Supplementary Material

D. Experimental Instructions

The following eight pages reproduce the experimental instructions given to subjects.

OVERVIEW

Welcome to our experiment. Thank you for participating! Before we begin, please turn off and put away your cell phones, and put away any other items you might have brought with you. If you have any questions during the instruction period, please raise your hand.

This experiment consists of 4 different “blocks.” In each block, you’ll be asked to make a bunch of decisions. (The decisions are numbered, but will appear in random order. For example, you may make decision #7, and then decision #2, and so on.) Your choices in one block will not affect your choices in the other blocks; the four blocks are completely independent. We’ll go over instructions at the start of each block. Your screens will also give instructions, and you’re free to refer back to the printed instructions at any time.

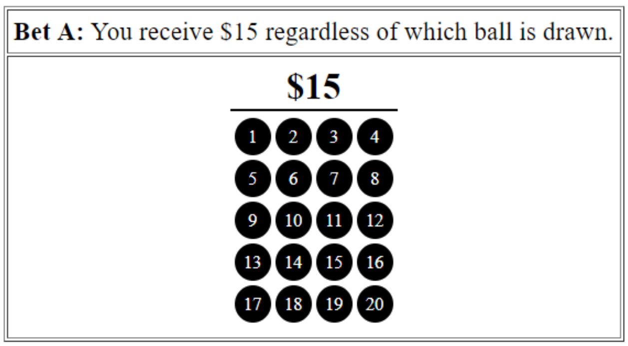
At the end of the experiment, one of the decisions will be randomly selected for payment. In each decision we will describe how that decision gets paid if it is selected.

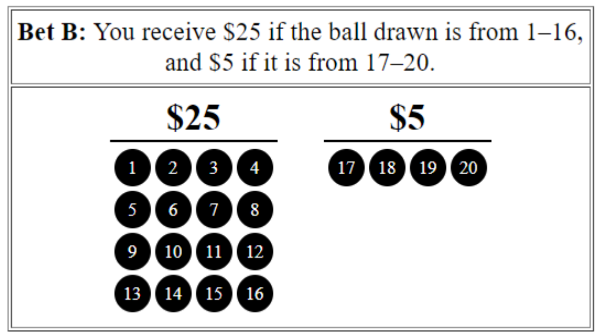
In addition to being paid for one decision, you will also receive a $5 participation payment for completing the experiment.

<u>BINGO CAGE BETS</u>

We have a Bingo cage filled with 20 balls, numbered 1-20.

In each question in this block, you will be offered two “bets” on which ball is drawn from the cage. We’ll actually draw a ball from the Bingo cage 20 times, and you’ll choose 20 bets, one for each draw. (After each draw we’ll put the ball back into the cage before the next draw.) In each decision you must choose between Bet A or Bet B, both of which will be shown on your computer screen. Here is an example of two bets you might be given:





Payment:

If one of these questions is chosen for payment, we’ll draw a ball from the Bingo cage 20 times. We’ll then roll a 20-sided die to determine which of the 20 draws to pay out. We’ll then look at which bet you chose for that draw, and pay you based on that draw.

For example, suppose the 20-sided die roll comes up “3”. That means we’re paying you for the bet you chose on the 3rd draw of the ball. Suppose you chose Bet B, shown above. Bet B pays $25 if the ball is 1-16.

If the 20 draws from the Bingo cage are

5, 3, 11, 5, 20, 8, 4, 9, 1, 15, 9, 9, 11, 2, 18, 12, 5, 8, 12, 10

then the 3rd draw is 11. You chose Bet B, and Bet B pays $25 for ball 11, so you’d actually be paid $25.

If the 20-sided die had come up “5” then we’d pay for the 5th draw, which is 20. In that case Bet B would only pay $5.

If you had chosen Bet A then you’d receive $15 regardless of what ball is drawn.

The actual bets offered may be different than this example, and you’ll make several choices like this. Read the description of the 2 bets carefully each time before making your 20 choices.

