Narrowly Rational

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Abstract

While individuals tend to behave consistently within a given setting as documented in revealed preference analysis, they also exhibit considerable inconsistency across different settings as shown in behavioral economics literature. Here we examine this narrowly rational behavior—consistency within each setting and inconsistency across settings—in an experimental framework. We compare portfolio allocations between two equiprobable Arrow securities in one setting, and between one safe asset and one risky asset, which delivers either a positive payoff or nothing in another setting. We find that subjects are narrowly rational; that is, their choice data are internally consistent within each setting but largely inconsistent across settings. We observe that a diversification heuristic—the tendency to choose allocation at the midpoint of the given budget line—may underpin the observed inconsistency. We explore the underlying mechanisms in two additional experiments and show that the inconsistency across settings can be reduced by framing the two settings similarly but not by further decreasing the likelihood of the securities to a low level. Our study contributes to the literature on revealed preference analysis and heuristic-based decision-making.

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Keyword: Revealed Preference, Rationality, Heuristic, Framing, Risk, Experiment

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1. Introduction

Central to economic analysis is the assumption of rationality, whereby a decision maker seeks to maximize her utility function subject to budget constraints (Samuelson, 1938).[1] Revealed preference analysis provides a powerful toolbox to characterize conditions under which the choice data can be rationalized by some well-behaved utility functions (Afriat 1967, 1972; Varian 1982, 1990; see Crawford and De Rock, 2014; Chambers and Echenique, 2016 for review). In experimental studies of risk, time, and social preferences in which subjects make a series of budgetary decisions, it is commonly observed that subjects' choice data are generally rationalizable (e.g., Andreoni and Miller, 2002; Choi et al., 2007; Fisman et al., 2007; Ahn et al., 2014; Choi et al., 2014; Halevy et al., 2018; Zame et al., 2020; Fisman et al., 2022; Lanier et al., 2022). Going beyond the lab, researchers also examine the rationality of consumers using expenditure surveys and scanner data from grocery stores and similarly show that most consumers make consistent choices (e.g., Crawford, 2010; Echenique et al., 2011; Dean and Martin, 2016).

However, voluminous studies in behavioral economics provide ample evidence that choice behavior of an individual is often inconsistent when different settings are compared. For example, inconsistency is commonly observed when comparing consequentially identical options framed as gains versus losses (Tversky and Kahneman, 1981); willingness to pay versus willingness to accept for the same object (Kahneman et al., 1990); and binary choice between two lotteries versus valuation of the same two lotteries (Grether and Plott, 1979). These observations seem to suggest that individual rationality is *narrowly* constrained: While they behave consistently within a given setting as in revealed preference analysis, they may exhibit considerable inconsistency across different contexts as in behavioral economics literature. Yet, little has been done to examine such narrowly rational behavior.

To this end, we examine individual choice consistency both within and across settings. We conduct a series of experiments with budgetary choices in the context of decision-making under risk. Our main experiment compares two classic experimental designs—Choi et al. (2007) and Gneezy and Potters (1997), in which subjects make portfolio choices given different budgets.

[1] In the literature, rationality is often broadly defined to encompass the adoption of decision rules and heuristics (Simon, 1955; Kahneman, 2003; Thaler, 2016). See also Gilboa (2009) and Wakker (2010) for discussions about rationality in decision under risk and uncertainty. For simplicity, in this paper, we follow some studies in the revealed preference literature, use "rationality" narrowly to refer to the extent of consistency with utility maximization, and use rationality and consistency interchangeably.

In Choi et al. (2007), subjects allocate their budget between two Arrow securities, each with a 50 percent chance of receiving the payment. In Gneezy and Potters (1997), subjects allocate their budget between one safe asset and one risky asset with a 50 percent chance of receiving a positive payment and otherwise receiving nothing. By properly choosing the returns of the risky asset, the second condition can be viewed as essentially the same allocation problem between two Arrow securities as in the first condition, but along a *truncated* budget line in which subjects are prohibited from allocating more to the (weakly) more expensive security (see Figure 1 in Section 2 for details).[2] We label the first the full-line condition and the second the truncated-line condition. In a within-subject experiment, subjects make 22 portfolio choices between two equiprobable Arrow securities in the full-line condition and 22 corresponding choices between one safe asset and one risky asset in the truncated-line condition. Given that the two Arrow securities are equiprobable, subjects who satisfy first-order stochastic dominance ought to allocate less to the more expensive security. As such, their behavior should not differ across the two conditions.

We first examine the aggregate behavior of subjects. On the one hand, subjects appear to respond to price changes in the correct direction in both conditions: They purchase more of the cheaper asset as its relative price decreases. On the other hand, they behave differently across the two conditions by allocating, on average, 10 percent more of their budget to the (weakly) cheaper security in the truncated-line condition, compared with that in the full-line condition. That is, subjects behave as if they are more risk-seeking in Gneezy and Potters (1997) than in Choi et al. (2007).

