9 respondents in each village) in accordance with later published guidelines (Johnston et al. 2017). We estimated all models with an interaction term between patrol frequency and fine (hereafter enforcement), dropping the level terms because the marginal effect of neither can be meaningfully estimated without consideration of the other. We similarly included an interaction term with actor type (1 and 2 vs. 3) to accommodate unit differences (cf. above).

Choice Models

Discrete choice models within the random-utility framework have been used to model choice behavior in a wide range of goods, including in low-income countries (Whittington 2010). We adopted a standard RUM model specification following, for example, Train (2003) (Supporting Information). The RRM approach is an alternative to RUM, assuming that respondents seek to minimize regret when choosing between alternatives rather than maximizing utility. Thus, the base measure is the difference between attribute levels. We adopted the RRM model specification following Chorus (2010) (Supporting Information). van Cranenburgh et al. (2015) suggest accounting for the profundity of regret because it may otherwise capture some level of utility maximization. To capture pure regret, we used the so-called P-RRM (Supporting Information).

Contrary to the assumptions inherent in comparing the RUM and RRM models, the decision rule may be attribute-specific so that some attributes are processed using a utility- maximization decision rule, while others are processed using a regret-minimizing decision rule. We, therefore, estimated an attribute-specific model following Chorus et al. (2013) (Supporting Information). Selection of attributes likely to be evaluated based on a regret minimizing decision rule is discussed in Supporting Information.

Finally, heterogeneity in decision-making may occur when one segment of a population chooses more in line with RUM premises, while others choose more in line with RRM premises. A class-specific model can be estimated using a latent-class approach to accommodate this. Following Hensher et al. (2016), we included two classes corresponding to each decision rule to allow for preference heterogeneity within each decision rule type. Examining individual characteristics of latent-class membership, we applied 2 different theories. The first is regret theory describing by whom and under which circumstances regret is likely to be felt (Zeelenberg & Pieters 2007). The second is the sustainable livelihoods framework, which argues that the choice of livelihood strategy is a function of the household's assets and capabilities (Scoones 1998). These frameworks suggest that it is a combination of characteristics rather than a few measures that differ between classes. Consequently, we did not include such characteristics in the class-membership probability function, but rather calculated the probability-weighted average class characteristic. Hence, we compared the classes ex post in terms of basic household sociodemographics (converted to adult equivalent units [AEU]; i.e., weighing household members according to age and gender following Cavendish [2002]) and evaluated their engagement in hunting and trading bushmeat hunting. The full list of variables is in Supporting Information.

We compared models with the Ben-Akiva and Swait test for nonnested choice models (Ben-Akiva & Swait 1986) (Supporting Information). We calculated elasticities by averaging the effect over the probability-weighted respondent specific elasticities (Hensher et al. 2013) (Supporting Information). Direct elasticities provide a measure of the relationship between a 1% change in the level of the attribute and the percent change in the probability of choosing the alternative characterized by that specific attribute. Cross-elasticities reflect the relationship between a 1% change in the level of an attribute in an alternative and the percent change in the probability of choosing a different alternative.

Results

RUM, P-RRM, and the Attribute-Specific Model

All parameter estimates of the attributes and the enforcement interaction in the RUM, P-RRM, and the attribute-specific model were significant and had the expected sign (Table 2). The RUM model outperformed the P-RRM model in terms of log likelihood and adjusted R^2; thus, hypothesis 1 was rejected. The Ben-Akiva and Swait test produced a probability of $p \leq \Phi(-10.77) \cong 0$, indicating that this difference was significant at the 0.01 level. In the attribute-specific model with the lowest log likelihood, salary and enforcement were RUM attributes and the rest were RRM attributes. The attribute-specific model had slightly higher adjusted R^2than the RUM model, and the Ben-Akiva and Swait test produced a probability of $p \leq \Phi(-2.71) \cong 0$), indicating that it performed significantly better at the 0.01 level, which supports hypothesis 2.

