Random Regret Minimization and Hypothetical Bias in Discrete Choice Experiments

Qi Jiang, The Ohio State University, jiang.1885@buckeyemail.osu.edu
Jerrod Penn, Louisiana State University/LSU AgCenter, jpenn@agcenter.lsu.edu
Wuyang Hu, The Ohio State University, hu.1851@osu.edu

Selected Paper prepared for presentation at the 2024 Agricultural & Applied Economics Association Annual Meeting, New Orleans, LA; July 28-July 30

Random Regret Minimization and Hypothetical Bias in Discrete Choice Experiments

Abstract
This paper explores the implications of Random Regret Minimization (RRM) and Random Utility Maximization (RUM) in real Discrete Choice Experiments (DCEs) and Hypothetical Bias (HB). We introduce a novel stated approach to differentiate between utility maximizers and regret minimizers and build our empirical analysis on this approach. We investigate the efficiency and viability of our stated approach as an alternative to existing inferred methods in controlling the heterogeneity of decision rules. Our findings suggest a mixed impact of the RRM framework on behavior interpretation and HB reduction, necessitating further investigations.

1. Introduction and Literature

Many valuation studies rely on Random Utility Maximization (RUM) as the theory underpinning the choice between different alternatives/options. RUM assumes that decision-makers prefer and choose the alternative that brings the highest utility. Due to its tractability, ease of use, and clear theoretical foundation, RUM is the predominant theoretical framework to model choice behavior, especially for discrete choice experiments (DCE). However, several alternative theories of decision-making exist, including Random Regret Minimization (RRM) (Chorus, 2010). Originally introduced to model transportation choices, RRM posits that decision-makers select the alternative that results in the lowest regret, explaining why a seemingly better alternative (in one or more of the attributes) may not be chosen. Neuroscientists and psychologists suggest that anticipated regret can occur in 70% of individuals' daily decisions such as those involving food consumption and travel choices (Piracci et al., 2023; Biondi et al., 2009; Chorus et al., 2008). Furthermore, due to its flexibility in capturing semi-compensatory behavior and compromise effects, compared to RUM, RRM may show promises with slightly better model fit, better out-of-sample validity, and stronger performance in choice probability forecast (Chorus, 2012).

However, three issues follow from the previous literature. First, all previous work comparing RRM and RUM are established on DCEs. The use of real DCEs has risen quickly in recent years. Because of the non-zero payment consequentiality in real DCEs, respondents may be more careful assessing the alternatives in each choice sets, thus possibly leading to the adoption of different decision rules (Michaud et al., 2013; Moser et al., 2014; Ready et al., 2010). As a result, the prevalence of RRM vs RUM may shift under real DCEs.

Second, all previous studies on Hypothetical Bias (HB) describing the gap between economic values elicited in hypothetical and real elicitations rely on RUM (Loomis, 2011; Hensher, 2010). HB is a long-existing issue facing stated preference practitioners, suggesting that respondents may behave differently in hypothetical and real elicitations (Penn and Hu, 2018). If RRM may explain behavior different to RUM, it may also affect HB differently. Thus, we aim to fill this void by examining the existence and extent of HB under the framework of RRM.

Third, previous empirical studies employing either RRM or RUM often assume that respondents fall exclusively into one of these categories: either they aim to maximize utility or minimize regret. However, in reality, both types may coexist in one dataset. While some studies have attempted to differentiate between these decision-making types, relying on inferred approaches such as latent class models and artificial neural network-based methods (Buckell et al., 2021; van Cranenburgh and Alwosheel, 2019). Building upon the extensive literature on attribute non-attendance, which has utilized and compared across inferred and stated approaches (Weller et al., 2014; Caputo et al., 2018), opportunities exist to explore the stated approach to distinguish between utility maximizers and regret minimizers. Specifically, we incorporate a follow-up question after the DCE choice tasks, allowing respondents to indicate the decision rule guiding their choices during the DCE.

To the best of our knowledge, our study pioneers the use of the stated approach in the context of RRM-RUM comparison. In addition, we compare results and test for consistency between the straightforward stated approach versus the intricate inferred approach, which involves much more complex computation and simulation. If so, the stated approach could serve as a viable alternative to distinguish between the two decision rules.