We further adopt the revealed preference toolkit to examine the rationality of each subject's choice behavior within and across the two conditions. Specifically, we measure the consistency of individual behaviors with the generalized axiom of revealed preference (GARP) and use the canonical index—the critical cost efficiency index (CCEI; Afriat, 1967, 1972)—to assess how closely individual choice behavior complies with GARP. We find that subjects' choices are largely consistent with utility maximization within each condition (mean CCEI: 0.96 in full-line condition; 0.95 in truncated-line condition). However, when we combine the datasets of the two conditions, the CCEI of the combined dataset drops significantly (mean CCEI: 0.89). This suggests that subjects' choices exhibit considerable inconsistency across the two conditions. The observed inconsistency across the two conditions is robust when we use

[2] Subjects are not allowed to short-sell the risky asset in the second condition, so their choice set is a strict subset of their choice set in the first condition.

alternative measures based on GARP violation, the degree of choice stochasticity, and the violation of Sen's alpha. Taken together, these are in support of the observation that individuals are narrowly rational, whereby their choice behavior is largely rational within each condition as in the revealed preference literature and substantially inconsistent across conditions as in the behavioral economics literature.

We then examine whether some heuristic rules may underpin the observed narrowly rational behavior. Two such rules are commonly discussed in experimental studies that adopt budgetary settings (Choi et al., 2006; Halevy and Mayraz, 2022). The first is related to price responsiveness, in which subjects, regardless of whether they are "solving" their real optimal portfolio in each choice problem, properly respond to price changes by increasing their allocations to the cheaper security when it becomes less expensive. The second heuristic is diversification, as in "don't put your eggs in one basket," in which subjects, again, can be agnostic regarding their real optimal choice, whereas they tend to allocate their budget evenly across the available options. Note that if subjects choose to allocate evenly across the two Arrow securities in the full-line condition and evenly across the safe and risky assets in the truncated-line condition, they will exhibit more risk-seeking behavior in the second condition, which results in inconsistency between the two conditions.[3] We measure the degree to which subjects' behavior is in line with the two heuristic rules and find that the price responsiveness heuristic significantly correlates with within-condition rationality. In contrast, the diversification heuristic is linked to cross-condition inconsistency. Moreover, subjects with greater cross-condition inconsistency tend to have lower scores in cognitive reflection test (CRT, Frederick, 2005) and exhibit a stronger tendency to falsely diversify (Rubinstein, 2002).

We explore the underlying mechanisms of narrowly rational behavior and examine how to reduce the cross-condition inconsistency in two additional experiments. Because the inconsistency may be partly due to the adoption of the diversification heuristic between the two Arrow securities in the full-line condition and between the safe and risky assets in the truncated-line condition, we conduct an additional experiment by using the same frame in the two conditions. More specifically, in the truncated-line condition, we remove the frame of allocation between the safe and risky assets and instead use the frame of allocation between two Arrow securities, as in the full-line condition. The only difference between the two

[3] Consider, for example, the case in which the relative price equals 1 between the two Arrow securities. Allocating evenly across the two securities results in a fully hedged portfolio that pays the same amount regardless of the state, whereas allocating evenly across the safe and risky assets results in a portfolio that still bears some risk.

conditions is that the dominated portfolios remain infeasible in the truncated-line condition. We call this the Same-frame experiment and hypothesize that the cross-condition inconsistency will be lower as subjects diversify between the two Arrow securities in both conditions. We find that subjects continue to exhibit high levels of within-condition rationality. Moreover, the cross-condition allocation difference is reduced by about 50 percent in the Same-frame experiment compared with that in the Main experiment.

We conduct another experiment to see whether the cross-condition inconsistency can be further reduced. We hypothesize that the inconsistency may have something to do with moderate chances, whereby subjects are more willing to diversify, and it may be reduced if we use small probabilities with respect to which subjects may be more risk-seeking (Kahneman and Tversky, 1979). To test this possibility, we build on the Same-frame experiment and further reduce the probabilities of the two states (corresponding to the two Arrow securities) from a 50 percent chance to a 5 percent chance, with the third state delivering zero with a 90 percent chance. We name this Low-probability experiment. We find that the cross-condition allocation difference in the Low-probability experiment is not further reduced. Specifically, compared with the Same-frame experiment, the within-condition rationality measured by CCEI remains, and the drop in CCEI for the combined dataset compared with within-condition rationality is not significantly changed in the Low-probability experiment. Taken together, the results from the two additional experiments suggest that the observed narrowly rational behavior is partly due to the frames of the choice environments but not to the likelihood of the Arrow securities.

Our paper adds to the experimental and empirical literature that uses the revealed preference approach to examine economic rationality. It has been observed that decision makers exhibit a relatively high level of rationality across different choice domains. Prior studies also link individual rationality to economic outcomes, such as occupation, income, and wealth differences, across individuals and developing gaps across countries (e.g., Choi et al., 2014; Carvalho et al., 2016; Fisman et al., 2017, Li et al., 2017; Kim et al., 2018; Cappelen et al., 2021; Li et al., 2023). Several studies adopt the revealed preference toolkit to examine preference heterogeneity across different individuals and across different time points for the same individual (e.g., Crawford and Pendakur, 2013; Castillo and Freer, 2018; Miao et al., 2021). This paper focuses on another dimension—rationality across settings and shows that individuals are rational within each setting and yet inconsistent across settings. In general, these observations suggest the need to incorporate both within-setting and cross-setting rationality into traditional revealed preference analysis.

