CONSISTENCY AND HETEROGENEITY IN CONSIDERATION AND CHOICE*

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Abstract. We empirically investigate the consideration and choice behaviors of individuals under uncertainty. Our experiment allows subjects to reveal their stochastic or deterministic consideration and choice. Most of the subjects have stochastic (limited) consideration and stochastic choice. Furthermore, consideration and choice data mostly violate monotonicity and regularity axioms, respectively, but they satisfy a proposed stochastic transitivity axiom. We show that observing both consideration and choice is crucial to drawing meaningful welfare inferences.

Date: November 18, 2025.

*We thank Marina Agranov, P. J. Healy, Nikolas Kuschnig, Paola Manzini, Efe Ok, Pietro Ortoleva, and the audiences of several seminar presentations for helpful comments and discussions. This study was reviewed by the Institutional Review Board at the University of Maryland, and the experiments are funded by the University of Maryland.

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1. Introduction

When individuals are repeatedly presented with the same choice problems, they often make different selections.[1] Modern choice theory acknowledges such stochastic departures from the classical preference-maximization framework and offers models that attribute the source of stochasticity to two main categories: (i) the stochasticity at the choice stage, where the decision maker considers all the available alternatives but may exhibit stochastic tastes (e.g., McFadden, 1977, McFadden and Richter, 1990) or may enjoy randomization (e.g., Cerreia-Vioglio et al., 2019) while choosing; and (ii) the stochasticity at the consideration stage, where the decision maker has a well-defined preference to maximize while choosing, but considers alternatives only stochastically due to limited attention or consideration (Manzini and Mariotti, 2014, Brady and Rehbeck, 2016, Cattaneo et al., 2020, 2023).[2] To separately identify stochasticity at these two stages of decision making and to assess compliance with the properties assumed by the corresponding models, we design an experiment consisting of two independent parts: one dedicated to eliciting consideration behavior and the other to eliciting choice behavior.

There are two main reasons why it is important to observe consideration behavior in addition to choice behavior, even though consideration is typically unobservable in field data. First, doing so is essential for directly identifying which class of stochastic models best describes human behavior. Most models with a consideration stage assume that choices, but not considerations, are observable. These models typically posit a particular consideration rule (such as the logit model proposed by Brady and Rehbeck, 2016) and characterize the resulting choice behavior consistent with that rule.[3] Our experimental design, by contrast, is free from such strong commitment to an underlying model, allowing us to study consideration behavior directly. Second, we show that observing consideration data is crucial for welfare analysis. Cattaneo

[1]For evidence on stochastic choice see e.g., Tversky [1969], Camerer [1989], Hey and Orme [1994], Hey [2001], Regenwetter et al. [2011], Agranov and Ortoleva [2017].

[2]Kashaev and Aguiar [2022] allows for being stochastic at both stages.

[3]The previous empirical work followed this idea and analyzed consideration indirectly based on choice (see e.g. Abaluck and Adams-Prassl, 2021, Aguiar et al., 2023).

et al. [2020] raised the concern that committing to a particular consideration rule can distort welfare assessments. They introduced the Random Attention Model, which remains agnostic about a specific rule by focusing on the broader class of monotonic consideration. Building on their insight, we show that, even within their framework, it is possible to construct examples (see our Example 1) in which identical observed choices are rationalized by both monotonic and non-monotonic consideration but imply different underlying preferences, leading to conflicting welfare conclusions. Therefore, understanding the consideration behavior of decision makers is essential for drawing meaningful welfare inferences.

We develop an experimental setup which allows for stochastic behavior in both consideration and choice stages by repeating each menu of alternatives within the corresponding stage of the experiment. Our data enables us to study the normatively appealing axioms employed in models of limited (stochastic) consideration and (stochastic) choice. Our design two key challenges one may encounter when collecting such rich data: (i) observing the decision-makers' consideration function on overlapping menus without altering the information they collect while considering, (ii) repeating the same consideration and choice problems several times to allow for (possibly) stochastic behavior for all the menus of interest without boring the subjects. Our unique design addresses both of these challenges and, to the best of our knowledge, ours is the first individual-level data set with both consideration and choice functions defined on the whole domain being observed.[4] Based on this data, we study descriptive properties of consideration and choice functions, document heterogeneity in complying with well-known axioms of interest (monotonicity and stochastic transitivity), and detect certain menu-dependent trends in consideration and choice behavior.

[4]Other empirical studies on consideration are either within the optimal search framework (Reutskaja et al., 2011 and Thomas et al., 2021 utilize eye-tracking technology and Honka and Chintagunta, 2017 collects search history of consumers to elicit consideration in search problems), or based on the recall survey of the consumers (Draganska and Klapper, 2011). These are not suitable methods for our purpose of eliciting full consideration function in the two-stage setup at the individual level without altering the decision makers' knowledge.

We employ a two-independent-part, within-subjects experimental design. In Part I, we elicit subjects' consideration functions; in Part II, their choice functions. Our design allows for stochastic behavior in both stages by repeating each menu for consideration and for choice. We also use a strategy method that ensures subjects' knowledge about options remains unchanged throughout the experiment.

Each problem in Part I presents a menu of ambiguous lotteries (prizes are known but the probabilities are unknown) and subjects indicate what options they want to consider for each menu without receiving any feedback on the probabilities between problems. Without feedback, the information content of an ambiguous lottery (the number of possible prizes and the associated payoffs) remains constant throughout this part of the experiment. The subjects consider options only after we fully elicit their consideration function. At the end of Part I, a subject is presented with one randomly selected problem and is asked to perform a real effort counting task to fully learn the probabilities of the ambiguous options that she had committed to consider earlier for this problem. Upon learning the probability information of the lotteries, she chooses one of the considered lotteries and is paid based on the outcome of this lottery. During the consideration elicitation part, the subjects know that what they indicated to consider on a menu will limit their options to choose at the payment stage of Part I. Hence, on the one hand, they may want to consider all the options to make better-informed decisions at the payment stage, but considering an option requires performing a counting task perfectly, and the subjects may want to consider a limited set of options to minimize the counting task.

Part II elicits the choice functions of the subjects. The same lotteries of Part I are used in Part II, but this time they are presented as standard risky lotteries where the prizes and their associated probabilities are known. The subjects indicate what they want to pick from each non-singleton subset of the grand set, and each menu is presented multiple times to allow for stochastic choice behavior.[5] After eliciting their

[5] Agranov and Ortoleva [2017] and McCausland et al. [2020] also repeat the choice problems and document stochastic choice. Earlier studies repeating choice problems in experiments include Balakrishnan et al. [2022] and Hey and Orme [1994]. Our design is closest to McCausland et al. [2020] but we have more granularity in choice frequencies as we repeat the menus 10 times rather 6.

possibly stochastic choice functions, we randomly select one choice problem, and pay the subjects based on the outcome of their choice in that decision problem. The subjects know the payment rule from the beginning of the experiment so they understand that what they indicated to choose in Part II will determine their earnings.

Results from Part I (Consideration) show that most subjects act stochastically rather than deterministically. They have limited consideration on every type of menu and this behavior is persistent throughout the experiment. They consider more alternatives on larger menus indicating that they understand the trade-off between making a better-informed decision and the cost of investigating more options. The subjects who had deterministic consideration (i.e., always consider the same options on a menu when repeated) satisfy the Attention Filter property (Masatlioglu et al., 2012) and Competition Filter property (Lleras et al., 2017). We have limited support for the Monotonic Consideration axiom (Cattaneo et al., 2020) and the Consideration Overload axiom (Cattaneo et al., 2023), although these are the weakest stochastic consideration axioms offered by the literature. We propose a new stochastic transitivity axiom for consideration, which is inspired by our choice experiment results and satisfied by a majority of subjects.

In Part II (Choice), most subjects acted stochastically on at least some menus. Our deterministic subjects (about 24%) satisfy the Weak Axiom of Revealed Preference. The others acted stochastically depending on the menu. We study regularity and different versions of stochastic transitivity axioms from stochastic choice theory. Similar to McCausland et al. [2020], we have limited support for the Regularity axiom. However, a majority of subjects satisfy Stochastic Transitivity axioms.

In sum, our contribution is threefold: (i) we offer a method to observe consideration and choice functions at the individual level, allowing for correct welfare inferences; (ii) we study stochastic properties of these functions, which have been the focus of recent literature; (iii) and we propose a transitivity property for consideration, inspired by choice data, that is consistent with the observed behavior of a majority of subjects.

Moreover, we demonstrate a strong consistency with a Stochastic Transitivity axiom in both choice and consideration domains.

In what follows, we explain the design in Section 2 and introduce the basic notation for the relevant theoretical models and axioms in Section 3. Section 4 first analyzes the consideration data (Part I) followed by the choice data (Part II). Then, we analyze a hypothetical choice function based on the observed consideration and choice behavior for each subject and demonstrate how a misleading welfare inferences can be performed if consideration is not observable. Section 4 also suggests a new stochastic transitivity axiom for the consideration function. Section 5 concludes. The supplementary information is in the Appendices.

2. Design of the Experiment

The experiment consists of two main parts followed by a demographics questionnaire and elicitation of risk and ambiguity preferences. We elicit what subjects want to consider on a set of options in Part I and what they want to choose from an option set in Part II. The same decision problems are presented multiple times to allow subjects to reveal their stochastic consideration or choice if they prefer to do so. The instructions are in Appendix A.