Class-Specific Model

Comparing model performance in terms of log likelihood and adjusted R^2, the class-specific model (Table 3) outperformed all other models. The Ben-Akiva and Swait test yielded a probability of $p \leq \Phi(-11.25) \cong 0$, indicating that the difference between the class- and the attribute-specific (as the best candidate) models was significant at the 0.01 level, which supports hypothesis 3 (i.e., decision makers differ and tend to make choices consistent with either P-RRM or RUM decision rules). The difference was facilitated by allowing preference heterogeneity within each decision rule. However, a model with only one class for each decision rule also outperformed the others. The sample was distributed relatively evenly with a small overweight in favor of regret minimizers (55.5%) compared with utility maximizers (44.5%). The larger proportions were in class 1and had more distinct preferences for both decision rules. All attributes were significant in the first RUM and P-RRM class (i.e., RUM1 and P-RRM1) and had the expected signs. However, some

Table 1. Attributes, their levels, and hypotheses about their effects on the choice to engage in hunting and trading bushmeat.

Notation	*Attribute*	*Levels*	*Hypothesis*
Cows	cows donated	0, 1, 2, 3, 4, and 5	A high number of cows reduces the inclination to devote effort to hunting and trading bushmeat illegally because it supplies meat and products for own use and income generation.
Salary	daily salary (TZS*per day) in an alternative occupation of similar strenuousness and risk	2.000, 3.000, 4.000, 5.000, 6.000, and 8.000	High wages reduce effort devoted to hunting and trading bushmeat.
Patrolling and magnitude of fine interaction term	patrolling frequency by law enforcement staff	once per year, 6 times per year, once every month, once every week	Product of patrolling frequency and magnitude of the fine is the expected costs of enforcement; therefore, high frequency and high fines reduce utility time effort devoted to hunting and trading bushmeat illegally.
	magnitude of the fine	30,000, 50,000, 100,000, and 300,000 (TZS/arrest)	
Effort	hunting trips or days spent trading per month	0, 1, 2, 3, 4, and 5	changes in an individual's domestic animal stock, salary in an alternative occupation, and expected cost of enforcement affect effort invested in hunting and trading bushmeat

**At the time of the study, €1 was approximately equal to 2000 TZS .*

Table 2. Coefficients and β values (SE) of a random utility maximizing (RUM), random regret minimizing (P-RRM), and an attribute-specific model of preferences in scenarios involving hunting and bushmeat trade, where salary and enforcement is processed using a RUM decision rule[a] and other attributes are processed using a RRM decision rule.

Attribute	*RUM model*	*P-RRM model*	*Attribute-specific model*
Cows donated (number per household)	0.305 (0.023)[b]	0.348 (0.026)[b]	0.212 (0.016)[b]
Salary (TZS per day)	0.469 (0.022)[b]	0.377 (0.021)[b]	0.474[a] (0.022)[b]
Enforcement (i.e., patrol frequency* fine) (times per year* TZS)	-5.0×10^{-4} (8.2×10^{-5})[b]	-4.3×10^{-4} (7.9×10^{-5})[b]	-5.4×10^{-4}[a] (8.3×10^{-5})[b]
Effort - actor group 1 and 2 (trips per month)[c]	0.281 (0.025)[b]	0.147 (0.015)[b]	0.191 (0.017)[b]
Effort – actor group 3 (days per month)[c]	0.266 (0.042)[b]	0.145 (0.024)[b]	0.176 (0.029)[b]
Choices/respondents	1292/323	1292/323	1292/323
Log likelihood (0)	−1414.66	−1419.40	−1414.66
Log likelihood	−936.59	−994.72	−938.24
Adjusted R^2	0.3367	0.2957	0.3393

[a] Random utility maximizing decision rule.
[b] Significance: $p < 0.01$.
[c] Effort interacts with a dummy for hunters and traders (actor groups 1 and 2) and retailers (actor group 3) to reflect that effort is recorded in trips per month for actor groups 1 and 2 and days per month for actor group 3.

attributes were not significant in the second RUM and P-RRM class (i.e., RUM2 and P-RRM2), including cows donated and enforcement in RUM2 and effort for actor 3 in the P-RRM2. The significant (on the 0.05 level) effect of effort for actor group 1 and 2 in P-RRM2 had the opposite sign relative to P-RRM1.