Our paper also adds to the literature on rule-based decision-making (Simon, 1955; Tversky and Kahneman, 1974; Gigerenzer et al., 1999), whereby people tend to use heuristic rules especially when facing difficult decisions.[4] In the budgetary choice settings, Choi et al. (2006) find that subjects' allocation decisions are mainly explained by several simple heuristics. Halevy and Mayraz (2022) offer a direct test that compares case-by-case and rule-based decisions and show that most subjects choose to use some simple rules for allocation decisions. One important heuristic in the budgetary choice settings is diversification heuristic, which is commonly observed in various environments (Read and Loewenstein, 1995; Benartzi and Thaler, 2001; Rubinstein, 2002; Gathergood et al., 2019; Beauchamp et al., 2019; Xiang et al., 2021). In line with these studies, we show that heuristic rules may underpin the degree of consistency both within and across settings. Specifically, the diversification heuristic, in conjunction with price responsiveness, works well for budgetary decisions so that decision makers can exhibit high levels of rationality within a specific setting. However, the same set of rules, when adapted to different settings, may result in inconsistency across settings and hence undermine global rationality. These findings highlight the importance of comparing different settings and distinguishing between heuristics and preferences. For example, individuals with well-behaved preference would choose consistently across settings and those with diversification heuristic would choose around the mid-point of the budget line in each setting.

The observed narrowly rational behavior is closely related to the notion of coherent arbitrariness proposed by Ariely et al. (2003). In their study, individuals having difficulty in evaluating their pain or pleasure may be subject to the influence of arbitrary factors such as a random anchor,[5] while still responding in a coherent fashion to noticeable changes in numerical parameters such as price, quantity, and quality. Relatedly, Enke and Graeber (2022) propose the notion of cognitive uncertainty, whereby subjects facing complex decisions are biased toward the intermediate option or cognitive default, for example, exhibiting the

[4] Complexity or choice difficulty may induce the use of heuristics, such as the status quo bias (Masatlioglu and Ok, 2005; Ortoleva, 2010), simplicity seeking (Iyengar and Kamenica, 2010), caution (Cerreia-Vioglio et al., 2015), and mental accounting (Gilboa et al., 2021). The complexity of thinking through uncertainty may lead to suboptimal decisions (see Shafir and Tversky, 1992; Charness and Levin, 2009; Martínez-Marquina et al., 2019). Oprea (2022) shows that complexity may underpin empirical patterns of prospect theory. Oprea (2020) examines what makes a rule complex to implement and the costs associated with procedural complexity. In our setting, compared with allocation between two Arrow securities (Choi et al., 2007), it may be more complex to allocate between safe and risky accounts because the final payoff for each contingency is not explicitly provided to subjects in the original experiment of Gneezy and Potters (1997). To mitigate this potential influence of complexity, we provide the same interface for subjects to respond, and we compute the final payoff for each contingent.

[5] In the anchoring and adjustment literature, a decision maker is affected by a randomly generated anchor, or choice recalled from one's memory database and imperfectly adjusts toward the direction of the true optimum (Tversky and Kahneman, 1974; Ariely et al., 2003; Bordalo et al., 2020).

tendency to switch around the middle of the choice list. Yet they respond to changes in probability and hence exhibit an S-shaped probability weighting function. In our study, it is likely that subjects find the decision tasks complex and thus adopt some heuristic rules, namely diversification between two assets and responsiveness to price changes at the same time. In the Discussion section, we examine several approaches that incorporate heuristics into the analysis to account for the observed narrowly rational behavior.

Finally, our study helps bridge the gap between the within-setting consistency as in revealed preference literature and the cross-setting inconsistency as in behavioral economics literature. In addition to the aforementioned studies, existing research has documented a high level of choice consistency with respect to GARP in children between 7 and 11 years old (Harbaugh, Krause and Berry, 2001),[6] monkeys (Chen et al., 2006), as well as rats and pigeons (Kagel et al., 1975). Moreover, both children and monkeys have been found to exhibit endowment effect (Harbaugh, Krause and Vesterlund, 2001) and framing effect (Lakshminarayanan et al., 2011). These observations may appear difficult to reconcile as it is unlikely for children and animals to comply with the notion of utility maximization. Instead, they suggest that narrowly rational behavior is prevalent. Our study contributes to this literature and points to heuristics as an important underpinning.

The rest of the paper is organized as follows. We detail the experimental design in Section 2 and present the theoretical background in Section 3. We report our main results in Section 4 and the results from two additional experiments to shed light on the mechanisms in Section 5. Section 6 discusses the theoretical implications and Section 7 concludes.