Throughout the experiment, the subjects make decisions involving four main options with uncertainty. Each option is a lottery but the subjects only see its possible outcomes (not the associated probabilities) in Part I. In Part II, the subjects see the lotteries fully (the payoffs and the corresponding probabilities). The lotteries used are in Table 1. Each lottery is presented as a box filled with 100 colored balls. We tell subjects that the color of a randomly picked ball from the box they select eventually will determine their earnings in the experiment. Note that Lotteries A and B have relatively larger ranges of prizes than C and D. E is the option we introduced for attention check throughout the experiment. Its highest outcome is lower than the lowest outcome of any other lottery and therefore it is dominated under any distribution. We use E to detect inattentive subjects to eliminate noise in the data.

In both parts of the experiment, subjects are presented a sequence of decision problems. We use all the subsets of $\{A, B, C, D\}$ of size two or greater to construct 11 decision problems (six binary, four trinary, one quaternary option sets) and repeat each one of those ten times to allow for stochastic behavior. This creates 110 decisions to make for each part. In addition to that, the option set $\{C, E\}$ is presented five times as an understanding check in Part I. Since lottery C clearly dominates E (even without knowing the probabilities of outcomes of C and E) we expected that any subject, who prefers more money to less and understands the experiment, should not consider E alone in Part I. The order of the 110 decisions is randomized at the subject level. For Part I, the five repetitions of $\{C, E\}$ are evenly distributed in that sequence. In total, 115 consideration decisions and 110 choice decisions were made in Parts I and II, respectively. In addition to those, at the end of Part I a randomly selected decision problem is picked to actually perform the consideration task. Below, the procedural details of Parts I and II are explained, separately.

Table 1. The lotteries used in the Experiment

Lottery	Payoffs			Probabilities		
A	20	128	360	50%	30%	20%
B	40	120	320	51%	29%	20%
C	80	84	160	20%	24%	56%
D	72	136	140	25%	50%	25%
E	4	8	16	33%	33%	34%

Part I. At the beginning of Part I, we tell subjects that when they see a box in this part, the colors of the individual balls are not specified, but they will know the possible colors and their corresponding prizes. Hence, they do not know how likely it is to pick a certain color in a box. We tell them that they will see a sequence of decision problems and in each one there will be a set of options for them to consider. In order to make subjects gain some experience with the difficulty of the consideration task that they will face in this experiment, we first provide three sample problems with different colors and payoffs than what we used in the actual experiment. Counting the color content of the presented boxes in this dry round should give the subjects an idea of how costly or pleasant the consideration task is, hence, they may have a better understanding of the trade-off considering more or less options.

Figure 1 presents an example of a consideration problem with two options. This figure is copied from one of the actual rounds we used in the experiment. Note that the content of the boxes are not revealed but the possible prizes of each box are announced. The subject needs to select what to consider, i.e., which boxes to investigate further to learn the content. They need to click on at least one box and they may click as many boxes as they want to learn the content. This determines what they want to consider for that problem. They decide what to consider for all 115 problems without feedback. This is an application of a strategy method. To incentivize Part I, one of the 115 problems is randomly selected for actual consideration after all the problems of this part are completed. The subject sees the color combinations of the boxes they had chosen to consider for that problem. She needs to count the color content of the boxes they consider correctly. Subjects are told that if they make a mistake in counting, then they will not be paid for Part I. So, if a subject wants to avoid counting several boxes in this stage, they should choose to consider fewer boxes in Part I; if they do not mind counting and believe they can perform the task perfectly, it is best to consider all the boxes to learn the probability of each prize and make an informed decision at that stage. After considering the selected boxes, they then choose one of the considered boxes and the realization of a random draw from that box determines the subject's payoff in this part. Subjects will learn whether they will be paid for this choice at the end of the experiment. This is to avoid any wealth effect impacting Part II performances.

There are three important design details that we cautiously implemented:

First, note that we incentivize the consideration decisions in Part I by making subjects eventually choose from what they considered on a randomly selected decision

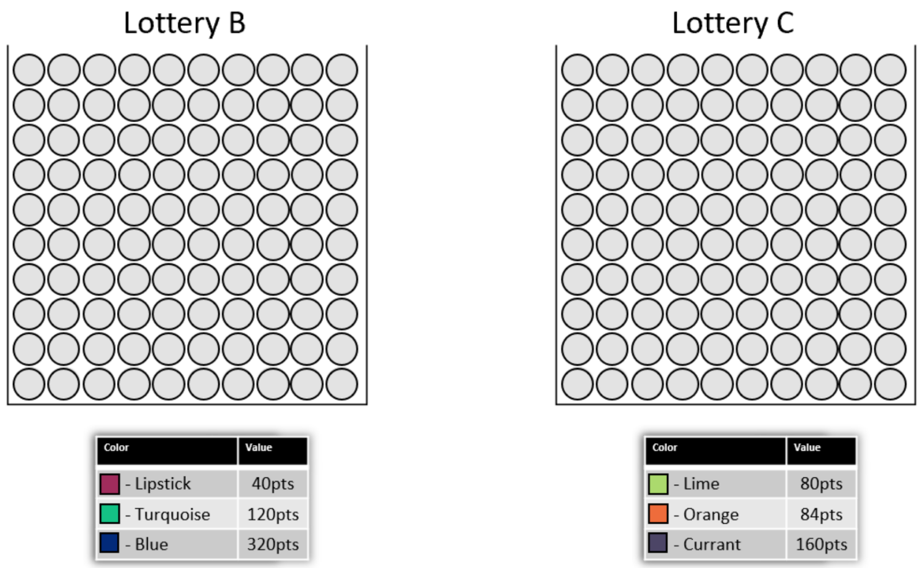


Figure 1. A sample consideration problem with two options.

problem. This is our method to elicit (possibly stochastic) consideration data in an incentivized way.

Second, no feedback is given between decision problems in Part I. Otherwise, if a subject considers a box in one problem and immediately learns its content, they would make an informed decision on whether to consider that box the next time it appears in a different problem. Then the decision problems would not be independent from each other because there would be some learning. Since the consideration models of interest are static, we needed to shut down such possibilities of learning. Our procedure gives us (possibly) stochastic consideration rules of decision makers at the individual level.

Third, even though there were 115 consideration problems where subjects had to reveal what they would consider on that problem, they performed this task only on one randomly selected problem. This serves two purposes: simplicity and elimination of learning. Note that counting the color content of boxes with 100 balls is a hard and boring task. Therefore, we can only ask subjects to perform this a limited number of times. Moreover, counting the content of a box once is enough to learn it, and the subjects know that the same options are offered throughout the experiments. So, if we made them perform the same consideration multiple times, they would not count it every time as they would remember the numbers.

Part II. This part is similar to Part I in terms of how 110 decision problems are generated. This time, a decision problem presents the available options by both showing the color content of the boxes and the corresponding prizes (see Figure 2). Hence, each option is presented as an objective lottery. The subjects need to choose a single option for each problem and after completion of this part, they are paid based on one randomly selected decision problem of Part II and the realization of the lottery they chose for that problem.

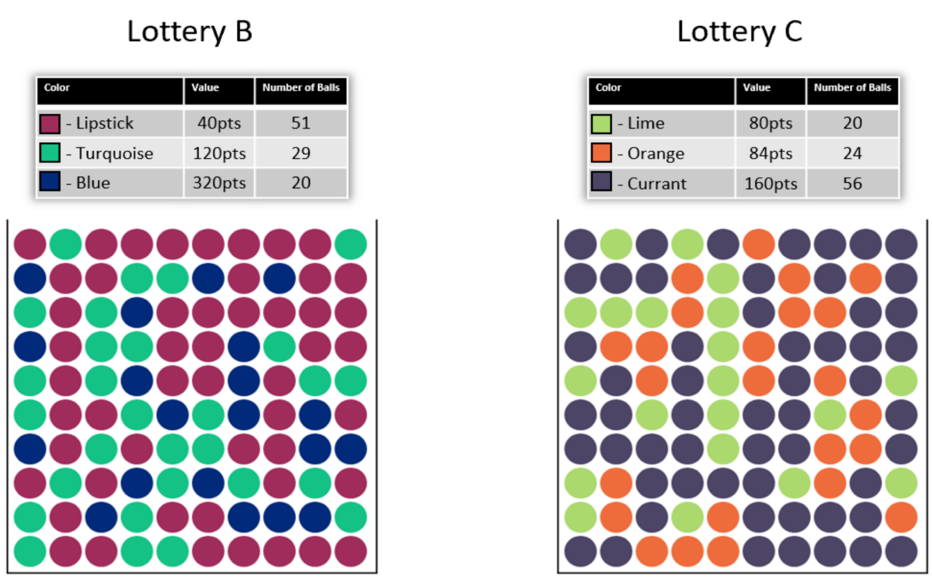


FIGURE 2. A sample choice problem with two options.

After Part II, a questionnaire takes place. The first two pages of the questionnaire elicit risk and ambiguity preferences using a standard multiple-price list method. The third page asks subjects for their age, gender, and the highest level of schooling achieved.

The experiment was conducted on Prolific with 402 subjects in September and October 2022. 201 and 189 specified their gender as male and female, respectively, and

12 of them did not specify their gender or did not identify as either male or female. The median age range was 28-37 and the median subject had a bachelor's degree. The details of the demographics of the subject pool can be found Tables 12, 13, and 14 and the relationship between the demographics data and the observed behaviors in Parts I and II can be found in Table 15 in Appendix B.