2. Experiment Design and Data Collection

Our study relies on a DCE aiming to understand consumer preference over crafting activities involving different types of animal skins. Data collection takes place online via Dynata, spanning from August 2023 to April 2024. Based on a D-efficiency design, each respondent is randomly assigned to a block of six choice sets and they are required to make a choice in each choice set. Figure 1 displays a sample choice set. As suggested, each choice set has four alternatives with one being the opt-out option. Each alternative is constructed by seven characteristics plus one price attribute. Figure 2 shows more details about the attributes and corresponding levels.

As our main objectives is through applying RRM on real DCE as well as the associated HB calculation, we have implemented a split-sample design, with one treatment being the real DCE where respondents are required to make actual purchases for the products they indicated to buy, while the other is a hypothetical treatment where respondents face no payment requirement.

3. Methods

3.1. Random Utility Maximization

Following McFadden (1974), each individual maximizes their utility by weighing tradeoffs between attributes and comparing available alternatives. This is captured by the linear additive utility function, which can take the following form:

$$U_{nti} = V_{nti} + \varepsilon_{nti} = \beta_p * P_{it} + \sum_m (\beta_{-p} * x_{imt}) + \varepsilon_{nti} \tag{1}$$

Where U_{nti} represents the utility for individual n choosing alternative i in choice set *t*. V_{nti} is the deterministic utility that can be observed by the researcher while ε_{nit} is the random component assumed to follow a type-I extreme value error distribution. P_{it} is the price and x_{imt} is the non-price attribute *m* for alternative i in choice set *t*. β_p and β_{-p} are the corresponding parameters to be estimated. The probability of choosing each alternative is:

$$Prob_{RUM,n} = \prod_{t=1}^{T} \sum_{i=1}^{I} (c_{nti}) \frac{\exp(V_{nti})}{\sum_{j=1..J} \exp(V_{ntj})} \tag{2}$$

where $Prob_{RUM,ni}$ is the probability of individual n's sequence of choices over T choice sets in the RUM framework. I and *J* are the total number of alternatives in choice set *t* and C_{nti} equals to one if alternative i is chosen in choice set t; zero otherwise.

3.2. Random Regret Minimization

Following Chorus (2010, 2012), each individual minimizes their regret generated by the pairwise comparison of attributes between the available alternatives. The feeling of regret occurs when the chosen alternative is outperformed by the other unchosen alternatives in terms of one or multiple attributes. The overall regret is defined as follows:

$$R_{nti} = R_{nti} + \varepsilon_{nti} = \sum_{j \neq i} \sum_m \ln\left(1 + \exp\left[\beta_m * \left(x_{jmt} - x_{imt}\right)\right]\right) + \varepsilon_{nti} \tag{3}$$

Where R_{nti} represents the total regret for individual n over alternative i, with R_i being the deterministic regret and ε_{nti} being the random component. x_{imt} is the level of attribute m for alternative i to be considered. x_{jmt} is the level of attribute m for alternative i to be compared against. β_m is the parameter to be estimated for attribute m. The estimation of choice probabilities parallels that of RUM, with the substitution of deterministic regret for deterministic utility. Given that regret represents a form of negative emotion, contrasting with utility which encompasses satisfaction and joy, it is necessary to incorporate the negative value of regret when substituting it into the probability function.

$$Prob_{RRM,n} = \prod_{t=1}^{T} \sum_{i=1}^{I} (c_{nti}) \frac{\exp{(-R_{nti})}}{\sum_{j=1..J} \exp{(-R_{ntj})}} \tag{4}$$

where $Prob_{RRM,n}$ denotes the probability of individual n's sequence of choices over T choice sets under the RRM framework.