2. Experimental Design

We build our experiment based on the classical budgetary design of choice under risk of Choi et al. (2007). The general setup can be viewed as a portfolio choice problem between two equiprobable Arrow securities, with each security delivering a unit of payoff in one state and nothing in the other. Let (x, y) be the demand for the two securities. Subjects in each decision task choose (x, y) given the constraint $p_x x + p_y y = w$. Across decision tasks, the price vector (p_x, p_y) differs and the wealth w is fixed. To facilitate comparison across conditions

[6] In a set of novel experiments, Brocas et al (2019) show that children learn to make consistent choices in some domains but not others, and suggest the importance of attentional control and the tendency to focus on a subset of choice attributes.

and individuals, we use a fixed set of budget lines adopted from Halevy et al. (2018) instead of randomly generated budget lines (see Table A1 in Appendix A for the complete set of parameters). The budget lines overlap sufficiently, which ensures adequate power to detect GARP violations in the experimental environment (Halevy et al., 2018). Based on this general setup, we use a between-subjects design with three experiments: the Main experiment, the Same-frame experiment, and the Low-probability experiment. In each experiment, we use a within-subject design with two conditions—a full-line condition and a truncated-line condition. We explain the experimental design below in detail.

Main experiment. The Main experiment compares two conditions. In the first condition, each decision problem is presented as a choice from a budget line. The interface is similar to standard budgetary experiments (Choi et al., 2007; Halevy et al., 2018), illustrated in Panel A of Figure 1. Subjects choose an allocation on the budget line, which represents the points allocated to accounts X and Y, and they can receive the points in one account with a 50 percent chance. In addition to the graphic interface, we present subjects with the following message: "*50% chance of ___points in X account; 50% chance of ___points in Y account*" when they make a choice. We call this the full-line condition since subjects can choose any allocation along a full budget line. In this condition, each subject makes 22 portfolio choices.

In the second condition, subjects are given a truncated budget line (henceforth, the truncated-line condition). Specifically, for the case of $p_x > p_y$, subjects can only choose an allocation with $x \leq y$ and vice versa. In the case of $p_x = p_y$, we randomly truncate the upper or lower half of the budget line. By truncating the budget line, we restrict subjects from allocating more to the more expensive security, which could have violated first-order stochastic dominance because the two states are equally likely.

Panel B of Figure 1 illustrates the interface for the truncated-line condition. We frame this truncated-line condition as a portfolio choice between a safe and a risky asset (Gneezy and Potters, 1997). The horizontal and vertical axes represent the states of Success or Failure (with equal probability) for investment in the risky account. For the safe account, subjects can always gain the points they allocate. For the risky account, subjects will receive points in the Success state and zero points in the Failure state. If subjects want to allocate all of the points to the safe account, they choose the intersection between the budget line and the 45-degree line; if they want to allocate all of the points to the risky account, they choose the intersection between the budget line and the axes; they can also choose any point in between. To simplify the computation, we sum up the payoffs from the two accounts and show the following message:

"*50% chance of ___points if Success; 50% chance of ___points if Failure.*" We truncate the same 22 budget lines from the full-line condition to obtain 22 corresponding budget lines for the truncated-line condition.

Same-frame experiment. In this experiment, we change the frame of the choice environment to reduce the difference, if any, between the two conditions in the Main experiment. Specifically, we keep the full-line condition identical to that in the Main experiment and change the truncated-line condition as follows. Instead of using the frame of a safe asset versus a risky asset, subjects are simply asked to make an allocation choice between X and Y accounts. As such, the truncated-line condition in this additional experiment shares the same frame as the full-line condition, and we call this the Same-frame experiment. The interfaces are similar to the Main experiment, and screenshots of the interfaces can be found in Figure A1 in Appendix A. As in the Main experiment, we have 22 budget lines for each condition.

Low-probability experiment. In this experiment, we change the likelihoods of the choice environment to examine whether the difference, if any, between the full-line and truncated-line conditions in the Same-frame experiment can be further reduced. Specifically, we reduce the probability of a 50 percent chance in the Same-frame experiment to a 5 percent chance. That is, subjects make an allocation choice between X and Y accounts, each with a 5 percent chance of receiving the corresponding points in the account and a 90 percent chance of receiving zero points in a third Z account, which does not show up on the two-dimensional budgetary interface. We hypothesize that subjects in this Low-probability experiment may act in a more risk-seeking manner (Kahneman and Tversky, 1979), which could lead to a smaller gap across the two conditions. The instructions resemble that of the Same-frame experiment except for the probabilities and the existence of a third fixed account. To make the small probability salient, we present to subjects with the following message: "*5% chance of ___points in X account; 5% chance of ___points in Y account; 90% chance of 0 points in Z account.*" The interface is otherwise similar to the Same-frame experiment; screenshots of the interface can be found in Figure A2 in Appendix A. Similarly, we have the same 22 budget lines in each of the two conditions.