We implemented an attention test to make sure that the subjects were engaged in our experiments fully: Those who considered only the dominated alternative E in the decision problem $\{C, E\}$ are labeled as inattentive and excluded from the analysis. Hence, the results are based on 315 subjects.[6] The average hourly payment was \$9.21 and it took approximately 27 minutes on average for a subject to finish the experiment.

3. Theoretical Framework

In Part I, we elicit what a subject wants to consider on a menu in 10 repetitions in an incentivized way. Let $X = \{A, B, C, D\}$ be the grand set of options. For each $S \subseteq X$, a subject's consideration function that is elicited in Part I is

$$\mu(. \mid S) : 2^S \setminus \varnothing \longrightarrow [0,1] \text{ such that } \sum_{\substack{T \subseteq S \\ T \neq \varnothing}} \mu(T \mid S) = 1$$

We say that a subject has a deterministic consideration function if, for each $S \subseteq X$, there is a unique $T \subseteq S$ such that $\mu(T \mid S) = 1$ and for all $T' \subseteq S$ such that $T' \neq T$, $\mu(T \mid S) = 0$. Otherwise, we say the subject has a stochastic consideration function. Note that a subject with a deterministic consideration would consider the same options every time the same decision problem appears in the experiment.

For deterministic consideration behavior, two well-known consideration axioms are Attention Filter and Competition Filter (Masatlioglu et al., 2012, Lleras et al., 2017). Let $\Gamma(S) \coloneqq \{T \mid \mu(T \mid S) = 1\}$ denote what is considered on a menu given a

[6]In addition to that we may filter those who did not complete the dry run of the consideration task successfully and that would drop the number of subjects to 249. The analysis does not qualitatively change with or without these subjects and they do not change the demographic composition of the subject pool. Nevertheless, we choose to include those since the dry round is not incentivized.

deterministic μ function. The Attention Filter property of Masatlioglu et al. [2012] requires that $\Gamma(S) = \Gamma(S \setminus \{x\})$ for $x \notin \Gamma(S)$ and the Competition Filter property of Lleras et al. [2017] requires that if $x \in S \subset T$ and $x \in \Gamma(T)$ then $x \in \Gamma(S)$.

For a stochastic consideration function, $\mu(. \mid S)$ (which is observed in Part I), one can calculate how much attention an option x attracts in the decision problem S by adding up the probabilities of each subset containing x being considered. Cattaneo et al. [2023] defines the attention frequency of an alternative in an option set S as follows: Given the consideration function $\mu(. \mid S)$, the attention attracted by option $x \in S$ is defined by

$$\phi_\mu(x \mid S) = \sum_{\substack{T \subseteq S \\ T \ni x}} \mu(T \mid S) \tag{1}$$

For example, when presented with set $\{x, y\}$ if a subject's consideration function is $\mu(\{x\} \mid \{x,y\}) = \mu(\{x,y\} \mid \{x,y\}) = 0.5$, then the attention frequency of x on menu $\{x, y\}$ is 1, because it is contained in every subset of the menu that has positive consideration weight. In sum, $\phi_\mu(x \mid S)$ measures how much attention option x attracts on menu S. For each subject, we denote the induced attention frequency function by $\phi(. \mid S)$ rather than $\phi_\mu(. \mid S)$ to simplify the notation. Since each subject has only one observed μ function, this simplification should not lead to any confusion.

For stochastic consideration behaviors, we use two monotonicity conditions offered in the literature. Cattaneo et al. [2020] propose the Random Attention Model (RAM), where consideration sets compete for attention; hence, the probability of considering a set in a menu increases when the menu gets smaller. This is captured by the monotonic consideration rule, μ, stated below.[7]

Monotonic Consideration. For any T, S, $x \in S$ such that $T \subset S \setminus \{x\} \subseteq X$,

$$\mu(T \mid S) \leq \mu(T \mid S \setminus \{x\})$$

[7] Cattaneo et al. [2020] call this property as monotonic attention as they name function μ as the attention function.

Cattaneo et al. [2023] impose a similar monotonicity requirement on attention frequency, ϕ, defined in Definition (1), instead.

Consideration Overload. For any T, S, x such that $x \in T \subseteq S \subseteq X$,

$$\phi(x \mid S) \leq \phi(x \mid T)$$

.

Next, we introduce a notation for the data observed in Part II of the experiment. For each $S \subseteq X$, the choice function of a subject in Part II is

$$\pi(\cdot \mid S) : S \longrightarrow [0,1] \text{ such that } \sum_{x \in S} \pi(x \mid S) = 1$$

We say that subject i has a deterministic choice function if, for each $S \subseteq X$, there exists a unique $x \in S$ such that $\pi(x \mid S) = 1$ and for all other $y \in S$ such that $y \neq x$, $\pi(y \mid S) = 0$. Otherwise, we say the subject has a stochastic choice function. In Part II, we elicit how frequently a subject chooses each option presented in all ten appearances of a decision problem in an incentivized way. Note that a subject with a deterministic choice would choose the same option every time the same decision problem is presented.

Regularity is a standard axiom for Random Utility theories offered by the literature to explain stochastic choice behavior. The Regularity axiom requires that the chance of choosing an option cannot decrease when another option is removed from the menu. It is analogous to the idea of monotonicity in the consideration domain.

Regularity. For any $x \neq y \in S$, $\pi(x \mid S) \leq \pi\left(x \mid S \setminus \{y\}\right)$.

The transitivity axiom in deterministic theories has been a cornerstone because it implies utility representation (Samuelson, 1953). The Strong Stochastic Transitivity is proposed as a natural extension of the deterministic version of transitivity and it is implied by all fixed utility theories such as Luce's (Rieskamp et al., 2006). Many empirical studies have found violations of this property (see Mellers and Biagini, 1994, for a review). The Weak Stochastic Transitivity and Moderate Stochastic Transitivity axioms are proposed as weaker versions of stochastic transitivity. The Moderate Stochastic Transitivity is often attributed to Chipman [1958, 1960] and a slightly stronger version of it characterizes the Moderate Utility Model (He and Natenzon, 2024).

Formally, for any $x, y, z \in S$ such that $\min\{\pi(x|\{x,y\}), \pi(y|\{y,z\})\} \geq 0.5$, these axioms imply:

Weak Stochastic Transitivity: $\pi(x|\{x,z\}) \geq 0.5$.

Moderate Stochastic Transitivity: $\pi(x|\{x,z\}) > \min\{\pi(x|\{x,y\}), \pi(y|\{y,z\})\}$ or $\pi(x|\{x,z\}) = \pi(x|\{x,y\}) = \pi(y|\{y,z\})$.

Strong Stochastic Transitivity: $\pi(x|\{x,z\}) \geq \max\{\pi(x|\{x,y\}), \pi(y|\{y,z\})\}$.

4. Results

We will present first the consideration results followed by the choice results based on Parts I and II of the experiment, respectively. For each case, descriptive analysis will be provided to identify certain trends in the data; then we will check consistency of the data with the axioms. We are reporting results for 315 subjects who passed the attention check and never considered option E alone.

When we classify a subject's behavior and check its consistency with an axiom, we compute results not only for full alignment with the rule in hand but also compute results allowing for one "error" relative to the requirements of the rule (Ellis and Freeman, 2024). We define an error as how many questions we need to change in subject's data to make a subject's behavior consistent with the rule. For instance, in checking deterministic consideration, a subject is within 1-error-allowance of being deterministic if changing one out of her 110 answers would lead to her consideration becoming deterministic. We say a subject is consistent with a rule at 0-error-allowance if no question needs to be changed to be consistent with the rule.

4.1. Descriptive Analysis of Consideration.

Note that the behavior in Part I may deviate from the standard full consideration hypothesis in two ways: A subject may consistently consider a unique subset of an option set or she may consider a different subset when the option set is presented repeatedly. The former behavior would be limited deterministic consideration and the later one would be stochastic consideration.

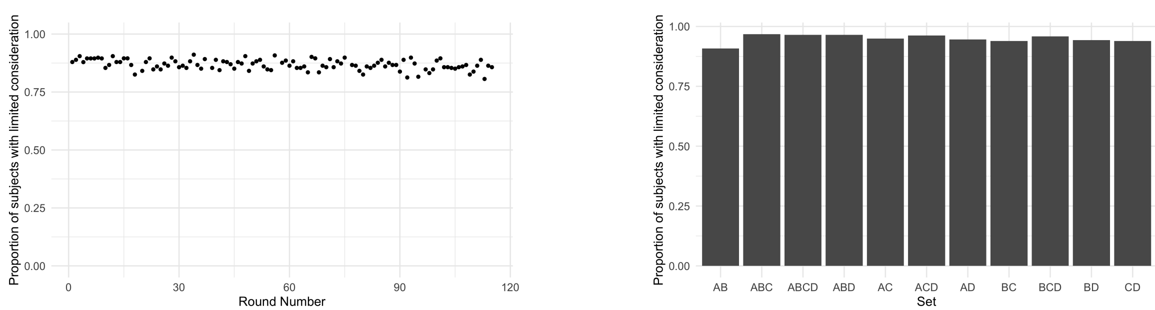
Full vs Limited Consideration. Recall that in Part I, each decision problem presents a set of two to four boxes (lotteries), and asks subjects which non-empty subset of these boxes they want to consider, i.e., count the color content. On one hand, a subject may want to learn the color content of *more* boxes so that they can make an informed lottery choice after learning the probability of each corresponding prize. On the other hand, they may want to count the balls in *fewer* boxes to reduce cognitive cost or the possibility of mistakes in counting (note that the subjects are not paid for Part I if they make a mistake in this part of the experiment). Out of 315 subjects, only seven subjects exhibit full consideration in all questions and full consideration is rare for any menu size (see Table 2, column 2 for the menu sized of two to four).