3.3. Willingness to Pay

One key difference between RUM and RRM is that RUM is fully compensatory and RRM is semi-compensatory. In other words, willingness to pay (WTP) in RRM versus RUM are not equivalent. Specifically, the WTP under RUM and RRM can be calculated as follows:

$$WTP_{RUM} = -\frac{\partial V_i / \partial x_i}{\partial V_i / \partial p_i} = -\frac{\beta_{-p}}{\beta_p} \tag{5}$$

$$WTP_{RRM} = -\frac{\partial R_i / \partial x_i}{\partial R_i / \partial p_i} = -\frac{\sum_{j \neq i} \beta_{-p} / (1 + 1/\exp{[\beta_{-p}(x_j - x_i)]})}{\sum_{j \neq i} \beta_p / (1 + 1/\exp{[\beta_p(p_j - p_i)]})} \tag{6}$$

3.4. Decision Rule Heterogeneity

3.4.1. Inferred Approach

Two primary inferred approaches are available to accommodate heterogeneous decision rules, namely RUM and RRM. The first approach is the latent class decision rule heterogeneous choice model (LADRH) (Hess & Chorus, 2015; Nielsen & Jacobsen, 2020). In this model, each latent class represents a distinct decision rule, and each individual can be estimated with a certain probability of belonging to specific latent classes, reflecting the likelihood of applying particular decision rules. Moreover, this model can be expanded by treating class membership as a random variable and addressing within-class preference heterogeneity. Further details on this model specifications are in Buckell et al. (2021).

The other approach applies Artificial Neural Networks (ANN), as proposed by van Cranenburgh and Alwosheel (2019). The primary concept is to initially train synthetic data generated based on the mathematical formulation of each decision rule, considering the attributes and their associated levels. These synthetic data are then simulated to account for preference heterogeneity and the correlation between choice sets in the sequence. Subsequently, the trained ANN can be applied to classify the collected survey respondents. For further information, refer to van Cranenburgh and Alwosheel (2019).

3.4.2. Stated Approach

To explicitly distinguish between utility maximizers and regret minimizers, we use a follow-up question as depicted in Figure 2. To begin with, we introduce the two decision rules of utility maximization and regret minimization. Subsequently, we prompt respondents to select the rule they believe governed their choices in the DCE. Moreover, we incorporate an “I don’t know” option to avoid forcing respondents to make a choice if they are still uncertain or unfamiliar with their decision rule even after our explanation.

4. Preliminary Results

After filtering out incomplete and inattentive respondents, our dataset comprises a total of 1304 participants, with 1093 allocated to the hypothetical treatment and 211 to the real treatment group. Our sample has passed a balanced check, indicating no significant differences between respondent characteristics in the two treatment groups, suggesting the effectiveness of our group assignment to ensure complete randomness.

4.1. Stated Decision Rule Heterogeneity

To begin, summary statistics regarding the decision rule derived from the follow-up question appear in Table 1. We find that 13.36% and 14.22% of respondents in the hypothetical and real treatment groups, respectively, indicate that their choices in the DCE are influenced by the principle of regret minimization. This slightly higher proportion of regret minimizers in the real treatment group aligns with our expectations. Given payment consequentiality, respondents may review alternatives in the real treatment group more carefully when making decisions. This decision-making process mirrors the level of scrutiny required for RRM, which involves detailed attribute-level pairwise comparisons. Regarding RUM, 82.62% and 76.30% of respondents in the hypothetical and real treatment groups, respectively, state that they adopted the utility maximization rule. Additionally, less than 10% of the respondents in the hypothetical (4.03%) and real treatment groups (9.48%) were unable to identify the decision rule they employed.

4.2. Opt-out Rate

We present a summary of the opt-out rates for both utility maximizers and regret minimizers across the real and hypothetical treatment groups (Table 2). To clarify the calculation process and the interpretation of the table, consider the example of the real treatment group, comprising 211 respondents. With each respondent tasked with answering six choice sets, this results in a total of 1266 choice sets. Among these, based on responses to the stated decision-rule question, 180 were answered by regret minimizers and 966 by utility maximizers. From these, we count the number of choice sets where the opt-out option was chosen, resulting in 100 and 600 opt-outs for regret minimizers and utility maximizers, respectively. Consequently, the opt-out rate is calculated as 100/180 = 55.6% for regret minimizers and 211/966 = 62.1% for utility maximizers in the real treatment group. A similar calculation process applies to the hypothetical treatment group. Consistent with the literature and our expectation, the opt-out rate in the real treatment group exceeds that of the hypothetical treatment group, suggesting the potential presence of HB. Additionally, our analysis indicates a higher proportion of opt-out responses among utility maximizers than regret minimizers in the real treatment group.