Procedure. We recruited 358 subjects from the United States via Prolific in June 2022 and randomly assigned them to each of the three experiments: 122 to the Main experiment, 114 to the Same-frame experiment, and 122 to the Low-probability experiment. We used the same first-page introduction and made the instructions and interfaces as similar as possible across the three experiments. We explained the experimental procedure and provided the experimental instructions and questionnaire in Appendix B. The Institutional Review Board of National University of Singapore approved the experiment.

Panel A. Full-line Condition

Panel B. Truncated-line Condition

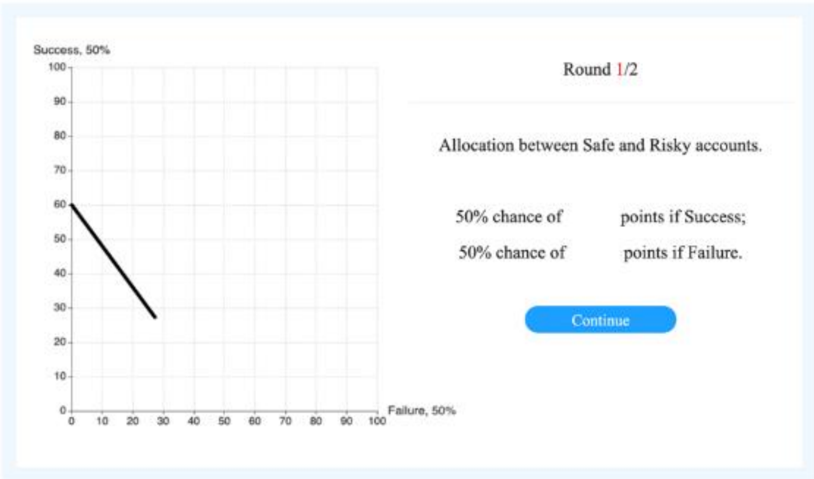

Figure 1—Experimental interfaces in the Main experiment. We present the interfaces of the first practice round in each condition. The Success state can be either horizontal or vertical for different budget lines in the truncated-line condition.

We included three test questions to help subjects understand the instructions. The first question was the same across the three experiments, which tested whether subjects could correctly understand the probability of receiving the points in one account/state. Subjects were informed that if they failed to answer the first test question correctly, they would be screened out of the experiment. The second and third questions tested whether subjects could correctly describe an allocation on the full line and another on the truncated line in each condition. As these two questions differ across experiments, to avoid selection into different experiments, we do not screen subjects based on these two questions. Instead, we rewarded subjects \$0.5 for each correct response and gave subjects feedback about the correct answers.

In each experiment, the two conditions were presented in random order. Within each condition, the order of the appearance of the 22 decisions was also randomized. After making 44 decisions, subjects completed a questionnaire that contained three questions from the cognitive reflection test (CRT, Frederick, 2005); two questions about false diversification (Rubinstein, 2002); three questions about financial literacy (Lusardi and Mitchell, 2011); one question about general risk attitudes (Dohmen et al., 2011); two questions about their choice confidence in their decisions; and a demographic survey of gender, age, income, education, occupation, partner, and number of children. Since we randomly assigned subjects to the three experiments, they did not differ significantly in most demographic characteristics (Table A2 in Appendix A).

We used the standard random incentive mechanism by randomly selecting one decision out of the 44 decisions to pay the subjects. The exchange rate is 10 points = \$1. In addition, subjects received a participation fee of \$3.34 and a bonus of \$0.5 each for correctly answering the two test questions. On average, subjects received \$6.2 in total and spent 28 minutes on the experiment.

3. Theoretical Background of Revealed Preference Analysis

In our experiment, a decision maker chooses a portfolio $\mathbf{x}$ from the budget set $\mathbf{B}\,(\mathbf{p}, w) = \{\mathbf{x} \in \mathbb{R}^2_+ : \mathbf{p} \cdot \mathbf{x} \le w\}$, with $(\mathbf{p}, w)$ varying in different choice problems. A dataset $\mathcal{O} = \{(\mathbf{p}^i, \mathbf{x}^i)\}_{i=1}^N$ refers to the collection of a decision maker's decisions in N choice problems. $\mathcal{O}$ is said to be rationalized by a utility function $U : \mathbb{R}^2_+ \to \mathbb{R}$ if, for every observed portfolio $\mathbf{x}^i$,

$$U(\mathbf{x}^i) \ge U(\mathbf{x}) \text{ for all } \mathbf{x} \in \mathbf{B}\,(\mathbf{p}^i, w^i).$$

A utility function is well behaved if it is continuous and strictly increasing. Afriat's Theorem (Afriat, 1967) states a necessary and sufficient condition for a dataset to be rationalized by a well-behaved utility function: The dataset obeys the generalized axiom of revealed preference (GARP).