Table 2. Number of subjects with full and limited consideration

	Full Consideration	Limited Consideration
All Data	7	308
$\|S\| = 2$	8	307
$\|S\| = 3$	9	306
$\|S\| = 4$	11	304

Next, we investigate whether this limited consideration is due to preference for limited consideration or due to a lack of capacity to choose alternatives to consider. Consider a subject with a limited consideration, i.e. considers a strict subset of menu T with a positive weight. This means there exists $Q \subset T$ such that $\mu(Q \mid T) > 0$. If she is capable of considering more options in a larger menu than she did on T, i.e. if there exist $R \subseteq T \subseteq S$ such that $\mu(R \mid S) > 0$, and $Q \subset R$, then we say such a subject did not suffer from a capacity constraint when she considered only Q on a small menu T because she was capable of considering a larger set R on a larger menu, S. This is a conservative notion and can determine a lower bound for capacity unconstrained subjects, because it is only a sufficient condition for not being constraint by a capacity. Out of 308 subjects who exhibit limited consideration, 224 subjects satisfy this condition. Together with the 7 subjects who have full consideration on all menus, the behavior of 231 subjects (73.3%) cannot be explained by having a capacity for consideration. 83 of the remaining 84 subjects always considered a single option in every question. In sum, the limited consideration is mainly driven by subjects' preferences rather than a capacity constraint.

The limited consideration results are robust. Figure 3a reports that about 87% of the subjects had limited consideration in each one of the 115 rounds. Figure 3b provides further evidence that limited consideration applies to any type of menu. Almost all the subjects had limited consideration for each of the 11 menus they saw.

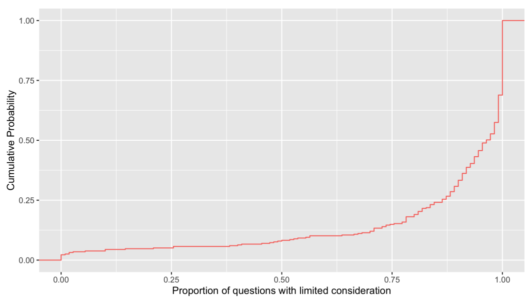


(A) Proportion of limited consideration subjects by round.

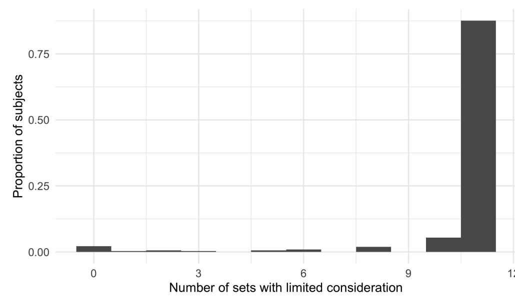
(B) Fraction of subjects with limited consideration by set.

FIGURE 3. Robustness of Limited Consideration

Figure 4a shows the distribution of proportions of questions with limited consideration by subjects. In other words, it calculates how many subjects considered a certain percentage of 110 questions in a limited fashion. Note that 98 subjects (31.1%) had limited consideration every time they faced a menu. These subjects are located on the far right of the cdf in Figure 4a where there is a big jump. 268 subjects (85.1%) had limited consideration on at least 75% of the questions out of 110 consideration questions they answered. In sum, limited consideration is robustly exhibited by almost every subject on every type of menu throughout the experiment. We may perform this analysis at the menu level as well. Figure 4b reports the percentages of subjects who considered a certain number of menus in a limited fashion. Note that 276 subjects (87.6%) had limited consideration on all 11 menus in Figure 4b. The 7 subjects who fully considered every menu (as reported in Table 2) appear on the very left of the distribution in this figure.



(A) Distribution of proportion of questions with limited consideration, by subject.



(B) Distribution of subjects by the number of sets that have limited consideration.

FIGURE 4. Robustness of Limited Consideration

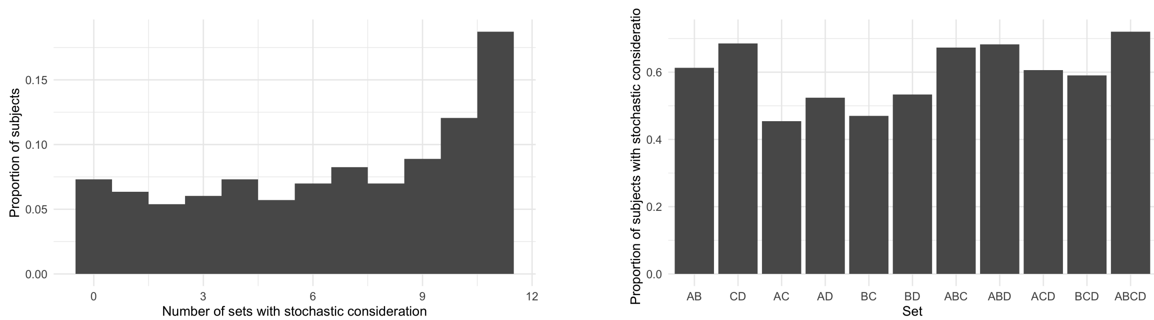
Result 1: Almost all subjects have limited consideration.

Stochastic vs. Deterministic Consideration. The limited consideration of the subjects mostly occurs in stochastic fashion. Recall that 7 out of 315 subjects had full consideration all the time and that behavior is trivially deterministic. Among the remaining 308 subjects, only 16 acted deterministically in their limited consideration, i.e., they considered the same sub-menu in every repetition. In addition to those 23 subjects, 37 subjects (11.7%) have deterministic consideration functions at 1-error-allowance.[8]

Unlike the behavior of limited consideration, stochasticity of consideration depends on the menu. Only 59 subjects (18.7%) acts stochastically on every menu. Figure 5a shows the distribution of subjects who have stochastic consideration by the number of menus. The set dependence of stochasticity in consideration can be further seen in Figure 5b. We see that more subjects act stochastically on some sets than the others.

[8]Among those deterministic ones at 1-error-allowance, only 1 subject had full consideration at 1-error-allowance and the rest behaved deterministic with limited consideration at 1-error-allowance.

Notably, among the binary menus, the subjects behaved more stochastically when two high range, $\{A, B\}$, or two low range, $\{C, D\}$, options are offered.



(A) Distribution of subjects by the number of menus that have stochastic consideration.

(B) Fraction of all subjects with stochastic consideration by set.

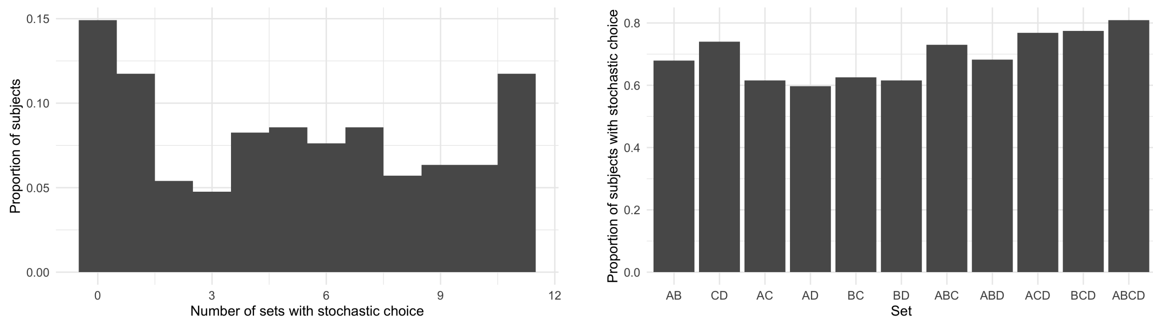
FIGURE 5. Robustness of Stochastic Consideration

There are some additional robust behavior on what subjects prefer to consider on different menus, indicating intentional stochasticity in consideration. First, the consideration behavior is sensitive to the offered options. The subjects are more likely to be deterministic if one low-range and one high-range options are offered together rather than two same type of options are offered (see Figure 7 in Appendix C)). Moreover, the same type of options are treated robustly in larger sets as well indicating futher the intentional consideration behavior throughout the experiment (see Figure 8 in Appendix C).

Result 2: Almost all subjects considered stochastically. Their stochastic behavior is menu-dependent.

4.2. **Descriptive Analysis of Choice.** In this subsection, we analyze the choice data from Part II, following the same structure that we used for the analysis of the consideration data.

Stochastic vs. Deterministic Choice. Deterministic behavior in choice decisions is much more frequent than it is for consideration decisions. Out of 315 subjects, 47 subjects (14.9%) exhibit deterministic choice in all questions (i.e., at 0-error-allowance). There are an additional 27 subjects (8.6%) who acts stochastically at 1-error allowance.



(A) Distribution of subjects by the number of sets that have stochastic choice.

(B) Fraction of subjects with stochastic choice by set.

FIGURE 6. The stochasticity of choice.

Hence, the stochastic behavior is less pronounced in choice problems than in consideration problems ($p = 0.0033$ by Fisher's exact test based on the numbers reported in Table 3). Moreover, 253 subjects are stochastic in both the consideration and choice domains. We are not aware of any other results from the literature documenting this observation.