GAMES AGAINST PAST PLAYERS

In these questions, you will play a “matrix game” against 20 people who participated in this experiment on some prior date.

On the screen we will now demonstrate how “matrix games” work.

In this block, you will be the ROW player and the past participants were COLUMN players.

ROW player choices:

You will actually play each game 20 times. For each of your 20 choices we will randomly draw one of the 20 past participants, and your choice will be paired against that past participant’s choice. But you won’t know which past participants you’re paired with in each choice until the end of the experiment.

Before you make your 20 decisions, we might give you some information about what all 20 past participants chose. For example, we could tell you that of the 20 past participants, 12 chose Left and 8 chose Right. This information will appear on your computer screen.

Payment:

If one of these games is chosen for payment, we’ll use draws from a Bingo cage to see which past participant is associated to each of your 20 choices (putting the ball back after each draw), and then we’ll roll a 20-sided die to see which of those choices is paid out. We’ll compare your Row choice to that person’s Column choice and pay you your payoff in the game for that Row and Column. (The Column player will not be paid; they were paid when they played this game previously.)

<u>GAMES AGAINST CURRENT PLAYERS</u>

In these questions, you will play a "matrix game" against one of the 20 other people in the room today.

On the screen we will now demonstrate how "matrix games" work.

In this block, you will play each game as the Column player *and* as the Row player. You'll actually proceed through 5 "Stages" of decision-making, numbered Stage 0 through Stage 4. We'll explain each now:

<u>"Stage 0:" COLUMN player choice:</u>

In Stage 0 you will play the game 1 time as the COLUMN player. Here is an example game:

	Left	Right
Up	\$25 \$5	\$5 \$25
Down	\$5 \$25	\$25 \$5

I choose [▾].

Left
Right

<u>"Stage 1:" ROW player choices:</u>

In Stage 1 you now play the same game, but as the ROW player. And you'll play it 20 times. For each choice we'll randomly draw the ID of another person in your room, and they will serve as the Column player if that choice is chosen for payment. For example, if your 3rd choice is against Column Player #17, then your 3rd Row choice will be compared to Player #17's Column choice from Stage 0.

Here is an example screenshot of your 20 choices:

	Left	Right
Up	$25 $5	$5 $25
Down	$5 $25	$25 $5

For **choice number 1** , I choose Down	For **choice number 2** , I choose Up	For **choice number 3** , I choose Up
For **choice number 4** , I choose Down	For **choice number 5** , I choose Up	For **choice number 6** , I choose Up / Down
For **choice number 7** , I choose Up	For **choice number 8** , I choose Down	For **choice number 9** , I choose
For **choice number 10**, I choose Up	For **choice number 11**, I choose Down	For **choice number 12**, I choose Down
For **choice number 13**, I choose Up	For **choice number 14**, I choose Up	For **choice number 15**, I choose Up
For **choice number 16**, I choose Down	For **choice number 17**, I choose Up	For **choice number 18**, I choose Up
For **choice number 19**, I choose Down	For **choice number 20**, I choose Down	

Payment:

If Stage 1 is chosen for payment, we'll randomly select one person in the room to be our Row player. And then we'll use draws from a Bingo cage to select the identity of the Column player for each of their 20 choices (putting the ball back after each draw). Finally, we'll use a 20-sided die to see which choice is paid out. That Row player and Column player will get paid based on how they played (the Row player is paid for their Row choice against that particular Column player, and the Column player is paid based on their Column choice from Stage 0.)

Everyone else in the room will receive a fixed payment of $15.