4.3. Model Analysis

In light of the divergence between hypothetical and real outcomes in Table 1 and Table 2, we proceed to model the two distinct underlying decision rules. In this preliminary analysis stage, our modeling does not control for preference heterogeneity. Furthermore, we estimate these models using three separate datasets: the pooled data combining hypothetical and real treatment groups, the hypothetical treatment group only, and the real treatment group only.[1] Table 3, 4, and 5 present these results, respectively. Across these tables, a total of nine models are estimated. These nine models can be divided into three subgroups representing the pooled sample of regret minimizers and utility maximizers, stated regret minimizers only, and stated utility maximizers

[1] For preliminary analysis, we simply drop the respondents who state "I don't know" in the follow-up question asking respondents their decision rule.

only. For each subgroup, we have three models with one traditional RUM model which is conditional logit model, and two RRM models which are classic RRM and Pure RRM.

In Table 3, three primary findings emerge. First, respondents exhibit a preference for options with lower prices, i.e., negative price coefficient across all models. Moreover, the negative coefficient for the opt-out option suggests a preference for purchasing options with reference product with none of the attributes estimated in the models. Also, respondents demonstrate a preference for the crafting product associated with a keychain and luggage tag over earrings. However, the results vary in terms of significance for other attributes. For instance, respondents in the pooled model prefer animal skins sourced locally in Louisiana over those from a national source with marginal significance.

Second, the signs and significance levels of coefficients remain largely consistent and stable across the conditional logit model, classic RRM, and Pure RRM models. Research by Chorus (2010) suggests that one should focus on the relative size of the coefficients when comparing the results from RUM and RRM models. The relative size can be calculated by taking the ratio of the coefficient of a non-price attribute to the coefficient of price. Under RUM, such ratios can be interpreted as marginal WTP as discussed in the previous section 3.3 but hold no specific meaning for RRM models. Equation (6) shows how to calculate WTP under the RRM model. Third, if we focus on the log-likelihood, RUM model (conditional logit) consistently outperforms the other two RRM models (Classic RRM and Pure RRM) in all three datasets: the pooled sample, the stated RRM sample, and the state RUM sample. This outcome appears counterintuitive, as one might expect a model to have better fit if it matches the respondents' stated decision rule. For instance, one would anticipate that the RUM model would outperform the RRM model when analyzing stated utility maximizers, and conversely, that the RRM model would be superior when analyzing stated regret minimizers.

One possible explanation can be the inclusion of responses selecting the "None of these" alternative (i.e., opt-out option) of the choice sets in our current analysis. Hess et al. (2014) suggests excluding such responses, as RRM models are considered inappropriate for modeling the opt-out option. Moving forward, our first step is to refine our analysis by excluding responses with the opt-out option from the sample. Additionally, we can explore other metrics to compare the performance of RRM and RUM models. For example, one can investigate out-of-sample validity, by splitting the sample into an estimation sample and a validation sample. After estimating the model based on the estimation sample, we use the estimated parameters to calculate the predicted choice probabilities for every alternative in the validation sample. Then, we compare whether our predicted probabilities match the chosen alternatives in the validation sample. The hit rate reflects the percentage of correct matches, providing insight into the model's predictive performance.

In Tables 4 and Table 5, the results largely align with the findings from Table 3. Two exceptions exist in Table 5 for the real treatment respondents. First, the coefficient for the opt-out option in becomes significantly positive, suggesting that respondents prefer not to pay for options with reference levels. Second, the price coefficient within the Stated RRM model results become insignificant. Apart from this observation, there are no new findings beyond what has been discussed in Table 3.

4.4. Hypothetical Bias (HB) Analysis

For our preliminary analysis, we first explore the issue of HB within the RUM framework, relying on the data from the pooled sample, the stated regret minimizer sample, and the stated utility maximizer sample. At this stage, we do not control for preference heterogeneity.

To capture HB, we generate a series of two-way interactions between all attributes and the hypothetical treatment group indicator. The outcomes are detailed in Table 6. Notably, for both the pooled and stated RUM samples, a significant positive interaction between price and the hypothetical treatment group indicator suggests the potential existence of HB. However, for the stated RRM sample, the price coefficient becomes insignificant, with no significant interaction observed with the hypothetical treatment group indicator.

Further analysis will estimate similar models but match model type with the corresponding stated decision rules. Additionally, we will calculate the WTP for all attributes post-estimation in both the hypothetical and real treatment groups, with the aim to provide deeper insights into the implications of RRM on HB.