Elasticities

Most attributes were inelastic (i.e., led to <1% change) (Table 4). Only the direct elasticity for salary was elastic. Hence, a 1% increase in salary led to 1.09% increase in choice probability for individuals in RUM1, whereas it was inelastic in P-RRM1 and other classes. Class 1 generally represented a more distinct decision rule, but sensitivity (i.e., level of response as indicated by the magnitude of the coefficient) to attributes varied among individuals with different decision rules. Cross elasticities were numerically smaller and mainly had the opposite sign of the direct elasticities, reflecting a lower probability and negative preference for choosing a different alternative when the level of the attribute increased by 1%.

Comparing Classes

Only minor differences were observed when mean sociodemographic and behavior characteristics were compared according to class membership (Supporting

Table 3. Coefficients and β values (SE) of preferences in scenarios involving hunting and bushmeat trade of the class-specific model, where 2 classes are random utility maximizing (RUM) and 2 are random regret minimizing (P-RRM).

Attributes	*RUM 1*	*RUM 2*	*P-RRM 1*	*P-RRM 2*
Cows donated (number per household)	0.272 (0.0534)[a]	−0.152 (0.211)	2.709 (1.298)[a]	0.125 (0.044)[b]
Salary (TZS per day)	0.658 (0.090)[a]	0.802 (0.224)[a]	2.219 (1.059)[a]	0.045 (0.040)[c]
Enforcement (i.e. patrol frequency*fine) (times per year*TZS)	−0.019 (0.004)[a]	−0.001 (0.001)	−0.003 (0.002)[a]	0.001 (0.000)[b]
Effort Actor 1 & 2 (trips per month)[b]	0.543 (0.110)[a]	1.036 (0.319)[a]	0.776 (0.257)[a]	−0.148 (0.061)[b]
Effort Actor 3 (days per month)[d]	0.862 (0.173)[a]	0.329 (0.228)[c]	0.663 (0.338)[b]	0.066 (0.089)
Class probability	0.3954	0.1593	0.3268	0.1185
Choices/respondents	1292/323			
Log likelihood (0)	−1419.40			
Log likelihood	−830.39			
Adj. R^2	0.3988			

[a] *Significance: $p<0.01$.*
[b] *Significance: $p<0.05$.*
[c] *Significance: $p<0.1$*
[d] *Effort interacts with a dummy for hunters and traders (actor groups 1 and 2) and retailers (actor group 3) to reflect that effort is recorded in trips per month for actor groups 1 and 2 and days per month for actor group 3.*

Table 4. Direct and cross-elasticities for coefficients in the individual-specific model of preferences in scenarios involving hunting and bushmeat trade calculated based on individual belonging to the class with the highest probability of class membership.

	Individual-specific model			
Direct elasticities	*RUM1*[a]	*RUM2*[a]	*P-RRM1*[a]	*P-RRM2*[a]
Cows donated (number per household)	0.42	NS	−0.09	0.26
Salary (TZS per day)	1.09	0.69	0.88	0.17
Enforcement (i.e., patrol frequency*fine) (times per year*TZS)	−0.36	NS	−0.08	0.06
Effort Actor 1 & 2 (trips per month)[b]	0.27	0.55	0.42	−0.17
Effort Actor 3 (days per month)[b]	0.14	0.12	0.10	NS
Cross elasticities				
Cows donated (no. per household)	−0.30	NS	−0.29	−0.15
Salary (TZS per day)	−0.89	0.00	−0.29	−0.10
Enforcement (i.e., patrol frequency*fine) (times per year*TZS)	0.15	NS	−0.06	−0.03
Effort Actor 1 & 2 (trips per month)[b]	−0.16	−0.54	−0.29	0.07
Effort Actor 3 (days per month)[b]	−0.10	−0.07	−0.06	NS

[a] *Abbreviations: RUM, random utility maximizing; P-RRM, random regret minimizing.*
[b] *Effort interacts with a dummy for hunters and traders (actor groups 1 and 2) and retailers (actor group 3) to reflect that effort is recorded in trips per month for actor groups 1 and 2 and days per month for actor group 3.*

Information). As a rough generalization, households represented by individuals using a P-RRM decision rule were smaller and less educated but generated more income from their other livelihood activities, which included a more livestock-based production strategy, than individuals using a RUM decision rule. Individuals using a P-RRM decision rule were also more likely to be traders and to invest more effort but generate less profit from bushmeat, and they were more likely to have been caught. Households represented by individuals using a RUM decision rule, in contrast, were more agriculture-production based, had greater cash needs, and were more likely to have experienced an idiosyncratic livelihood shock. Individuals using a RUM decision rule were also more likely to be hunters and experience higher bushmeat profit.