<u>"Stage 2:" Probabilities:</u>

In Stage 2 we want to know how likely you think it is that Column players play "Left" in this game. One way we could do this is to ask you the following list of 100 questions:

Q#		Option A		Option B
1	Would you rather have	$20 if COLUMN chose Left	or	1% chance of $20
2	Would you rather have	$20 if COLUMN chose Left	or	2% chance of $20
3	Would you rather have	$20 if COLUMN chose Left	or	3% chance of $20
⋮	⋮	⋮	⋮	⋮
99	Would you rather have	$20 if COLUMN chose Left	or	99% chance of $20
100	Would you rather have	$20 if COLUMN chose Left	or	100% chance of $20

In each question, you'd pick either Option A or Option B. Presumably you'd want Option A in the first few questions, but at some point would switch to taking Option B. So rather than telling us your choice to all 100 questions, we can just ask you to tell us at what percent chance you'd switch. And that "switch point" is exactly where you're indifferent between Option A and Option B, because that switch point would be exactly at the probability that you think the Column players are choosing Left.

For example, suppose your switch point is 73%. That means you're indifferent between getting $20 if COLUMN plays Left, and getting $20 with 73% chance. But if you're indifferent between those choices, then you must think COLUMN is playing Left 73% of the time. In other words, your switch point is exactly your probability that they play Left.

How would you be paid if Stage 2 is chosen for payment? You enter your probability that the Column player plays left (for example, 73%). Then we draw one of the 100 questions above and see what you'd choose on that question. If it's #1-72 then you chose Option A. So we'd pay you $20 if a randomly-selected Column player actually chose Left in Stage 0. If the question drawn is #73-100 then you chose Option B. So we'd pay you $20 with the probability given in that row. (For example, if we pick question #83, then you'd get $20 with an 83% chance.)

We'll use two 10-sided dice to pick which row is actually chosen. If you choose Option B then we'll use another roll of the two 10-sided dice to determine whether you win the $20 or not. (For example, if the chosen row is #83, then you're getting an 83% chance of $20. That means we'll pay you $20 if the second roll comes up 1-83.)

Obviously you have an incentive to announce your "true" probability that you think the Column player is playing Left. If you misreport your true probability then you'll end up choosing an option you like less on some of the rows above.

Here is an example screenshot of this decision:

	Left	Right
Up	$25 $5	$5 $25
Down	$5 $25	$25 $5

I think the probability that they chose Left is 73 **%.**

<u>"Stage 3:" Row player with a Hint</u>

In Stage 3 we'll show you a "hint" of how an actual Column player played today. Here's how the hint works:

First, the computer will randomly select 1 of the other 20 players. The computer knows whether this player chose Left or Right as COLUMN player, so the computer can give you a hint about which they chose. The hint will either say "Left" or "Right", but it's not very accurate; the hint will be correct 55% of the time and wrong 45% of the time.

This means that if you see the hint that COLUMN chose Left, then it's slightly more likely that the COLUMN player really did choose Left. And if the hint says "Right" then it's slightly more likely that the COLUMN player really did choose Right.

After you see this hint, you will play the game 20 more times as the ROW player, each time matched with a randomly-drawn person in the room, just as you did back in Stage 1. The only difference is that you've now seen a hint.

<u>"Stage 4:" Probabilities with a Hint</u>

In Stage 4 we'll once again ask you your probability that a random Column player chose Left. The payments will work just like in Stage 2. Again, your incentive is to report your belief truthfully. This is exactly as in Stage 2; the only difference is that now you've seen a hint.

You will play 2 matrix games in this block. In each game you will go through all 5 stages (0 through 4). Notice that the games' payoffs may be different, but the procedures for each stage are exactly the same.

INVESTMENT QUESTIONS

In the investment questions, you will be given $10.00, and you can choose to invest any amount of that money in a risky project. The money you don't invest you keep for yourself.

The project can either be a success or a failure.

If it's successful then the amount you invested in it will be multiplied by some number and paid to you. If it's a failure then that money will be lost.

In either case you get to keep the money that you chose *not* to invest.

Your screen will include detailed instructions about these questions, so read the information carefully. Here is an example screenshot:

- The risky project has a **40%** chance of succeeding.
- If it succeeds, the money you invested will be multiplied by **3**.
- If it does not succeed, the money you invested is lost.
- You always keep any money that you did not invest.