5. Conclusions and Implications

This study aims to examine the implications of Random Regret Minimization (RRM) on real discrete choice experiments (DCEs) and hypothetical bias (HB). Additionally, we seek to introduce a stated approach to distinguish between utility maximizers and regret minimizers within a sample containing both types of decision-makers. We compare and contrast the proposed stated approach with the currently available inferred approaches for making such distinctions.

Our results show mixed evidence that the RRM framework provides some benefits in behavior interpretation and HB reduction. As our current analysis remains incomplete, we have several directions to explore further. Firstly, we will continue investigating the counterintuitive results observed when estimating models matched with the underlying stated decision rules. Additionally, we will explore out-of-sample validity (i.e., hit rate) to further compare model performance under RRM and RUM. Furthermore, we will control preference heterogeneity in subsequent steps. Second, we will delve deeper into the analysis of HB under the framework of RRM. We will also calculate the Willingness-To-Pay (WTP) for all attributes in both hypothetical and real treatment groups for both regret minimizers and utility maximizers.

Third, we will compare the effectiveness of our stated decision rule to identify consumer types with inferred approaches, including using latent class models and Artificial Neural Networks (ANN). These modeling approaches will contribute to informing selection of different approaches to control consumer heterogeneity in stated preference surveys. Fourth, acknowledging the potential context specific results in our current analysis, we will employ two additional DCE studies to examine the external validity of our findings. These studies are underway for data collection, and we anticipate sharing further insights in the due course.

Table 1. Stated RUM and stated RRM in hypothetical and real treatment groups

%	Hypo	Real	Total
Stated RRM	13.36	14.22	13.5
Stated RUM	82.62	76.3	81.6
I don't know	4.03	9.48	4.91
Total	100	100	100

Table 2. Optout rate

%	Real	Hypo
Stated RRM	55.56	10.73
Stated RUM	62.11	10.15

Table 3. Model analysis based on pooled hypothetical and real treatment groups

	Pooled Sample: Hypothetical + Real								
	Pooled: RRM+RUM			Stated RRM			Stated RUM		
Variable	Clogit	Classic RRM	Pure RRM	Clogit	Classic RRM	Pure RRM	Clogit	Classic RRM	Pure RRM
price	-0.0310***	-0.0151***	-0.0129***	-0.0212***	-0.0103***	-0.0075***	-0.0326***	-0.0158***	-0.0137***
optout	-0.7564***	-0.3442***	-0.1815***	-0.7488***	-0.3476***	-0.1850***	-0.8600***	-0.3896***	-0.2145***
gator	0.0227	0.0123	0.0217	-0.0749	-0.0353	-0.011	0.0343	0.0183	0.0262
keychain	0.3187***	0.1609***	0.2063***	0.1778**	0.0895*	0.1331*	0.3617***	0.1829***	0.2316***
luggage	0.3031***	0.1541***	0.2124***	0.1014	0.0502	0.0486	0.3483***	0.1774***	0.2462***
wild	-0.0378	-0.0189	-0.0122	-0.1326	-0.0656	-0.1048	-0.024	-0.012	-0.0015
Louisiana	0.0784**	0.0386*	0.0214	0.1147	0.0558	0.0265	0.0482	0.0231	0.0135
smallscar	-0.0653*	-0.0314*	-0.0026	-0.0409	-0.0205	-0.0081	-0.0650*	-0.031	0.0007
largescar	-0.0971	-0.0492	-0.0261	-0.1103	-0.0559	-0.0423	-0.0911	-0.046	-0.0227
largescale	-0.0268	-0.0141	-0.0612*	0.0762	0.0377	0.05	-0.0315	-0.0166	-0.0747*
intermediate	-0.0416	-0.0209	-0.0255	0.0808	0.0398	0.0357	-0.0597*	-0.0299*	-0.033
Model Statistics									
N	7,814	7,814	7,814	1,056	1,056	1,056	6,384	6,384	6,384
ll	-10495.2	-10497.6	-10535.1	-1433.0	-1433.3	-1437.3	-8489.8	-8492.2	-8526.8