GARP. Given two observed choices $\mathbf{x}^i$ and $\mathbf{x}^j$, if a decision maker chooses $\mathbf{x}^i$ when $\mathbf{x}^j$ is affordable (i.e., $\mathbf{x}^j \in \mathbf{B}\left(\mathbf{p}^i, w^i\right)$), we say that $\mathbf{x}^i$ is directly revealed preferred to $\mathbf{x}^j$, denoted as $\mathbf{x}^i \succsim^* \mathbf{x}^j$. Denote $\succ^*$ the asymmetric part of $\succsim^*$, and $\succsim^{**}$ the transitive closure of $\succsim^*$. We say a dataset $\mathcal{O}$ obeys GARP if

$$\text{for all } \mathbf{x}^i \text{ and } \mathbf{x}^j,\ \mathbf{x}^i \succsim^{**} \mathbf{x}^j, \text{ implies } \mathbf{x}^j \nsucc^* \mathbf{x}^i.$$

The GARP test yields a 0/1 result, and a continuous measure of rationality frequently used in the literature is the critical cost efficiency index (CCEI, Afriat, 1972). We say that a dataset $\mathcal{O}$ is e-rationalized by a utility function $U: : \mathbb{R}_+^2 \to \mathbb{R}$ if, for every observed portfolio $\mathbf{x}^i$,

$$U\left(\mathbf{x}^i\right) \geq U(\mathbf{x}) \text{ for all } \mathbf{x} \in \mathbf{B}\left(\mathbf{p}^i, e w^i\right).$$

The CCEI is defined as the supreme value of $e \in [0,1]$ such that the dataset can be e-rationalized (note that if the dataset can be e-rationalized, it can also be e'-rationalized for all $e' < e$).

We use CCEI to measure the degree of consistency within each condition. Note that when we perform the GARP test in the truncated-line condition, the decision makers respect first-order stochastic dominance in each decision task as they are not allowed to allocate more to the more expensive account.

More tests. While the GARP test informs us whether a well-behaved utility exists, it is silent about the specific forms of the utility functions. Recent developments in the revealed preference literature enable us to impose further restrictions on utility functions. In our setting, we can further test whether $\mathcal{O}$ can be rationalized by a utility function that conforms with first-order stochastic dominance (Nishimura et al., 2017) or admits the forms of expected utility and rank-dependent utility (Polisson et al., 2020).

Testing consistency across datasets. In our experiment, we obtain two datasets $\mathcal{O}^1 = \{(\mathbf{p}^{i,1}, \mathbf{x}^{i,1})\}_{i=1}^{N_1}$ and $\mathcal{O}^2 = \{(\mathbf{p}^{i,2}, \mathbf{x}^{i,2})\}_{i=1}^{N_2}$ from the same decision maker in each condition. Let e_1 and e_2 be the CCEIs for the two datasets. That is, there exist U_1 and U_2 for every observed chosen portfolio $\mathbf{x}^{i,1}$ in Condition 1 and $\mathbf{x}^{i,2}$ in Condition 2:

$$U_1\left(\mathbf{x}^{i,1}\right) \geq U_1(\mathbf{x}) \text{ for all } \mathbf{x} \in \mathbf{B}\left(\mathbf{p}^{i,1}, e_1 w^{i,1}\right),$$

$$U_2\left(\mathbf{x}^{i,2}\right) \geq U_2(\mathbf{x}) \text{ for all } \mathbf{x} \in \mathbf{B}\left(\mathbf{p}^{i,2}, e_2 w^{i,2}\right).$$

We can combine the two datasets to obtain $\mathcal{O}_{1\cup 2}$ and let e_{12} be the CCEI for this combined dataset. It should always be the case that $e_{12} \leq \min\{e_1, e_2\}$. Moreover, if $e_{12} < \min\{e_1, e_2\}$, it must be that U_1 and U_2 represent distinct preferences, since otherwise we should have $e_{12} = \min\{e_1, e_2\}$. Therefore, a comparison between e_{12} and $\min\{e_1, e_2\}$ could partially inform "preference heterogeneity" between the two conditions.[7]

Finally, our specific design enables us to adopt two additional nonparametric approaches to examine choice consistency between $\mathcal{O}^1 = \{(\mathbf{p}^{i,1}, \mathbf{x}^{i,1})\}_{i=1}^{N_1}$ and $\mathcal{O}^2 = \{(\mathbf{p}^{i,2}, \mathbf{x}^{i,2})\}_{i=1}^{N_2}$. The first approach is *choice stochasticity*: the rate of which a decision maker's choices differ across the two conditions. Specifically, we first calculate the normalized distance between the chosen portfolio $\mathbf{x}^{i,1}$ in the full-line condition and the corresponding chosen portfolio $\mathbf{x}^{i,2}$ in the truncated-line condition $d^i = \frac{|\mathbf{x}^{i,1} - \mathbf{x}^{i,2}|}{\sqrt{(w^i/\mathbf{p}_1^i)^2 + (w^i/\mathbf{p}_2^i)^2}}$. As $N_1 = N_2 = 22$ in our experiment, we have 22 normalized distances. Then, we measure cross-condition choice stochasticity using the proportion of incidences out of 22 comparisons in which the normalized distances exceed a given threshold value (1 percent or 10 percent). Moreover, since we have 10 pairs of symmetric budget lines within each condition (see Table A1 in Appendix A for details), we also compute the normalized distances between the symmetric budgets, which yields two additional measures of within-condition choice stochasticity.[8]