Discussion

Findings and Implications

Policies to regulate bushmeat markets across the Global South are usually informed by expectations about actor's response to different initiatives based on analyses informed by utility maximization theory. However, if individuals make choices using a different decision rule, this may lead to flawed information and misinform the design of interventions. We did not find that the P-RRM model performed better than the RUM model (rejecting hypothesis 1). Allowing some attributes to be modelled according to a RUM decision rule (salary and enforcement) and others according to a RRM decision rule (cows donated and effort) improved model fit (supporting hypothesis 2). However, allowing heterogeneity between individuals provided the best model fit, indicating that people used different decision rules (supporting hypothesis 3). Importantly, we found that over half the respondents were more likely to use a P-RRM decision rule than an RUM decision rule.

Comparing the decisions of individuals using P-RRM decision rules with those using RUM, we found that they are much less influenced (i.e. they were less sensitive) by enforcement and salary in an alternative occupation and less sensitive to the donation of cows. These three measures are often targeted in policies and management strategies that aim to increase the level of enforcement (preferably both the likelihood of apprehension and the sanction) in order to increase the cost and hence reduce the profitability of engaging in the bushmeat trade; provide alternative income-generating opportunities to increase the opportunity cost of hunting and trading bushmeat; and improve extension services or provide low-interest loans to increase livestock production and hence provide substitute protein and income sources, reducing demand for bushmeat (also affects alternative income generation). However, we found these measures were not very effective for the P-RRM group, which represented more than half the sample. For the other part of the sample (using a RUM decision rule), enforcement and donation of cows had a larger, but still inelastic effect, on their choice of livelihood strategy. However, they were likely to be more sensitive to this form of carrot and stick policy. Individuals using a P-RRM decision rule, were more sensitive to the effort attribute. In particular, actor groups 1 and 2 (hunters and traders) had a strong preference for investing effort in these illegal activities (at least in P-RRM1). The wage in the salary-paying alternative-employment option produced the only elastic response, and only from individuals using a RUM decision rule in class 1. This result suggests that the alternative livelihood strategy provided by wage employment options that by design excludes the option of hunting the same day is likely to have the largest effect on reducing bushmeat hunting for this group. Individuals in actor group 3 (retailers) using a RUM decision rule, in contrast, had a slightly stronger preference for investing effort in the bushmeat trade than individuals in the same group using a P-RRM decision rule.

The result that salary-paying employment was among the most effective disincentives to engaging in hunting and trading bushmeat (at least for those using a RUM decision rule) was supported by the binary discrete choice experiment (cf. above) conducted with the same sample but in a different survey (Nielsen et al. 2014) as well as a study in the Greater Serengeti Ecosystem with a sample of mainly nonhunters (Moro et al. 2013). Despite the focus on providing alternative livelihood strategies to reduce bushmeat hunting, evaluation of the impact of such projects is often hindered by a lack of baseline data and monitoring of hunter behavior (Wicander & Coad 2015). However, a study tracking the socio-ecological dynamics of the hunting system in two villages in Gabon over ten years showed that hunting tends to decline in periods of rapid economic growth when hunters migrate out of rural areas to take advantage of employment options (Coad et al. 2013). Furthermore, a survey of nearly 8000 households in 333 communities across 24 countries in the Global South showed an inverted U-shaped relationship between mean community annual cash income and the importance of bushmeat in the communities (Nielsen et al. 2017). Specifically, the prevalence of hunting, mean absolute bushmeat income, and mean reliance on bushmeat as the share in total household income declined from a maximum in the middle of the cash income distribution.

Unfortunately, our results provide few clues as to what specific incentives or strategies may be devised to better influence the majority of respondents using the P-RRM decision rule, who have stronger preferences for investing more effort in hunting and trading bushmeat. Such alternative incentives or strategies would have to be included as attributes in the choice experiment before conclusions can be drawn from a study such as ours.