Table 4. Model analysis based on hypothetical treatment group

	Hypothetical Sample								
	Pooled: RRM+RUM			Stated RRM			Stated RUM		
Variable	Clogit	Classic RRM	Pure RRM	Clogit	Classic RRM	Pure RRM	Clogit	Classic RRM	Pure RRM
price	-0.0303***	-0.0146***	-0.0123***	-0.0226***	-0.0109***	-0.0081***	-0.0313***	-0.0151***	-0.0128***
optout	-1.4362***	-0.6464***	-0.4061***	-1.3837***	-0.6296***	-0.3858***	-1.5204***	-0.6813***	-0.4351***
gator	0.0079	0.006	0.0215	-0.0734	-0.0343	-0.0204	0.0176	0.0111	0.0266
keychain	0.3223***	0.1628***	0.2191***	0.133	0.0664	0.0906	0.3724***	0.1885***	0.2525***
luggage	0.2989***	0.1512***	0.2077***	0.0952	0.0468	0.0538	0.3479***	0.1765***	0.2449***
wild	-0.0416	-0.0206	-0.0204	-0.1244	-0.0615	-0.0747	-0.0293	-0.0144	-0.0145
Louisiana	0.0923**	0.0444**	0.0244*	0.124	0.0604	0.0239	0.0645	0.0302	0.018
smallscar	-0.0728*	-0.0356*	-0.0066	-0.0681	-0.0341	-0.0167	-0.0692*	-0.0335	-0.0021
largescar	-0.1204*	-0.0607*	-0.0382*	-0.0151	-0.0089	0.0027	-0.1302*	-0.0653*	-0.0421*
largescale	-0.0264	-0.0139	-0.0701*	0.1166	0.0582	0.1184	-0.0375	-0.0195	-0.0946**
intermediate	-0.0497	-0.0252	-0.0345*	0.1141	0.0569	0.0839	-0.0776**	-0.0390**	-0.0538**
Model Statistics									
N	6,558	6,558	6,558	876	876	876	5,418	5,418	5,418
ll	-8438.9	-8441.5	-8472.8	-1140.8	-1141.0	-1144.3	-6899.3	-6901.6	-6923.0

Table 5. Model analysis based on real treatment group

	Real Sample								
	Pooled: RRM+RUM			Stated RRM			Stated RUM		
Variable	Clogit	Classic RRM	Pure RRM	Clogit	Classic RRM	Pure RRM	Clogit	Classic RRM	Pure RRM
price	-0.0468***	-0.0232***	-0.0212***	-0.0132	-0.0065	-0.0038	-0.0575***	-0.0283***	-0.0267***
optout	1.1825***	0.6737***	0.4702***	1.0012***	0.5465**	0.3260***	1.0524***	0.6143***	0.4532***
gator	0.1838	0.0864	0.0711	-0.1656	-0.0868	0.0204	0.2409	0.1127	0.0784
keychain	0.3477***	0.1753***	0.1761**	0.6160**	0.3172**	0.4411**	0.2967**	0.1489**	0.1334
luggage	0.4256***	0.2234***	0.3128***	0.2302	0.1162	0.0363	0.4417***	0.2342***	0.3546***
wild	-0.0249	-0.0143	0.0226	-0.2792	-0.1319	-0.4299	0.0238	0.0097	0.0924
louisiana	-0.0001	0.0068	0.0026	0.1676	0.0792	0.0961	-0.0634	-0.0224	-0.0192
smallscar	0.0217	0.0153	0.0408	0.2204	0.115	0.0795	-0.0169	-0.0024	0.0329
largescar	0.0949	0.0461	0.0502	-0.9833	-0.4549*	-0.4058**	0.3029	0.1524	0.1325*
largescale	-0.0513	-0.0278	-0.0523	-0.3343	-0.1586	-0.5658*	0.0484	0.0213	0.0772
intermediate	0.0538	0.0281	0.0238	-0.2499	-0.1159	-0.3502**	0.1657	0.0855	0.1250*
Model Statistics									
N	1,266	1,266	1,266	180	180	180	966	966	966
ll	-1278.154	-1278.241	-1285.46	-206.211	-206.248	-203.68	-979.031	-979.255	-983.746