The second approach is the violation of Sen's alpha. In our setting, Sen's alpha states that if $\mathbf{x}^{i,1}$ is chosen in some choice problem in the full-line condition and it is available in the corresponding choice problem in the truncated-line condition, then $\mathbf{x}^{i,1}$ should also be chosen in the latter choice problem. In such case, we say that a subject's behavior violates Sen's alpha if the normalized distance between $\mathbf{x}^{i,1}$ and the corresponding $\mathbf{x}^{i,2}$ exceeds a given threshold value (1 percent or 10 percent). As subjects may differ in the number of incidences in which the chosen $\mathbf{x}^{i,1}$ belongs to the corresponding budget set in the truncated-line condition, we use the violation rate to measure how far a subject's behavior deviate from Sen's alpha. Note that when the allocation in the full-line condition lies in the truncated budget, the chosen portfolio is not dominated. Therefore, our measure of violation of Sen's alpha is in fact conditional on those choices conforming with first-order stochastic dominance.

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[7] Miao et al. (2021) develop a necessary and sufficient test for U_1 and U_2 to represent the same preference.

[8] An implicit assumption here is symmetry—i.e., the subject's allocation behavior is symmetric in the two symmetric budgetary choices. Therefore, two budgets with a price ratio of 1 are incomparable.

4. Results from the Main Experiment

This section analyzes subjects' behavior within and across the two conditions in our Main experiment. We first present the aggregate allocation patterns. Then we apply the revealed preference toolkit and two nonparametric measures to investigate the consistency of choice behavior. Finally, we examine two potential heuristics that may underpin the observed behavior patterns.

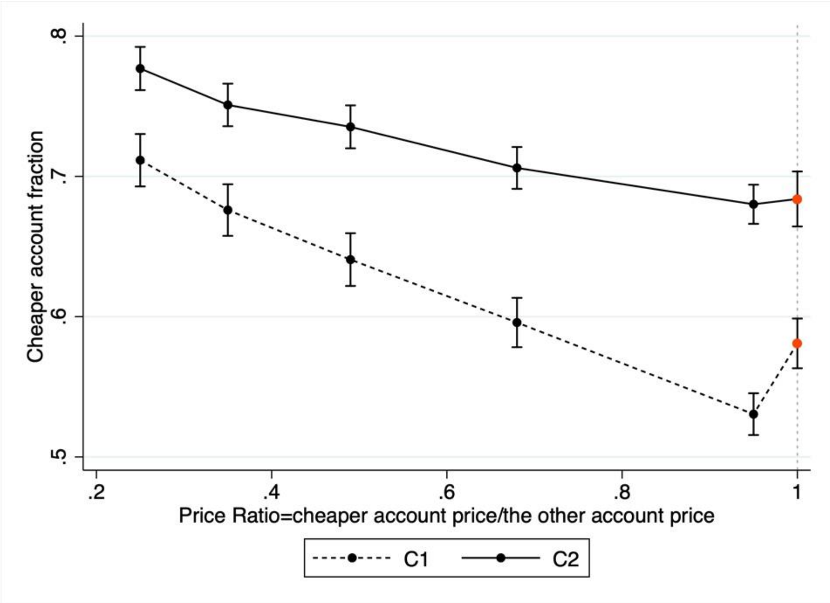

Figure 2—Mean cheaper account fractions in the Main experiment. C1 refers to the full-line condition and C2 to the truncated-line condition. Throughout the paper, we define the price ratio as the cheaper account price divided by the other account price. The price ratio ranges from 0.25 to 1. For the red points with the price ratio = 1, since there is not a strictly cheaper option between the two accounts in the experiment, we choose the weakly higher fraction of the two accounts in the full-line condition.

4.1 Allocation behavior within and across conditions

Figure 2 presents the average fraction of the points subjects allocate to the cheaper account out of the total points in both accounts at different price ratios across the two conditions.[9] In both conditions, we observe a downward-sloping trend whereby subjects allocate fewer points to

[9] As explained in Section 2, subjects were asked to allocate between the safe and risky assets in the truncated-line condition, which is equivalent to allocating a fraction between 50 and 100 percent to the weakly cheaper account in the full-line condition. Here and for the rest of the results, we compare the two conditions in terms of the fraction allocated to the weakly cheaper account.

the cheaper account when its price ratio increases from 0.25 to 1. Subjects behave differently between the two conditions when they are not allowed to allocate more to the (weakly) more expensive account. Specifically, they allocate more points to the cheaper account in the truncated-line condition than in the full-line condition at all price ratios, and thus behave as if they are more risk-seeking in the truncated-line condition than in the full-line condition. On average, subjects allocate around 10 percent more points to the cheaper account in the truncated-line condition, and the gap becomes larger when the price ratio increases. At individual level, 48% of subjects allocate 10 percent or more points to the cheaper account in the truncated-line condition, 37% of subjects allocate 0 to 10 percent more points to the cheaper account in the truncated-line condition, and the rest 15% of subjects allocate fewer points to the cheaper account in the truncated-line condition.