I choose to invest $ 7.23 of my $10.00 in the risky project.
(The remaining $2.77 I will not invest.)

You will face two different investment choices, each with a different chance of success and multiplier. Please read the screen carefully before making your choice each time.

E. Notions of Dominance, Mixing, and Incentive Compatibility

For the interested reader, we provide supplementary information about various notions of dominance in our experiment, and the related notions of monotonicity that require preferences respect dominance. We explore which notions of monotonicity are violated by mixing behavior. We also discuss under which monotonicity assumptions our experiment is incentive compatible, implications for models of random preferences, and provide a modification of monotonicity—called myopic preference—that can capture mixing in the SEQ treatment.

E.1. Setup and Experimental Design

Choice objects are acts $f: B \to X$, where $B = \{1,\dots,n\}$ is the set of possible draws from a Bingo cage containing n numbered balls and $X = \{\$2,\$1,\$0\}$ is the set of possible monetary prizes.[56] Each ball in B is drawn with objective probability $1/n$, but we generally model choice objects as acts. We can describe f as an n-vector—such as $f = (2,0,\dots,1,1)$—to indicate the prize awarded in each state. For any two prizes $x, y \in X$ and any $k \in \{0,1,\dots,n\}$ let $x_k y$ be the act that pays x in the first k states and y otherwise. For example, $2_{10}0$ is the bet that pays \$2 in states 1–10 and \$0 otherwise. The constant act that pays x in every state is denoted simply as x.

The subject is given m different decision problems, each of which is a choice between two acts. Denote the ith problem by $D_i = \{f_i, g_i\}$. The subject makes each of these choices n times. The subject's choice on the jth replicate of the ith problem is given by $a_{ij} \in D_i$. Let $a = (a_{ij})_{i,j} \in \times_{i=1}^{m} D_i^n$ be the entire matrix of choices and $a_i = (a_{i1},\dots,a_{in}) \in D_i^n$ be the vector of choices made across the n replicates of the ith problem.

In our baseline condition one ball is drawn (with replacement) for each of the n replicates. Let $b = (b_1,\dots,b_n) \in B^n$ be the vector of all n draws. Act a_{ij} is paid based on draw $b_j \in B$. The final payment is therefore $a_{ij}(b_j) \in X$.

We employ the RPS mechanism, meaning one of the mn choices is chosen randomly for payment. The decision problem chosen (the "row" of the matrix a) is determined by a randomization device with realizations $r \in R = \{1,\dots,m\}$, and the replicate ("column") is determined by a separate randomization device with realizations $c \in C = \{1,\dots,n\}$. Thus, the combined state (r,c) determines which problem and which replicate is paid. The announcement of $a = (a_{ij})_{i,j}$ generates an act which pays act a_{ij} in state

[56] In the actual experiment $X = \{\$25,\$15,\$5\}$; we use $\{\$2,\$1,\$0\}$ only for notational convenience.

$(r,c) = (i,j)$. And the act a_{ij} pays $a_{ij}(b_j)$ in each state $b_j \in B$. The entire state space for the experiment is therefore given by $R \times C \times B^n$, and the whole matrix of choices a is an act in $X^{R\times C\times B^n}$.

We set $n = 20$ throughout our experiment. Probability matching (PM) questions are given by $f = 2_k 0$ and $g = 0_k 2$, where $k \in \{11,12,\ldots,16\}$. Risky-Safe (RS) questions offer $f = 2_k 0$ and $g = 1$, where again $k \in \{11,12,\ldots,16\}$. We do not model games here, though the games of strategic certainty (SC) are identical to the PM choices except in framing.

The IND and SIM treatments are as described above. In the CORR treatment only one ball $b_1 \in B$ is drawn, and each a_{ij} pays $a_{ij}(b_1)$. The entire state space is therefore $R \times C \times B$, and so $\succeq^*$ is defined over $X^{R\times C\times B}$. In the SEQ treatment there are n ball draws, as in IND, but now the column chosen for payment (c_i) is drawn in advance, the subject chooses each a_{ij} sequentially, starting at $j = 1$ and proceeding until $j = c_i$. The ONE treatment simply sets $n = 1$.