Comparing sociodemographic characteristics among individuals using the two decision rules in the class-specific model, we found mainly minor differences, and these were as much within as between decision-rule types. However, rough generalizations are possible (cf. above). Several hypotheses can be formulated to explain the observed patterns (Supporting Information). However, these would depart from regret theory, and it is unclear how well-aligned regret theory and RRM modeling are. Validation and comparison with the findings of other studies using RRM models are also constrained by the lack of similar studies conducted in a relevant context.

Limitations and Future Research

Our overall result, that individuals used different decision rules, was unlikely determined by location characteristics or the specific timing of the survey. Instead, there are common characteristics of the decision to engage in the bushmeat trade, as well as other illegal extractive activities, extending across locations in the Global South and periods, that are likely to induce feelings of anticipated regret in decision-making (cf. above). The generalization that regret-minimizing decision rules are highly prevalent is further supported by reanalysis of data sets in transport economics. These show that model fit in four out of ten data sets were substantially improved when RRM is estimated, specifically P-RRM, compared with RUM models (van Cranenburgh et al. 2015).

Empirical evidence suggests that RRM models perform better than RUM models when respondents are less familiar with the choice situation, which may reflect less clearly defined preferences (Boeri et al. 2014). In our study, all respondents were confessed active actors in the bushmeat trade, and hence made choices considering the selected attributes on a regular basis. However, in other similar studies, respondents' actual livelihood strategies may be less apparent. In studies that may involve unfamiliar scenarios to respondents, attribute-specific models may improve model performance.

However, fundamental differences between RUM and RRM models need to be considered before deciding to use RRM models in a low-income country context. These include low school achievement and the possibility of fundamentally different worldviews from that of the experimenter leading to measurement error that may have different implications in the two models. In RRM models, individuals are assumed to assess regret by comparing choice alternatives systematically. The error terms in RRM models may, therefore, be affected differently by the degree of uncertainty, causing larger bias relative to a RUM model (Jang et al. 2017). Where measurement error is nonnegligible, the variance of the errors of the choice alternatives in a RRM model will be heterogeneous not only across alternatives, but also across individuals. The assumption of independently and by value identically Gumbel distributed error terms in RRM models, may therefore not represent individuals' behaviors and lead to false policy recommendations (Jang et al. 2017). Jang et al. (2017) recommend using heterogeneous scale factors to estimate the parameters of RRM models. However, in our study, the class-specific model was already relatively complex. Modeling heterogeneous scale explicitly, in a complex model with a relatively small sample, may lead to overspecification and was therefore omitted. However, for simpler specifications, it may be recommended.

Uncertainty could also be incorporated directly as an attribute. Incorporating uncertainty may be particularly important if it is unclear who will benefit from suggested policy changes. For instance, the salary in an alternative employment option in our design may be irrelevant to a respondent if the respondent believes that other individuals are more likely to get the job due to higher education, better language skills, or elite capture. Uncertainty perceptions in terms of attribute provision may also, therefore, be important in RRM models.

We asked respondents first to pick their most preferred of three alternatives and, subsequently, to pick the least preferred alternative. Combined with the fact that we emphasized the hypothetical nature of the choices, this may have affected respondents' perceptions of the consequentiality of the study. We also highlighted that we guaranteed respondents anonymity at both the individual and the community level. We chose this approach in consideration of the illegal nature of the subject under investigation to enable respondents to share information about their activities and preferences in relation to the illegal bushmeat trade in which they were involved. Confidentiality was also required due to the potentially severe consequences for respondents if arrested (Nielsen et al. 2016). A relevant question is how much this matters for the results. Because the goods, services, and dis-services under evaluation were private goods, the risk of free riding likely mattered less than in public-good valuation studies. Furthermore, empirical studies provide mixed evidence on the importance of lack of consequentiality in choice-experiment designs (Hassan et al. 2017).

Finally, more effort than we made should be invested in explicitly modeling the choice context and underlying reasons. This includes evaluating how individual decisions covary with sociodemographic and psychological characteristics of the decision makers.