TABLE 3. Stochasticity in choice and consideration domains

(A) 0-error-allowance

		Consideration		
		Det.	Stoch.	Total
Choice	Det.	8	39	47
	Stoch.	15	253	268
	Total	23	292	315

(B) 1-error-allowance

		Consideration		
		Det.	Stoch.	Total
Choice	Det.	16	58	74
	Stoch.	21	220	241
	Total	37	278	315

Moreover, the subjects who choose stochastically do not act that way on all the menus (see Figure 6a). Recall that in the consideration domain Figure 5a was a counterpart of Figure 6a and notably, the stochastic consideration summarized in Figure 5a was much more skewed to the left than that in Figure 6a indicating further evidence for a higher rate of stochasticity in the consideration domain than the choice domain.

In Figure 6b, we document the frequency of subjects with stochastic choice by menu, and see that the randomness in choice increases when the menu is larger as the bars in this figure tend to be taller for the menus of sizes 3 and 4 ($p < 0.001$, Wilcoxon signed-rank test).

Result 3: A majority of subjects chooses stochastically. However, the stochastic choice is less likely than stochastic consideration.

4.3. **Consideration Axioms.** We report the subjects whose behavior is consistent with the consideration axioms of Section 2 in Table 4. The first column reports consistency with a given axiom at 0-error-allowance and checks the axioms based on all 110 observations from a subject. 1-error-allowance in the second column checks consistency with an axiom by possibly changing at most 1 question. Although they are a minority, all of the 23 subjects with deterministic consideration at 0-error-allowance satisfy the two well-known properties of limited consideration: the Attention Filter and the Competition Filter. 37 subjects (11.7%) satisfy the Competition Filter at 1-error-allowance.

For the 23 subjects with deterministic consideration behavior, the Competition Filter property trivially implies Monotonic Consideration as it is the stochastic version of the Competition Filter. Thus, while in total 41 subjects (13.0%) satisfy this property, only 18 subjects (5.7%) satisfy it non-trivially at 0-error-allowance.[9] When we relax the consistency requirement to 1-error-allowance, Monotonic Consideration is still supported by a minority of the subjects. Recall that Consideration Overload is a monotonicity requirement on ϕ function. Table 4 reports that again a minority of subjects act in line with this axiom at both 0-error-allowance and 1-error-allowance.

4.4. **Choice Axioms.** For the 47 subjects who chose fully deterministically, it is possible to check the Weak Axiom of Revealed Preferences (WARP) as the main axiom of rationality in standard choice theory. Strikingly, all of them satisfy WARP (see Table 5). Moreover, all of the 74 subjects whose choices are deterministic at 1-error-allowance satisfy WARP at 1-error-allowance as well.

[9] The independent attention model (Manzini and Mariotti, 2014) and the logit consideration model (Brady and Rehbeck, 2016) are special cases of Monotonic Consideration and hence they cannot be satisfied by our mostly non-monotonic subjects who were acting stochastically.

Table 4. The percentage (number) of subjects consistent with consideration axioms

Consideration Property	0-error-allowance	1-error-allowance
Competition Filter Lleras et al. [2017]	7.3% (23)	11.7% (37)
Monotonic Consideration Cattaneo et al. [2020]	13.0% (41)	23.8% (75)
Consideration Overload Cattaneo et al. [2023]	13.3% (42)	22.9% (72)

Next, we analyze the data for other well-known stochastic choice axioms in Table 5. We focus on two classes of axioms: Regularity (how menu size affects the choice probabilities) and versions of Transitivity (stochastic generalizations of the standard transitivity axiom).

Table 5. The percentage (number) of subjects consistent with choice axioms.

Choice Property	0-error-allowance	1-error-allowance
WARP	14.9% (47)	23.5% (74)
Regularity	20.3% (64)	31.7% (100)
Weak Stochastic Transitivity	98.7% (311)	100% (315)
Moderate Stochastic Transitivity	66.0% (208)	87.3% (275)
Strong Stochastic Transitivity	56.2% (177)	81.3% (256)

Since all the other stochastic choice axioms of interest imply WARP for the deterministic behavior, the 47 subjects who are consistent with WARP will trivially satisfy the remaining stochastic axioms in Table 5. Only 64 subjects (20.3%) satisfy the Regularity at 0-error-allowance. The support increases to 100 subjects (31.7%) at 1-error-allowance.

177 subjects (56.2%) are consistent with Strong Stochastic Transitivity at 0-error-allowance. This number increases to 208 subjects (66.0%) for the moderate version.

Weakening it further to Weak Stochastic Transitivity improves the result further to 311 subjects (98.7%). Table 5 also reports the corresponding percentages at 1-error allowance , and the support for the Stochastic Transitivity further improves.[10] We also evaluate the Bayesian posterior likelihood of satisfying an axiom starting from a uniform prior (similar in spirit to de Clippel and Rozen, 2022). In our data set, 235 subjects (74.6%) have a Bayesian posterior above 95% for satisfying at least one form of transitivity. The details of this analysis are explained in Appendix D.

4.5. **Importance of Observing the Consideration Data.** The existing two-stage stochastic models, where the decision maker chooses from what is considered, are built primarily on choice data. For example, Manzini and Mariotti [2012] or Cattaneo et al. [2020] assume the choice data as the only observables of the model and study the underlying consideration or attention functions for the first stage based on their modeling assumptions. This approach became standard because consideration data is typically unobservable.

In this subsection we argue that without direct observation of the consideration function, welfare inferences drawn from choice data may be misleading. This extends the critique of Cattaneo et al. [2020], which underscores the potential for misleading welfare inferences when a researcher commits to a specific attention rule, such as the logit attention model of Brady and Rehbeck [2016]. Instead they offered the Random Attention Model (RAM) which only requires the consideration to be monotonic rather than imposing a specific rule on it. Example 1 shows that a similar type of misinference can still arise in the RAM framework. In particular, it demonstrates that imposing a particular property on the consideration function, such as monotonicity, can lead to incorrect conclusions about the revealed preferences. This example highlights the critical role of understanding consideration behavior in welfare analysis, and further justifies the need for consideration data as we collected in our experiment.

[10] Earlier research also found robust violations of the Regularity but support for the Stochastic Transitivity (see Rieskamp et al., 2006).

Example 1 (Misleading Inference)**:** Let there be three products, a, b and c, to keep the example simple. A consumer's true preferences rank $c \succ b \succ a$, however, this ranking is unobservable to the researcher. The consumer is already familiar with product a, which is always included in her consideration set whenever it is available. In contrast, she must search for and learn about products b and c. Her search behavior follows the following rules. When visiting a small store (i.e., one offering two products) that stocks a, she explores the store with a 50% probability. If she explores, she considers a and the other available product; otherwise, she does not explore and remains unaware of the other option. If a is not in the small store, she explores with certainty and considers both b and c. When visiting a large store that offers all three products, she becomes overwhelmed by the number of options and does not explore at all. This procedure is summarized in Table 6.

TABLE 6. A Non-Monotonic consideration function, μ for options a, b, c

$\mu(T\|S)$	{a,b,c}	{a,b}	{a,c}	{b,c}
{a}	1	0.5	0.5	-
{b}	0	0	-	0
{c}	0	-	0	0
{a,b}	0	0.5	-	-
{a,c}	0	-	0.5	-
{b,c}	0	-	-	1
{a,b,c}	0	-	-	-

Together with the consumer's underlying preferences, the stochastic choice in Table 7 is observed.

TABLE 7. Stochastic choice function, π for options a, b, c

$\pi(x\|S)$	$\{a, b, c\}$	$\{a, b\}$	$\{a, c\}$	$\{b, c\}$
{a}	1	0.5	0.5	-
{b}	0	0.5	-	0
{c}	0	-	0.5	1

It is straightforward to show that this stochastic choice behavior can be represented within the RAM framework (as a maximization of a preference under a monotonic stochastic consideration function). Note that there are two Regularity violations in the stochastic choice: $\pi(a|\{a,b,c\}) > \pi(a|\{a,b\})$ and $\pi(a|\{a,b,c\}) > \pi(a|\{a,c\})$. According to Lemma 1 in Cattaneo et al. [2020], such Regularity violations reveal that a is the most preferred product for the consumer. However, a is actually the least preferred product in the consumer's true preference ranking.

The example illustrates how a researcher may draw incorrect inferences about a consumer's underlying preferences if they impose a specific property, such as monotonicity, on the consideration function. This example further highlights the importance of explicitly accounting for consideration behavior in the welfare analysis.

Such misinference about the consideration behavior of a decision maker can be illustrated in our data as well. If a researcher relies only on the final choice of a decision maker, the researcher may wrongly infer the preferences of the decision maker. For this purpose, we utilize Part I and Part II data to create an implied choice function, ρ, for each subject, based on the observed μ and π of that subject. This is interpreted as how the subject would behave if she first considered according to her μ function and then chose from what she considered according to her π function:

$$\rho(x \mid S) = \sum_{\substack{T \subset S \\ x \in T}} \mu(T \mid S)\pi(x \mid T)$$

Let us say the researcher observes ρ and investigates if the observed behavior is consistent with the two-stage models of the literature, such as RAM of Cattaneo et al. [2020] or AOM of Cattaneo et al. [2023]. Both of those models assume stochastic consideration at the consideration stage and a preference maximization at the choice stage. RAM requries the consideration function μ to satisfy the Consideration Monotonicity; AOM requires the attention frequency, ϕ, to satify the Consideration Overload. Table 8 reports that for 197 subjects (62.5%) ρ admits a RAM representation and for 145 subjects (46.0%) ρ admits an AOM representation at 0-error allowance. The consistencies with RAM and AOM increase to 232 (73.7%) and 197 (62.5%), respectively, at 1-error allowance.