To model choices, we start by assuming the subject has a preference $\succeq^*$ over the entire choice matrix $a \in X^{R\times C\times B^n}$. This is useful later for describing the assumptions under which our payment mechanism is incentive compatible. But for now our focus is on how the subject chooses across the n replications of a single decision problem. In other words, for each decision problem i, we are interested in studying preferences over $a_i \in X^{C\times B^n}$. To capture this we define $\succeq$ over various a_i by

$$a_i \succeq a'_i \Leftrightarrow \begin{pmatrix} a_i \\ a_i \\ \vdots \\ a_i \end{pmatrix} \succeq^* \begin{pmatrix} a'_i \\ a'_i \\ \vdots \\ a'_i \end{pmatrix}. \tag{2}$$

We can then derive a preference $\succeq_0$ over single choice objects in X^B by

$$a_{ij} \succeq_0 a'_{ij} \Leftrightarrow (a_{ij}, a_{ij}, \ldots, a_{ij}) \succeq (a'_{ij}, a'_{ij}, \ldots, a'_{ij}). \tag{3}$$

E.2. Dominance, Monotonicity, and Mixing

Consider a subject who faces only one decision problem D_i, and does so n times. Thus, their only choices are $a_i = (a_{i1}, \ldots, a_{in})$. We can view this as equivalent to having m rows but choosing the same vector a_i in every row, because then the draw of the row would be irrelevant.

Given these derived preferences, we can formulate several useful notions of dominance. The first is simply stochastic dominance, while the others are various notions of statewise dominance.

Definition 2. Let ρ be an objective probability measure on (the discrete topology of) B.

1. f *stochastically dominates* g if, for every $x \in X$, $\rho(\{b : f(b) \leq x\}) \leq \rho(\{b : g(b) \leq x\})$.
2. f *B-dominates* g if, for all b, $f(b) \geq g(b)$.
3. a_i *C-dominates* a'_i if, for all j, $a_{ij} \succeq_0 a'_{ij}$.
4. a_i *C-stochastically dominates* a'_i if, for all j, a_{ij} stochastically dominates a'_{ij}.
5. a_i *$C \times B^n$-dominates* a'_i if, for all j and b_j, $a_{ij}(b_j) \geq a'_{ij}(b_j)$.
6. a *R-dominates* a' if, for all i, $a_i \succeq a'_i$.

In general, an object is said to be *dominant* (under the appropriate notion of dominance) if it dominates all other alternatives. For example, a_i is C-dominant if it C-dominates every a'_i.[57]

For each notion of dominance we can also define an equivalent notion of monotonicity (with respect to dominance) of the subject's preference.[58]

Definition 3.

1. $\succeq_0$ satisfies *stochastic monotonicity* if $f \succeq_0 g$ whenever f stochastically dominates g.
2. $\succeq_0$ satisfies *B-monotonicity* if $f \succeq_0 g$ whenever f B-dominates g.
3. $\succeq$ satisfies *C-monotonicity* if $a_i \succeq a'_i$ whenever a_i C-dominates a'_i.

[57] In Appendix C C-dominance was called replicate dominance, and C-stochastic dominance was simply called stochastic dominance.

[58] In earlier drafts R-monotonicity was called "row monotonicity" and C-monotonicity was called "replicate monotonicity."

4. $\succeq$ satisfies *C-stochastic monotonicity* if $a_i \succeq a'_i$ whenever a_i C-stochastically dominates a'_i.

5. $\succeq$ satisfies *$C \times B^n$-monotonicity* if $a_i \succeq a'_i$ whenever a_i $C \times B^n$-dominates a'_i.