Hence, despite the superior performance of models that allow both RUM and RRM decision rules (here the class-specific model), there are drawbacks to the RRM paradigm that need to be considered particularly before use in a low-income countries where little is known about the social-psychology of decision-making (Rad et al. 2018). However, our findings reveal that using choice experiments to inform the design of management interventions to regulate illegal bushmeat trade needs to apply modelling frameworks that acknowledge that resource users may use other decision rules than utility maximization and hence may respond differently to often used behavioral-change incentives. This insight constitutes an important contribution to conservation psychology at its interphase with behavioral economics in view of the objective of identifying strategies producing individual behavioral change.

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Supporting Information

A description of the selection of attributes (Appendix S1), design of the choice experiment, including an example choice card (Appendix S2)„ choice-model specifications (Appendix S3), attributes specified as RRM versus RUM in the attribute-specific model (Appendix S4), comparison of class membership (Appendix S5), method for model comparison (Appendix S6), and calculation of elasticities (Appendix S7) are available online. The authors are solely responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author.

Literature Cited

Ben-Akiva, M, Swait, J. 1986. The Akaike likelihood ratio index. Transport Science **20:**133–136.

Boeri, M, Scarpa, R, Chorus, CG. 2014. Stated choices and benefit estimates in the context of traffic calming schemes: utility maximization, regret minimization, or both? Transport Research Part A Policy and Practice **61:**121–135.

Cavendish, W. 2002. Quantitative methods for estimating the economic value of resource use to rural households. Pages 17–65 in B. Campbell and M. Luckert, editors. Uncovering the hidden harvest. Valuation methods for woodland and forest resources. People and plants conservation series. Earthscan, London, United Kingdom.

Cialdini, RB. 2018. Why the world is turning to behavioral science. In A. Samson (Ed.), The behavioral economics guide 2018, pp. VII–XIII. https://www.behavioraleconomics.com/the-behavioral-economics-guide-2018/.

Chorus, C. 2012. Random regret minimization: an overview of model properties and empirical evidence. Transport Reviews **32:**75–92.

Chorus, C. 2010. A new model of random regret minimization. Ejtir **10:**181–196.

Chorus, C, Rose, JM, Hensher, DM. 2013. Regret minimization or utility maximization: it depends on the attribute. Environment and Planning B: Planning and Design **40:**154–169.

Coad, L., et al. 2013. Social and ecological change over a decade in a village hunting system, central gabon. Conservation Biology **27:**270–280.

Conteh, A, Gavin, MC, Solomon, J. 2014. Quantifying illegal hunting: a novel application of the quantitative randomized response technique. Biological Conservation **189:**16–23.

Hassan, S, Olsen, SB, Thorsen, BJ. 2017. Appropriate payment vehicles in stated preference studies in developing economies. Environment and Resource Economics 1–23.

Hensher, DA, Greene, WH, Chorus, CG. 2013. Random regret minimization or random utility maximization: an exploratory analysis in the context of automobile fuel choice. Journal of Advanced Transportation **47:**667–678.

Hensher, DA, Greene, WH, Ho, CQ. 2016. Random regret minimization and random utility maximization in the presence of preference heterogeneity: An empirical contrast. Journal of Transportation Engineering 142.

Hess, S, Stathopoulos, A. 2013. A mixed random utility: random regret model linking the choice of decision rule to latent character traits. Journal of Choice Modeling **9:**27–38.

Jang, S, Rasouli, S, Timmermans, H. 2017. Bias in random regret models due to measurement error: formal and empirical comparison with random utility model. Transportmetrica A. Transport Science **13:**405–434.

Johnston, RJ, et al. 2017. Contemporary guidance for stated preference studies. Journal of the Association of Environmental and Resource Economists **4:**319–405.

Kümpel, NF, Rowcliffe, M, Cowlishaw, G, Milner-Gulland, EJ. 2009. Trapper profiles and strategies: insights into sustainability from hunter behaviour. Animal Conservation **12:**531–539.

Loomes, G, Sugden, R. 1982. Regret theory: an alternative theory of rational choice under uncertainty. The Economic Journal **92:**805–824.

Messer, KD. 2010. Protecting endangered species: when are shoot-on-sight policies the only viable option to stop poaching? Ecological Economics **69:**2334–2340.