TABLE 8. The percentage (number) of subjects whose constructed π^* consistent with RAM and AOM.

Choice Property	0-error-allowance	1-error-allowance
RAM	62.5% (197)	73.7% (232)
AOM	46.0% (145)	62.5% (197)

According to these models, all these subjects' implied choice data, ρ, can be represented by a two-stage procedure where the consideration stage satisfies the corresponding monotonicity property, and the choice stage has a preference maximization. However, the correct consideration and choice generating the implied choice rarely satisfy the monotonicity in the consideration stage and the preference maximization in the choice stage, as reported in Tables 9 and 10.

TABLE 9. Consistency with RAM: Rational choice and monotonic consideration

(A) 0-error-allowance

		Monotonic Consideration		
		Pass	Fail	Total
WARP	Pass	11	36	47
	Fail	30	238	268
	Total	41	274	315

(B) 1-error-allowance

		Monotonic Consideration		
		Pass	Fail	Total
WARP	Pass	25	49	74
	Fail	50	191	241
	Total	75	240	315

Only 11 subjects satisfy WARP and Monotonic Consideration at 0-error allowance and 25 at 1-error allowance (see Table 9) and hence, are consistent with RAM. Similarly, only 12 subjects satisfy WARP and the Consideration Overload at 0-error allowance and 24 at 1-error allowance (see Table 10) and hence, are consistent with AOM.

Table 10. Consistency with AOM: Rational choice and consideration overload

(a) 0-error-allowance

		Consideration Overload		
		Pass	Fail	Total
WARP	Pass	12	35	47
	Fail	30	238	268
	Total	42	273	315

(b) 1-error-allowance

		Consideration Overload		
		Pass	Fail	Total
WARP	Pass	24	50	74
	Fail	48	193	241
	Total	72	243	315

Note that the departure from these models in our data is caused by both the stochastic nature of choice (i.e. the lack of preference in the second stage) and non-monotonicity of consideration behavior. However, the researcher only observing the implied choice, ρ, cannot detect these. This is in the same spirit as Example 1.

4.6. **Revisiting the consideration data.** We have noted earlier that the monotonicity property for stochastic consideration was analogous to the regularity property in stochastic choice. Regularity in choice is often violated (including our data), so, the limited support for the monotonicity in consideration is not surprising.

The other stochastic rationality property in choice domain is Stochastic Transitivity. As far as we know, this axiom has not been introduced to the consideration domain. The stochastic transitivity axioms are defined over binaries and they compare the relative likelihood of an alternative with respect to another alternative, hence they are not directly applicable to μ since it is defined on subsets rather than elements of a menu. ϕ on the other hand is defined for elements of a menu but it is not a probability distribution. So Stochastic Transitivity is not directly applicable to ϕ either. However, one may naturally apply these axioms to the normalized attention frequency, ψ, as defined by: $\psi(y|S) \coloneqq \phi(y|S)/\sum_{x\in S}\phi(x|S)$. This function is obviously a probability distribution, which allows for testing of ψ-analogs of stochastic transitivity axioms. 206 subjects (65.4%) satisfy ψ Moderate Stochastic Transitivity at 0-error-allowance. 272 subjects (86.3%) satisfies it at 1-error-allowance.

Given the high level of support for the Moderate Stochastic Transitivity in both choice and consideration domains, in Table 11 we report the relation between satisfying Moderate Stochastic Transitivity in the two domains at the individual level. Note that 141 subjects satisfied this axiom in both choice and consideration domains and the relation is even higher at 1-error-allowance. Note that the induced ψ for the non-Monotonic consideration function of Example 1 (see Table 6) satisfies the Monotone Stochastic Transitivity. Hence, one may be outside of the RAM framework and still satisfy the stochastic transitivity in such two-stage models. While the literature offers a stochastic choice model characterized by Moderate Stochastic Transitivity (He and Natenzon, 2024), we are not aware of an analogous model for the consideration domain. We leave this as an open question for the theoretical literature.

Table 11. Moderate Stochastic Transitivity (MST) in choice and consideration domains

(a) 0-error-allowance

		ψ **MST**		
		Pass	Fail	Total
π **MST**	Pass	141	67	208
	Fail	65	42	107
	Total	206	109	315

(b) 1-error-allowance

		ψ **MST**		
		Pass	Fail	Total
π **MST**	Pass	238	37	275
	Fail	34	6	40
	Total	272	43	315

5. Conclusion

We design and implement an experiment to fully observe consideration and choice functions. We generate multiple observations per menu, providing us with potentially stochastic consideration and choice without altering the information collected when considering. With this data, we can (i) evaluate consideration properties directly on consideration data, without inferring it from choice; (ii) evaluate choice properties independently; and (iii) when combining consideration and choice data, we can evaluate discrepancies with “as if” consideration recovery from choice data.

Overall, we find limited support for monotonicity axioms in both consideration (e.g. Monotonic Consideration, Consideration Overload) and choice (Regularity). In contrast, choice data is mostly consistent with stochastic transitivity, which inspires us to analyze a measure of stochastic transitivity in the consideration domain. We find support for stochastic transitivity in consideration, with high correlation between compliance of the consideration and choice forms of stochastic transitivity. Finally, we show that the "as if" consideration implied by choice data is largely representable by monotonic consideration, despite observed consideration overwhelmingly not satisfying the conditions. This result emphasizes the importance of consideration when making welfare conclusions.

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Appendices

A. Experiment Screenshots

Section I

In this Section, you will be presented a collection of bins. Your task is to select which bins' content to examine and to choose one among from the examined bins. The bin you choose at the end will determine your payoff.

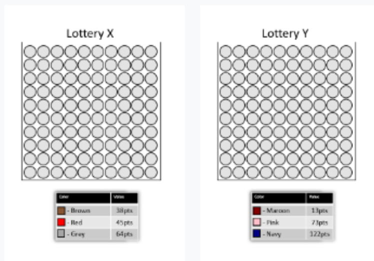
What is a bin?

A bin corresponds to a lottery with monetary prizes. There are 100 balls in each bin and the color of a randomly drawn ball from a bin determines the prize. You will know the prize associated to each color in a bin, but in order to learn number of balls in each color in a bin, you need to examine the bin further.

For illustration of your task, we show you below two lotteries corresponding to two bins. Note that each bin has 100 balls with unidentified color compositions.

The first bin consists of Brown, Red and Grey balls. The corresponding lottery X pays you based on the color of a randomly drawn ball from this bin. If a randomly drawn ball from this bin is Brown, Lottery X pays 38 points. If it is Red, it pays 45 points. If it is Grey, it pays 64 points.

The second bin, corresponding to lottery Y, pays 73 points if it is Pink, 122 points if it is Navy, and 13 points if it is Maroon.



Choosing bins to examine

Since you don't know how many balls there are in each color in a bin, at this stage you cannot know how likely it is to draw a certain color. You may learn the exact color composition of a bin, by choosing to examine that bin.

YOUR TASK IS TO CHOOSE WHICH BINS YOU WANT TO EXAMINE. You may examine any number of bins you want!

The content of a bin that you selected for further examination will be revealed to you. For example, the figure below shows you the content of the first bin above corresponding to lottery X.

Color	Number of Balls
Red	
Brown	
Grey	

You need to count each color in a bin you selected, and type those numbers correctly in the corresponding box. For example, there are 21 Brown, 33 Red, and 46 Grey balls in the bin of lottery X. So you have to enter these numbers correctly for the corresponding colors.

What happens in a round?

In this experiment there are four bins: A, B, C, and D. In each round, you will be presented with a subset of bins A, B, C, and D. You will know the corresponding prizes on each bin but you will not know the color combinations unless you choose to examine them.

From the set of presented bins, choose the ones you want to examine and learn the color content.

In each round you will make such decisions on a set of bins.

There are 115 rounds with similar decision problems. Once 115 rounds are completed, one of the rounds will be randomly selected and you will examine the bins that you chose to examine for that round.

Remember that on the bins you examine, you need to count the colored balls and enter the number of balls in each color correctly. If you make any mistakes, your payment in this section will be zero.

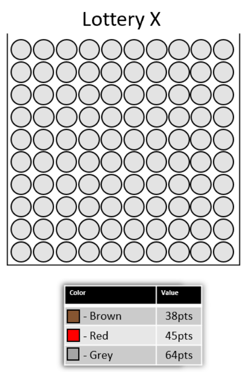
If you enter the number of balls in each color correctly, then you will be asked to choose one of the bins you examined for that round and your payment for this section will be the payoff of the randomly drawn ball from the bin you chose.

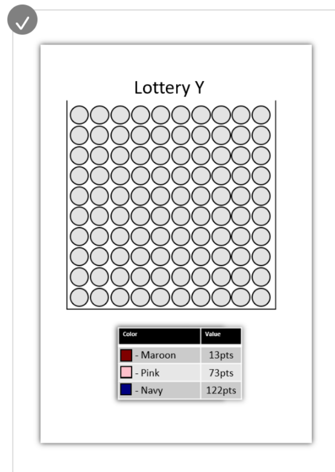
Next

2

Sample question 1 out of 3:

Please see the available lotteries with the corresponding prizes below and click on the ones you want to examine further to understand the color content. You may choose as many or as few as you want to examine later. Note that if this round is selected at the end of the sample questions, you need to count the balls in all the bins you selected to examine in this round correctly.