6. $\succeq^*$ satisfies *R-monotonicity* if $a \succeq^* a'$ whenever a R-dominates a'.

Each of these can equivalently be defined in terms of deviations in a single state. For example, an equivalent definition of R-monotonicity is that, for all i, a_i, a'_i, and a'',

$$\begin{pmatrix} a''_1 \\ \vdots \\ a''_{i-1} \\ a_i \\ a''_{i+1} \\ \vdots \\ a''_m \end{pmatrix} \succeq^* \begin{pmatrix} a''_1 \\ \vdots \\ a''_{i-1} \\ a'_i \\ a''_{i+1} \\ \vdots \\ a''_m \end{pmatrix} \Leftrightarrow a_i \succeq a'_i.$$

And an equivalent defition of C-monotonicity is that, for all i, j, a_{ij}, a'_{ij}, and a''_i,

$$(a''_{i1},\ldots,a''_{ij-1},a_{ij},a''_{ij+1},\ldots,a''_{in}) \succeq (a''_{i1},\ldots,a''_{ij-1},a'_{ij},a''_{ij+1},\ldots,a''_{in}) \Leftrightarrow a_{ij} \succeq_0 a'_{ij}.^{59}$$

We can also talk about a subject whose preferences satisfy certain monotonicity concepts on some problems, but not others. For example, $\succeq$ may satisfy C-monotonicity on D_i, but not on $D_{i'}$.

In our experiment the main object of focus is $\succeq$—how people choose across multiple replicates of the same problem. Thus, we want $\succeq$ to be revealed truthfully. Azrieli et al. (2018) show that this is true if (and, essentially, only if) $\succeq^*$ satisfies R-monotonicity. The argument is simple: Picking the $\succeq$-most preferred a_i on each i generates matrix a, and any deviation a' would lead to at least one row i on which $a_i \succ a'_i$. Thus, a R-dominates a'. If $\succeq^*$ satisfies R-dominance, then the subject would never prefer such a deviation. Thus, we assume R-monotonicity throughout, but do not assume any other form of monotonicity listed above. Justification for this comes from Brown

[59] One could instead define C-monotonicity identically to R-monotonicity, mutatis mutandis, by first defining a relation over entire columns and then requiring that this preference be independent of what is chosen in other columns. This would be strictly stronger than our definition of C-monotonicity because ours only applies to the special case where all rows are identical (which corresponds to the case of only having a single decision problem).

and Healy (2018), who show that monotonicity assumptions may be violated when all decisions are shown on the same screen, but not when they are shown on separate screens and in random order. In our experiment the decision problems are shown on separate screens and in random order, so we expect R-monotonicity to hold. The replicates, however, are all shown on the same screen, and so we may expect violations of other forms of monotonicity for $\succeq$.

R-monotonicity is not innocuous, however. It forces a form of independence across decision problems: if a_i is chosen in row i, then it must be chosen regardless of what was chosen in other rows.[60]

It is useful to highlight the relationships between the three dominance concepts that apply to $\succeq$.

Lemma 1. 1. $\succeq$ satisfies C-stochastic monotonicity $\Rightarrow$ $\succeq$ satisfies $C \times B^n$-monotonicity.

2. Suppose $\succeq_0$ satisfies B-monotonicity. Then $\succeq$ satisfies C-monotonicity $\Rightarrow$ $\succeq$ satisfies $C \times B^n$-monotonicity.

3. Suppose $\succeq_0$ satisfies stochastic monotonicity. Then $\succeq$ satisfies C-monotonicity $\Rightarrow$ $\succeq$ satisfies C-stochastic monotonicity $\Rightarrow$ $\succeq$ satisfies $C \times B^n$-monotonicity.

We are interested in studying *mixing* behavior, where subjects vary their choices from one replicate to the next.

Definition 4. A subject exhibits *mixing* on decision problem D_i if there exist replicates j and j' such that $a_{ij} \neq a_{ij'}$.

The various notions of monotonicity of $\succeq$ rule out mixing behavior in different types of problems.