Table 6. Conditional logit for HB analysis

	Stated RRM & Stated RUM			Stated RRM			Stated RUM		
	Coefficient	Std. err.		Coefficient	Std. err.		Coefficient	Std. err.	
price	-0.0468	0.0054	***	-0.0116	0.0114		-0.0575	0.0063	***
price_hypo	0.0165	0.0057	***	-0.0145	0.0121		0.0262	0.0066	***
optout	1.1825	0.1614	***	1.7676	0.3659	***	1.0524	0.1826	***
optout_hypo	-2.6187	0.1724	***	-2.8591	0.3916	***	-2.5728	0.1946	***
gator	0.1838	0.1725		-0.1170	0.3972		0.2409	0.1942	
gator_hypo	-0.1759	0.1801		0.0650	0.4168		-0.2232	0.2025	
keychain	0.3477	0.1248	***	0.6043	0.2762	**	0.2967	0.1416	**
keychain_hypo	-0.0253	0.1299		-0.5009	0.2889	*	0.0757	0.1472	
luggage	0.4256	0.1288	***	0.4613	0.2864		0.4417	0.1458	***
luggage_hypo	-0.1267	0.1342		-0.3802	0.3000		-0.0938	0.1516	
wild	-0.0249	0.1208		-0.2072	0.2883		0.0238	0.1341	
wild_hypo	-0.0168	0.1260		0.1046	0.3009		-0.0530	0.1399	
louisiana	-0.0001	0.1331		0.3289	0.3061		-0.0634	0.1502	
louisiana_hypo	0.0924	0.1396		-0.1069	0.3226		0.1279	0.1571	
smallscar	0.0217	0.1239		0.2740	0.2898		-0.0169	0.1387	
smallscar_hypo	-0.0945	0.1294		-0.3486	0.3038		-0.0523	0.1447	
largescar	0.0949	0.2062		-0.7126	0.5141		0.3029	0.2298	
largescar_hypo	-0.2153	0.2161		0.6654	0.5377		-0.4331	0.2406	*
largescale	-0.0513	0.1287		-0.4195	0.3050		0.0484	0.1442	
largescale_hypo	0.0249	0.1344		0.4505	0.3191		-0.0859	0.1503	
intermediate	0.0538	0.1053		-0.3701	0.2370		0.1657	0.1193	
intermediate_hypo	-0.1035	0.1099		0.4559	0.2490	*	-0.2433	0.1242	**
Model Statistics									
# of observations	7,824			1,440			6,384		
Loglikelihood	-9717.1			-1800.9			-7878.3		

Figures

Figure 1. A sample choice set

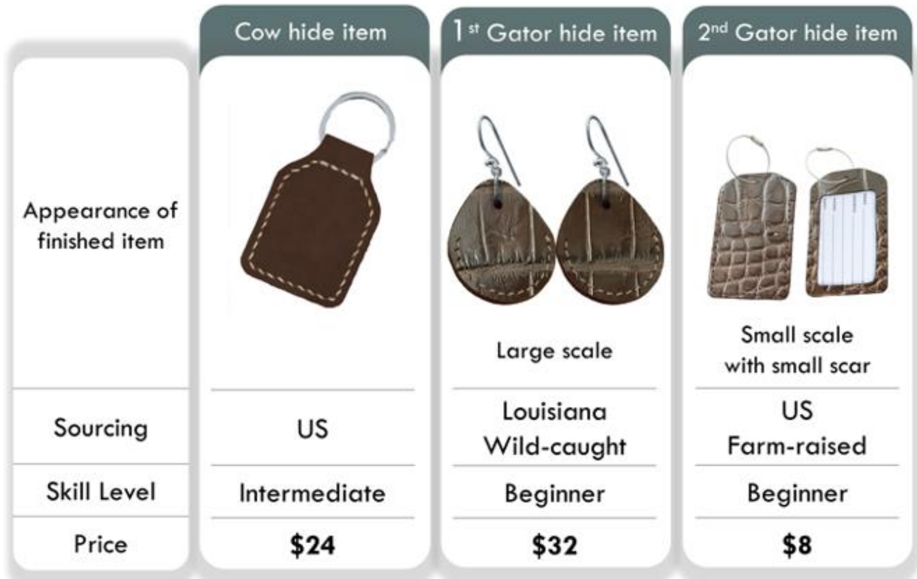

Figure 2. Attributes and levels

- **Item & Appearance of finished kit:**
  The type of item (earring, luggage tag, or keychain) and how it looks like when finished.
- **Sourcing:**
  Whether the animal was farm-raised or wild-caught either in Louisiana or elsewhere in the Southeastern US.
- **Skill level:**
  Beginner: Contains finished, pre-cut leather with stitching holes are already punched. It still requires stitching. No additional tools required.