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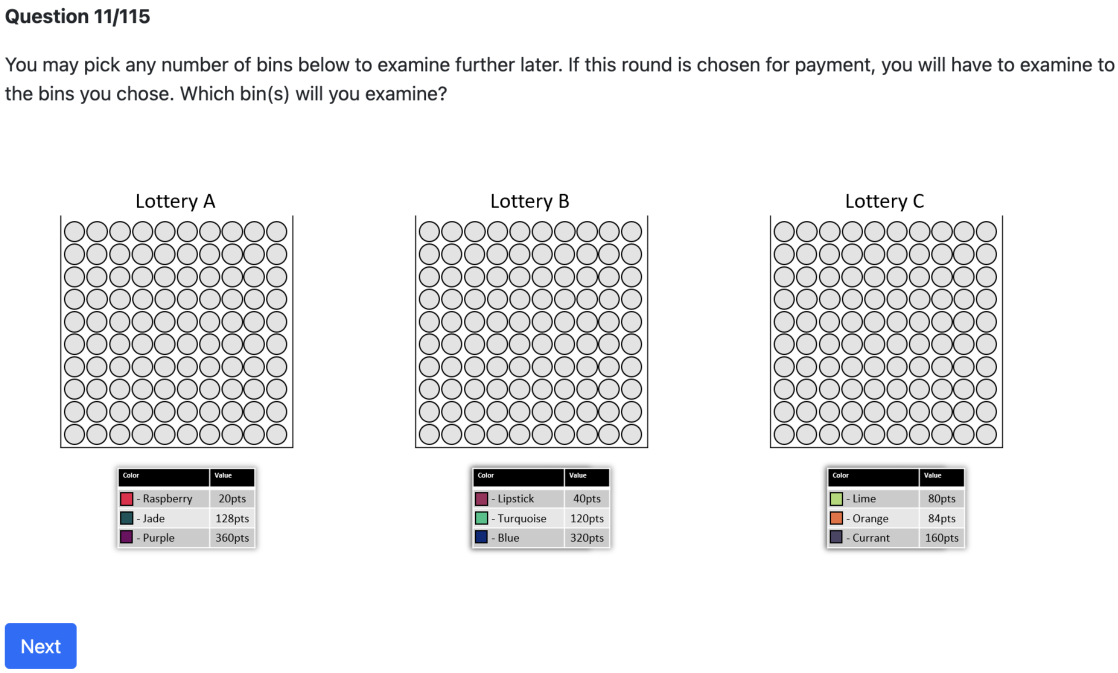


A sample consideration screen. Subjects click on the alternatives to select them for consideration. Once the experiment starts, subjects see 115 consideration screens similar to the sample questions, where menus are subsets of $\{A, B, C, D, E\}$.

Section 2

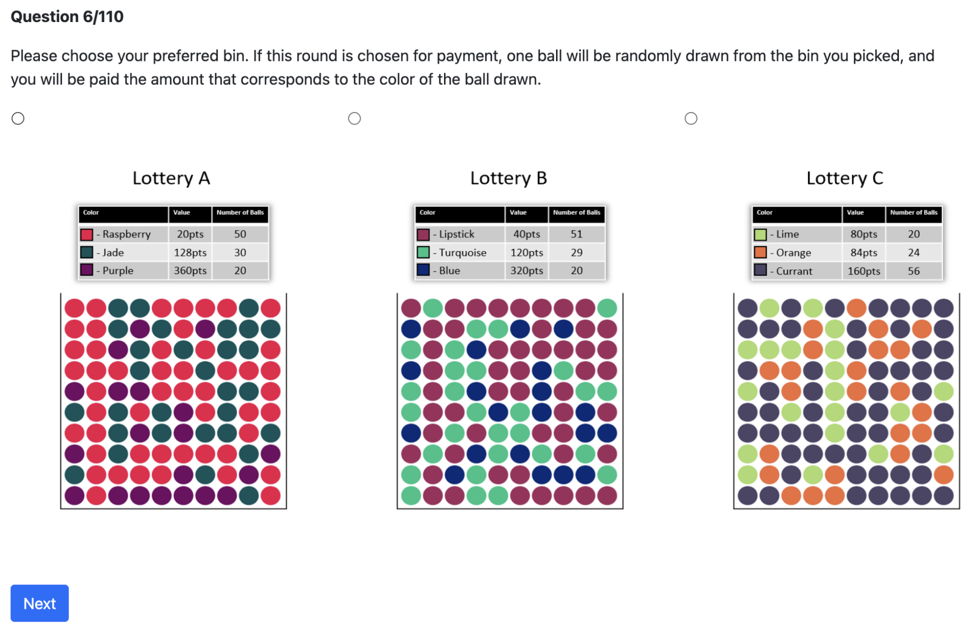
In this section you are dealing with the same bins A, B, C, and D as in Section 1. This time you **will know** the color composition of each bin. Therefore, you will know the likelihood of drawing a ball in certain color from any bin.

In each round we will show you a subset of bins A, B, C, and D. Your task is to choose exactly one bin to draw a ball from. For example, if you are offered bins {A, B, C} and if you choose bin A, this means you want a ball to be randomly drawn from A for this round and be paid according to that draw.

There are 110 rounds in this section. In each round you have to pick exactly one bin to base your payment on.

Once you finish all the rounds of the section, one round will be randomly drawn, and we will draw a random ball from the bin you selected for that round.

Next



A sample choice screen. Subjects click on a single alternative to choose it. Once the experiment starts, subjects see 110 choice screens similar to the sample questions, where menus are subsets of $\{A, B, C, D\}$.

Section III

This situation involves drawing randomly one ball from a bin of 10 balls, comprising 5 red and 5 blue balls. In next 10 questions you choose between two options:

Option A: You receive 60 points if the color of a randomly drawn ball is red; otherwise you receive nothing. Hence, **50% chance of receiving 60 points** and **50% chance of receiving 0 points**.

Option B: You receive a **sure payment** indicated in the associated row. The option B column lists ten amounts each corresponding to what you will receive for sure if you choose this option.

Please answer the following questions.

Option A			Option B
60 points with 50% chance, 0 points with 50% chance.	◯	◯	15 points for sure.
60 points with 50% chance, 0 points with 50% chance.	◯	◯	17 points for sure.
60 points with 50% chance, 0 points with 50% chance.	◯	◯	19 points for sure.
60 points with 50% chance, 0 points with 50% chance.	◯	◯	21 points for sure.
60 points with 50% chance, 0 points with 50% chance.	◯	◯	23 points for sure.
60 points with 50% chance, 0 points with 50% chance.	◯	◯	25 points for sure.
60 points with 50% chance, 0 points with 50% chance.	◯	◯	27 points for sure.
60 points with 50% chance, 0 points with 50% chance.	◯	◯	29 points for sure.
60 points with 50% chance, 0 points with 50% chance.	◯	◯	31 points for sure.
60 points with 50% chance, 0 points with 50% chance.	◯	◯	33 points for sure.
60 points with 50% chance, 0 points with 50% chance.	◯	◯	35 points for sure.

Next

Section III

This situation involves your guessing the color -red or blue- of a ball drawn randomly from a bin of 10 balls, with unknown proportions of red and blue balls. In next 10 questions you choose between two options:

Option A: You receive **60 points if the color of a randomly drawn ball matches with your guess** (in other words, your guess is correct); **otherwise you receive 0 points**.

Option B: You receive a sure payment indicated in the associated row. The option B column lists ten amounts each corresponding to what you will receive for sure if you choose this option.

Guess the color of a ball to be drawn randomly from this box with unknown composition of red and blue balls.

Your guess for the color of a randomly drawn ball is: ◯ Red ◯ Blue

Option A			Option B
60 points if your guess is correct, 0 points otherwise.	◯	◯	15 points for sure.
60 points if your guess is correct, 0 points otherwise.	◯	◯	17 points for sure.
60 points if your guess is correct, 0 points otherwise.	◯	◯	19 points for sure.
60 points if your guess is correct, 0 points otherwise.	◯	◯	21 points for sure.
60 points if your guess is correct, 0 points otherwise.	◯	◯	23 points for sure.
60 points if your guess is correct, 0 points otherwise.	◯	◯	25 points for sure.
60 points if your guess is correct, 0 points otherwise.	◯	◯	27 points for sure.
60 points if your guess is correct, 0 points otherwise.	◯	◯	29 points for sure.
60 points if your guess is correct, 0 points otherwise.	◯	◯	31 points for sure.
60 points if your guess is correct, 0 points otherwise.	◯	◯	33 points for sure.
60 points if your guess is correct, 0 points otherwise.	◯	◯	35 points for sure.

Next

Please answer the following questions.

What is your age?

- ◯ 18-27
- ◯ 28-37
- ◯ 38-47
- ◯ 48-57
- ◯ 58+
- ◯ Prefer not to answer

What is your gender?

- ◯ Male
- ◯ Female
- ◯ Other
- ◯ Prefer not to answer

What is the highest degree or level of school you have completed?

- ◯ Less than high school diploma
- ◯ High school diploma or GED
- ◯ Some college, but no degree
- ◯ Associate's Degree (for example: AA, AS)
- ◯ Bachelor's Degree (for example: BA, BBA, and BS)
- ◯ Master's Degree (for example: MA, MS, and MEng)
- ◯ Professional Degree (for example: MD, DDS, JD)
- ◯ Doctorate (for example: PhD, EdD)
- ◯ Prefer not to answer

Please continue to the next page of the survey.