[60] To illustrate, consider a subject facing $D_1 = \{2_9 0, 1\}$ and $D_2 = \{2_{10} 0, 1\}$, each two times (so $m = n = 2$). Suppose his preferences are given by

$$\begin{pmatrix} 1 & 1 \\ 2_{10}0 & 2_{10}0 \end{pmatrix} \succ^* \begin{pmatrix} 1 & 2_9 0 \\ 1 & 2_{10}0 \end{pmatrix} \succ^* \begin{pmatrix} 1 & 2_9 0 \\ 2_{10}0 & 2_{10}0 \end{pmatrix} \succ^* \begin{pmatrix} 1 & 1 \\ 1 & 2_{10}0 \end{pmatrix}.$$

This may be because he most-prefers to receive the safe option in exactly two states, but doesn't care which, but does prefer having $2_{10}0$ in place of $2_9 0$. Unfortunately this violates R-monotonicity since

$$\begin{pmatrix} 1 & 2_9 0 \\ 1 & 2_{10}0 \end{pmatrix} \succ^* \begin{pmatrix} 1 & 2_9 0 \\ 2_{10}0 & 2_{10}0 \end{pmatrix} \Rightarrow \begin{pmatrix} 1 & 2_{10}0 \end{pmatrix} \succeq \begin{pmatrix} 2_{10}0 & 2_{10}0 \end{pmatrix} \Rightarrow \begin{pmatrix} 1 & 1 \\ 1 & 2_{10}0 \end{pmatrix} \succeq^* \begin{pmatrix} 1 & 1 \\ 2_{10}0 & 2_{10}0 \end{pmatrix}.$$

Proposition 1. 1. If $\succeq$ satisfies C-monotonicity then the subject will never mix on any decision problem $D_i = \{f_i, g_i\}$, because they will always choose the option (f_i or g_i) that they prefer.

2. If $\succeq$ satisfies C-stochastic monotonicity then the subject will never mix on any decision problem $D_i = \{f_i, g_i\}$ in which f_i stochastically dominates g_i, because they will always choose f_i.

3. If $\succeq$ satisfies $C \times B^n$-monotonicity then the subject will never mix on any decision problem $D_i = \{f_i, g_i\}$ in which f_i B-dominates g_i, because they will always choose f_i.

In our experiment we do not offer decision problems with objects that are ranked by B-dominance; thus, we do not test $C \times B^n$-monotonicity separately from the other two notions of monotonicity.

As a shorthand, we say that a subject has *convex preferences* if $\succeq$ violates the relevant monotonicity concept. Subjects with convex preferences will exhibit mixing behavior (choosing different options on different replicates) for at least some decision problems.

E.3. Mixing and Random Preferences

An obvious explanation for mixing is that subjects simply have convex preferences, meaning they fail to satisfy C-monotonicity (or C-stochastic monotonicity if the options are ranked by stochastic dominance). An alternative explanation for mixing is that subject's preferences simply change from one choice to the next. We argue that such behavior can persist even when C-monotonicity (appropriately re-interpreted) is satisfied.

To formalize this claim, we adapt the framework of Azrieli et al. (2018, online appendix). Specifically, we model preferences as being affected by some unknown state $\theta \in \Theta$. Information about θ is revealed before each decision is made; to capture this simply, we let $\theta = ((\theta_{ij})_{j=1}^{n})_{i=1}^{m}$ and assume that at each decision ij the subject observes $\theta_{ij} \in \Theta_{ij}$.[61] The subject selects a *plan* $s = ((s_{ij})_{j=1}^{n})_{i=1}^{m}$, where each $s_{ij} : \Theta_{ij} \to D_i$ indicates what the subject will pick for every possible θ_{ij}. A plan s therefore generates

[61]To capture dynamic information revelation we think of θ_{ij} as including all information from all $\theta_{i'j'}$ for which $i' \leq i$ and $j' \leq j$.