Moro, M, Fischer, A, Czajkowski, M, Brennan, D, Lowassa, A, Naiman, LC, Hanley, N. 2013. An investigation using the choice experiment method into options for reducing illegal bushmeat hunting in western Serengeti. Conservation Letters **6:**37–45.

Moro, M, Fischer, A, Milner-Gulland, EJ, Lowassa, A, Naiman, LC, Hanley, N. 2015. A stated preference investigation of household demand for illegally hunted bushmeat in the Serengeti, Tanzania. Animal Conservation **18:**377–386.

Nielsen, MR, Jacobsen, JB, Thorsen, BJ. 2014. Factors determining the choice of hunting and trading bushmeat in the Kilombero Valley, Tanzania. Conservation Biology **28:**382–391.

Nielsen, MR, Meilby, H. 2015. Hunting and trading bushmeat in the Kilombero Valley, Tanzania: motivations, cost-benefit ratios and meat prices. Environmental Conservation **42:**61–72.

Nielsen, MR, Meilby, H, Smith-Hall, C. 2016. How could the bushmeat trade in the Kilombero Valley of Tanzania be regulated? Insights from the rural value chain. Oryx **50:**84–93.

Nielsen, MR, Meilby, H, Smith-Hall, C, Pouliot, M, Treue, T. 2018. The importance of wild meat in the Global South. Ecological Economics **146:**696–705.

Nielsen, MR, Pouliot, M, Meilby, H, Smith-Hall, C, Angelsen, A. 2017. Global patterns and determinants of the economic importance of bushmeat. Biological Conservation **215:**277–287.

Nuno, A, Bunnefeld, N, Naiman, LC, Milner-Gulland, EJ. 2013. A novel approach to assessing the prevalence and drivers of illegal bushmeat hunting in the Serengeti. Conservation Biology **27:**1355–1365.

Rad, MS, Martingano, AJ, Ginges, J. 2018. Towards a psychology of Homo sapiens: making psychological science more representative of the human population. Proceedings of the National Academy of Science **115:**11401–11405.

Ripple, WJ, et al. 2016. Bushmeat hunting and extinction risk to the world's mammals. Royal Society Open Science **3:**160498.

Saunders, CD. 2003. The emerging field of conservation psychology. Human Ecology Review **10:**137–149.

Schultz, PW. 2011. Conservation means behaviour. Conservation Biology **25:**1080–1083.

Scoones, I. 1998. Sustainable rural livelihoods: a framework for analysis. IDS Workshop paper 72. Institute of Development Studies, Brighton, United Kingdom.

Starkey, M, Birnie, N, Cameron, A, Daffa, RA, Haddelsey, L, Hood, L. 2002. The Kilombero Valley Wildlife Project: An ecological and social survey in the Kilombero Valley, Tanzania. The Kilombero Valley Wildlife Project, Edinburgh, United Kingdom.

Train, KE. 2003. Discrete choice methods with simulations. Cambridge University Press, Cambridge, United Kingdom.

van Cranenburgh, S, Guevara, CA, Chorus, CG. 2015. New insights on random regret minimization models. Transport Research Part A: Policy and Practice **74:**91–109.

Walelign, SZ, Nielsen, MR, Jacobsen, JB. 2019*a*. Price elasticity of bushmeat demand in the Greater Serengeti Ecosystem: Insights for managing the bushmeat trade. Frontiers in Ecoloy and Evolution. https://doi.org/10.3389/fevo.2019.00162.

Walelign, SZ, Nielsen, MR, Jacobsen, JB. 2019*b*. Roads and livelihood activity choices in the Greater Serengeti Ecosystem, Tanzania. PLoS ONE **14**(3)**:** e0213089.

Whittington, D. 2010. What have we learned from 20 Years of stated preference research in less-developed countries? Annual Review of Resource Economics **2:**209–236.

Wicander, S, Coad, L. 2015. Learning our lessons: A review of alternative livelihood projects in Central Africa. International Union for Conservation of Nature (IUCN), Oxford, United Kingdom.

Zeelenberg, M, Pieters, R. 2007. A theory of regret regulation 1.0. J. Consumer Psychology **17:**29–35.