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B. Demographics

Table 12. Gender identity frequency

Gender	Frequency
Male	201
Female	189
Other	9
Did not respond	3

Table 13. Age bracket frequency

Age bracket	Frequency
18-27	129
28-37	140
38-47	76
48-57	35
58+	21
Did not answer	1

Table 14. Educational attainment frequency

Highest education level	Frequency
Less than high school diploma	4
High school diploma or GED	35
Some college, but no degree	95
Associate's Degree (for example: AA, AS)	36
Bachelor's Degree (for example: BA, BBA, and BS)	159
Master's Degree (for example: MA, MS, and MEng)	52
Professional Degree (for example: MD, DDS, JD)	13
Doctorate (for example: PhD, EdD)	5
Did not answer	3

TABLE 15. The relationship between demographics and uncertainty attitudes with choice and consideration stochasticity.

	Dependent variable:	
	No. Stochastic Sets	
	Choice	Consideration
	(1)	(2)
Switching Point		
Risk	−0.213**	0.015
	(0.091)	(0.090)
Ambiguity	0.173*	−0.099
	(0.091)	(0.091)
Female	−1.340***	−0.463
	(0.428)	(0.424)
Education (yrs)	0.049	0.071
	(0.107)	(0.106)
Age (yrs)	0.010	0.030
	(0.019)	(0.019)
Constant	5.757***	3.004*
	(1.772)	(1.755)
Observations	312	312
R^2	0.048	0.018
Adjusted R^2	0.032	0.001
Res. Std. Error (df = 306)	3.701	3.665
F Statistic (df = 5; 306)	3.061**	1.090
Note:	*p<0.1; **p<0.05; ***p<0.01	

Three subjects did not report demographic information. Base gender group is non-female (male or other). Switching points denote, on an 11-point scale, the lowest certain value that a subject preferred over the risky option (see Appendix A). Education and age are imputed from categorical values that subjects chose.

C. Intentional Stochastic Behavior in Consideration

There are some additional robust behavior on what subjects prefer to consider on different menus. Since it is easier to graph the behavior on binaries, we explain the data on binary menus as summarized by Figure 7. Each triangle represents the consideration data on a binary menu, such as $\{A, B\}$, $\{C, D\}$, etc.. Each vertex of a triangle is a possible consideration set. The size of a red circle on a triangle shows the number of subjects who have that type of consideration function. The subjects with deterministic considerations are on the vertices and those with stochastic considerations are either on the edges or in the interior of a triangle. A red circle that is closer to a vertex means the frequency of considering the sub-menu on that vertex is higher. For example, if a subject always considered only A on menu $\{A, B\}$, she is denoted on the left bottom vertex of the first triangle in Figure 7. If she considered A alone half of the time and together with B half of the time, then her data is denoted on the mid-point of the bottom edge of this triangle.

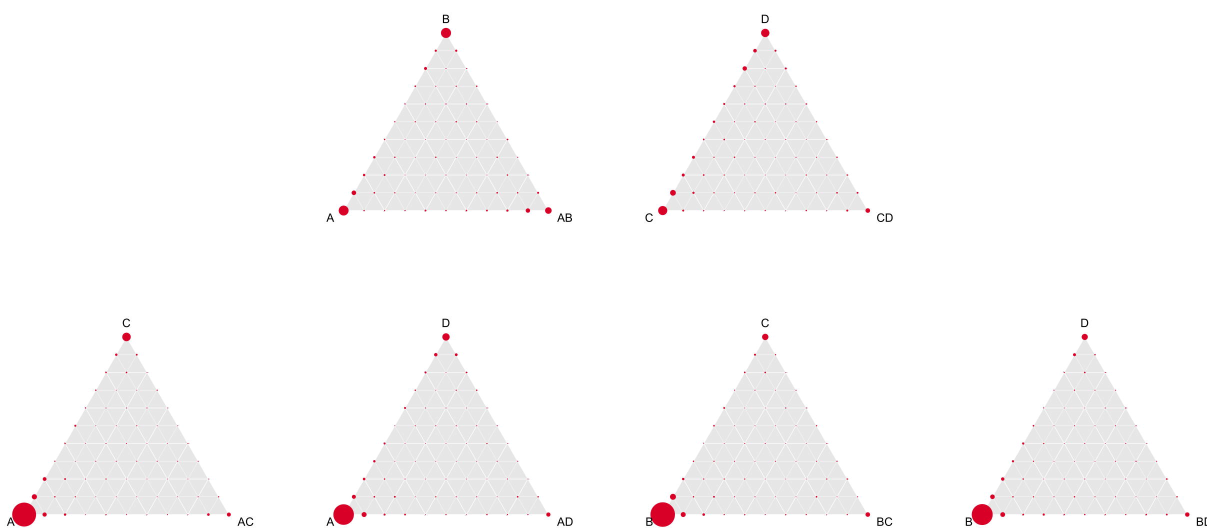


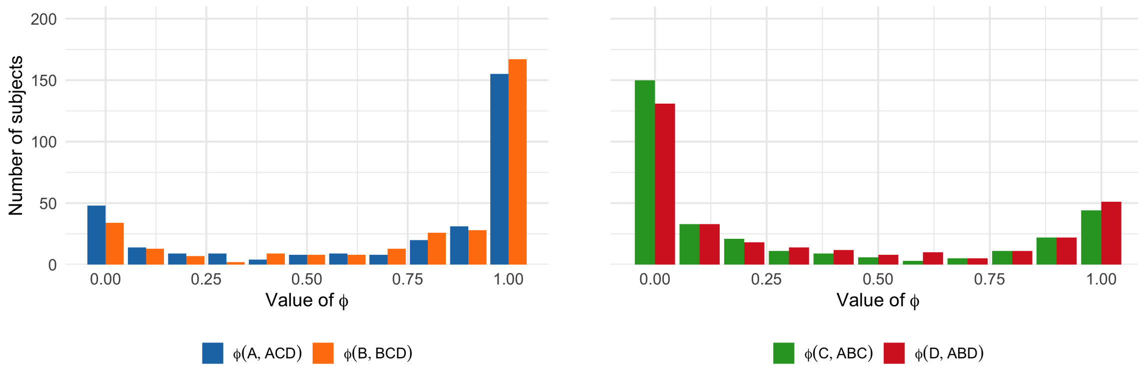
Figure 7. Consideration behavior on binary menus. A coordinate in the triangle simplex shows the frequency with which the single options or the binary option are considered. Vertices are deterministic behavior.

We observe three robust behavior in Figure 7. First, the right bottom corner of each triangle has little data indicating that discrete full consideration is rare in all of these four menus. This observation is a piece of further evidence on the extensive limited consideration that we observed in Figure 3b.

Second, the consideration behavior is robustly sensitive to the offered options. Note that the behaviors in the first row triangles are similar to each other and the same is true for the second row of the figure. The first-row menus include either two high-range (A, B) or two low-range (C, D) lotteries. The second-row menus include one high-range and one low-range lotteries. The robustness of behavior within the first-row and second-row menus of Figure 7 is a further assurance of intentional and systematic preference for exhibiting stochastic consideration.

Third, deterministic consideration is more pronounced when one low-range and one high-range options are presented, as the masses on the left bottom vertices of all the triangles in the second row are larger. The majority of those who act deterministically on these menus have preferences for considering the higher range option. For example, the mass of subjects deterministically considering A on menu $\{A, C\}$ is much higher than those considering C deterministically. This contrasting tendency for a high range option when it is compared with a low range one is robust, as can be seen in all four menus in the second row of the figure. This means that the subjects who want to commit to one option choose the one with a jackpot.

Since it is not possible to plot consideration function triangles for tripletons, as we did for the binary menus, we can instead analyze the attention frequencies, based on the definition (1) on tripletons. Figure 8 reports the relevant attention frequencies, ϕ. Note that the attention frequencies of A on menu $\{A, C, D\}$, and that of B on menu $\{B, C, D\}$ are similar. To sum up, the same type of options are treated robustly when each is presented together with a set of other options (Figures 7 and 8a and 8b), indicating the intentional consideration behavior of the subjects.



(A) Attention frequencies of A and B in the presence of both C and D.

(B) Attention frequencies of C and D in the presence of both A and B.

Figure 8. Attention frequencies of similar options are similar in tripletons

D. Econometric Tests

We implement a Bayesian analysis of model satisfaction using Monte Carlo simulation to generate the priors and posteriors, using 10,000,000 simulations for both the prior and posterior for each subject. The procedure starts from a random uniform prior over data generating processes, learns a posterior given observed data $\hat{\pi}$, and calculates the probability of a model $\mathcal{M}$ in each contingency to generate the statistic

$$\text{Prob}(\mathcal{M} \mid \hat{\pi})$$

The posterior is generated by a Dirichlet-multinomial update for each set. For example, if the prior distribution for $\pi(\circ \mid ABC)$ is the uniform distribution over the simplex, Dirichlet$(1,1,1)$, then the posterior observing A chosen α times, B chosen β times, and C chosen $10-\alpha-\beta$ times is Dirichlet$(\alpha+1, \beta+1, 10-\alpha-\beta+1)$. The corresponding Dirichlet-multinomial distributions for each set are then drawn from independently. To allow for imprecision, as done in de Clippel and Rozen [2022], we implement a γ-relaxation of the model class to generate

$$\mathcal{M}^{\gamma} = \{\pi \mid 1 - \inf_{m \in \mathcal{M}} \max_{x \in S \subseteq X} |\pi(x \mid S) - m(x \mid S)| \geq \gamma\}.$$

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While de Clippel and Rozen [2022] endogenously determine γ based on the best fitting relaxation of their model class, we instead choose to leave it as a constant $\gamma = 0.95$.