$\succeq_0 \setminus \succeq$	Convex	Linear
Random	RC	RL
Fixed	FC	FL

Table XVI: The general typology of subjects.

an act that not only depends on r, c, and b, but also on the realized θ. The preference $\succeq^*$ is now defined over the space of such acts. R-monotonicity and C-monotonicity are defined exactly as above, except now a_{ij} is an act that depends on θ as well as b (it lists what would be chosen for every θ). A plan s^* is *truthful* if, at every ij and θ_{ij}, $s^*_{ij}(\theta_{ij})$ is the most-preferred option in D_{ij}, conditional on observing θ_{ij}. Preferences on a_{ij} are assumed to respect dominance, in the sense that $a_{ij}(\theta_{ij}) \succeq_0 a'_{ij}(\theta_{ij})$ for all θ_{ij} implies $a_{ij} \succeq_0 a'_{ij}$.[62]

In this framework, C-monotonicity guarantees that the subject will report their true favorite choices in each replicate, even as the information they observe about their preferences changes from one replicate to the next (Azrieli et al., 2018). It does *not* guarantee that choices will be identical across replicates, only that they will be truthful. This gives our second explanation for mixing:

Observation 1. A subject with random preferences may mix in some decision problems even if they satisfy C-monotonicity.

Thus we have two general explanations for mixing: random preferences and a failure of C-monotonicity (or C-stochastic monotonicity). For simplicity we say those that satisfy monotonicity have *linear* preferences while those who fail it have conevex preferences. We can thus type subjects into four categories, as shown in XVI.

E.4. Mixing in The Sequential Treatment

We propose instead that the sequential treatment triggers myopic preferences. The idea is that the subject faces a "current choice" and "future choices." In SEQ the current choice at each j is simple: pick between f_i and g_i. This choice is guided by $\succeq_0$ over f_i and g_i. The subject ignores future choices. In SIM there is only one "current choice," which is a choice over the entire vector a_i. This is guided by $\succeq$.

[62]Here, $a_{ij}(\theta_{ij}) \in D_{ij}$ is the constant act that pays the same gamble for all r, c, and θ, and abusing notation, $\succeq_0$ also represents preferences over these acts.

Formally, let $C(j) \subseteq C$ represent those states in C that are still possible at information set j, but not at information set $j+1$. In our SEQ treatment, $C(j) = \{j\}$ for all j. In the IND and SIM treatments the only information set is $j = 1$, so $C(1) = C$. For each j, define $\succeq^j$ as the subject's preference over acts of the form $a_i^j = (a_{ij})_{j \in C(j)} \in X^{C(j) \times B^{\#C(j)}}$.[63]

Definition 5. Preference $\succeq$ is *myopic* if, for all information sets j, $a_i^j \succeq^j a_i^{j\prime}$ then we have $a_i \succeq a_i'$.

This definition does not necessarily pin down the entire ranking $\succeq$, but it does pin down a most-preferred element. Specifically, if there are J information sets and a_i^j is the most-preferred element at each j according to $\succeq^j$, then under myopic preferences $a_i = (a_i^1, \ldots, a_i^J)$ must be the most-preferred element according to $\succeq$.

In SEQ $C(j) = \{j\}$ for each j, so $a_i^j = a_{ij}$ and $\succeq^j = \succeq_0$. Having myopic preferences is therefore equivalent to having preferences that respect C-dominance. In IND and SIM, $C(1) = C$, so $a_i^1 = a_i$ and $\succeq^1 = \succeq$. In those treatments myopic preferences place no restriction whatsoever on $\succeq$; the definition becomes vacuous.

The SIM treatment occurs after the SEQ treatment. It is possible that subject learn to adapt myopic preferences in the SEQ treatment and apply them in the SIM treatment that follows.

Subjects with random preferences will continue to mix in the SEQ treatment, as $\succeq_0$ changes from one information set to the next.

[63] $\#C(j)$ denotes the number of states in $C(j)$.