  Intermediate: Contains finished, pre-cut leather, but no stitching holes. You'll need a leather hole punch tool to do hole punches yourself, then stitching to finish.
- **Price:**
  $8, $16, $24, or $32.

If you want to go back to survey, please close this tab

References

Biondi, B., Van der Lans, I. A., Mazzocchi, M., Fischer, A. R., Van Trijp, H. C., & Camanzi, L. (2019). Modelling consumer choice through the random regret minimization model: An application in the food domain. *Food Quality and Preference*, 73, 97-109.

Buckell, J., Vasavada, V., Wordsworth, S., Regier, D. A., & Quaife, M. (2022). Utility maximization versus regret minimization in health choice behavior: Evidence from four datasets. *Health Economics*, *31*(2), 363-381.

Caputo, V., Van Loo, E. J., Scarpa, R., Nayga Jr, R. M., & Verbeke, W. (2018). Comparing serial, and choice task stated and inferred attribute non-attendance methods in food choice experiments. *Journal of agricultural economics*, *69*(1), 35-57.

Chorus, C. G., Arentze, T. A., & Timmermans, H. J. (2008). A random regret-minimization model of travel choice. *Transportation Research Part B: Methodological*, 42(1), 1-18.

Chorus, Caspar G. "A new model of random regret minimization." *European Journal of Transport and Infrastructure Research* 10.2 (2010).

Chorus, C. (2012). Random regret minimization: an overview of model properties and empirical evidence. *Transport reviews*, *32*(1), 75-92.

Hensher, D. A. (2010). Hypothetical bias, choice experiments and willingness to pay. *transportation research part B: methodological*, *44*(6), 735-752.

Hess, Stephane et al. "Contrasts between utility maximization and regret minimization in the presence of opt out alternatives." *Transportation Research Part A: Policy and Practice* 66 (2014).

Hess, S., & Chorus, C. G. (2015). Utility maximisation and regret minimisation: A mixture of a generalisation. In Bounded rational choice behaviour: applications in transport (pp. 31-47). Emerald Group Publishing Limited.

Loomis, J. (2011). What's to know about hypothetical bias in stated preference valuation studies?. *Journal of Economic Surveys*, *25*(2), 363-370.

McFadden, D. (1972). Conditional logit analysis of qualitative choice behavior.

Michaud, C., D. Llerena, and I. Joly. 2013. "Willingness to pay for environmental attributes of non-food agricultural products: a real choice experiment." *European Review of Agricultural Economics* 40(2):313-329.

Moser, Riccarda, Roberta Raffaelli, and Sandra Notaro. "Testing hypothetical bias with a real choice experiment using respondents' own money." *European Review of Agricultural Economics* 41.1 (2014): 25-46.

Nielsen, M. R., & Jacobsen, J. B. (2020). Effect of decision rules in choice experiments on hunting and bushmeat trade. *Conservation Biology*, *34*(6), 1393-1403.

Penn, J. M., & Hu, W. (2018). Understanding hypothetical bias: An enhanced meta-analysis. *American Journal of Agricultural Economics*, *100*(4), 1186-1206.

Piracci, G., Boncinelli, F., & Casini, L. (2023). Investigating consumer preferences for sustainable packaging through a different behavioural approach: a random regret minimization application. Environmental and Resource Economics, 86(1), 1-27.

Ready, R.C., P.A. Champ, and J.L. Lawton. 2010. "Using respondent uncertainty to mitigate hypothetical bias in a stated choice experiment." *Land Economics* 86(2):363-381.

van Cranenburgh, Sander, and Ahmad Alwosheel. "An artificial neural network based approach to investigate travelers' decision rules." *Transportation Research Part C: Emerging Technologies* 98 (2019).

Weller, P., Oehlmann, M., Mariel, P., & Meyerhoff, J. (2014). Stated and inferred attribute non-attendance in a design of designs approach. *Journal of choice modelling*, *11*, 43-56.