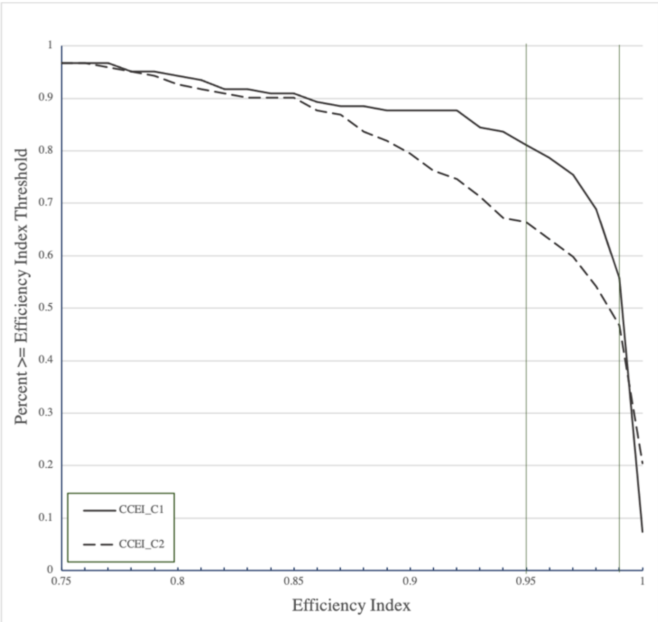

Figure 3—Decumulative distribution of the CCEI in two conditions. C1 refers to the full-line condition and C2 to the truncated-line condition.

The allocations require some attention and explanation when the price ratio equals 1 as there is no strictly cheaper account. We refer to the plotted fraction as the larger one of the two fractions of points in the two accounts. Under this approach, the fraction is always weakly greater than 0.5 at the price ratio of 1, whereas it can be lower than 0.5 at other price ratios in the full-line condition, which leads to a reversed trend in Figure 2. Another noteworthy point is that strictly risk-averse subjects should allocate 50:50 between the two accounts when the price ratio is 1—yet their allocation is further from 50:50 in the truncated-line condition than in the full-line condition. Specifically, the mean fraction is 58 percent in the full-line condition and 68 percent in the truncated-line condition.

4.2 Individual rationality within and across conditions

We next examine the consistency of subjects' behavior within and across conditions. Specifically, we first apply the revealed preference toolkit and compute CCEI for the individual choice dataset in each condition separately to examine within-condition rationality. We then compute the CCEI of the combined dataset of the two conditions and compare it with within-condition CCEIs to infer how "globally rational" an individual is. At last, we use two nonparametric measures—choice stochasticity and violation of Sen's alpha—to examine individual-level inconsistency across the two conditions.

Figure 3 presents the decumulative distribution of the CCEIs for the two conditions separately. The mean CCEI is 0.96 for the full-line condition and 0.95 for the truncated-line condition. With a threshold of 0.99, 56 percent of subjects in the full-line condition and 47 percent in the truncated-line condition pass the GARP test. With a threshold of 0.95, 80 percent of subjects in the full-line condition and 65 percent in the truncated-line condition pass the GARP test. Overall, these observations suggest that subjects are generally rational in each condition, which is in line with the observation in existing studies; for example, the mean CCEI is 0.94 in Choi et al. (2007) and 0.98 in Halevy et al. (2018).[10]

The observed high CCEIs within each condition may be due to our experiment's choice of budget lines. We use two methods to check the power of our tests. In the first method, we generate 10,000 hypothetical datasets with 22 uniform random choices (Bronars, 1987) on the full budgets and another 22 choices on the truncated budgets. In the second method, we first pool subjects' choices and then generate a dataset by randomly resampling (22 choices from different subjects) from the pooled set in each condition. Figure A3 in Appendix A presents the results of these power tests. We find that the mean CCEI is 0.71 in the full-line condition

[10] How best to capture the extent of GARP violation has been a question of recent discussions (Echenique, 2021; Polisson and Quah, 2022). In addition to CCEI, several measures have been proposed to assess how closely individual choice dataset complies with GARP, including Houtman-Maks Index (HMI, Houtman and Maks, 1985), Money Pump Index (MPI, Echenique et al. 2011), and Minimum Cost Index (MCI, Dean and Martin, 2016). These indices are highly correlated in our data, with Spearman's rank correlations ranging from 0.52 to 0.99 with an average of 0.81 (see Table A3 in Appendix A). To simplify the presentation of our results, we focus on the more conventional index of CCEI in the main analyses.

and 0.87 in the truncated-line condition using the first method, and 0.82 in the full-line condition and 0.86 in the truncated-line condition using the second method. Overall, the power tests suggest that the chosen parameters have the power to detect GARP violations.

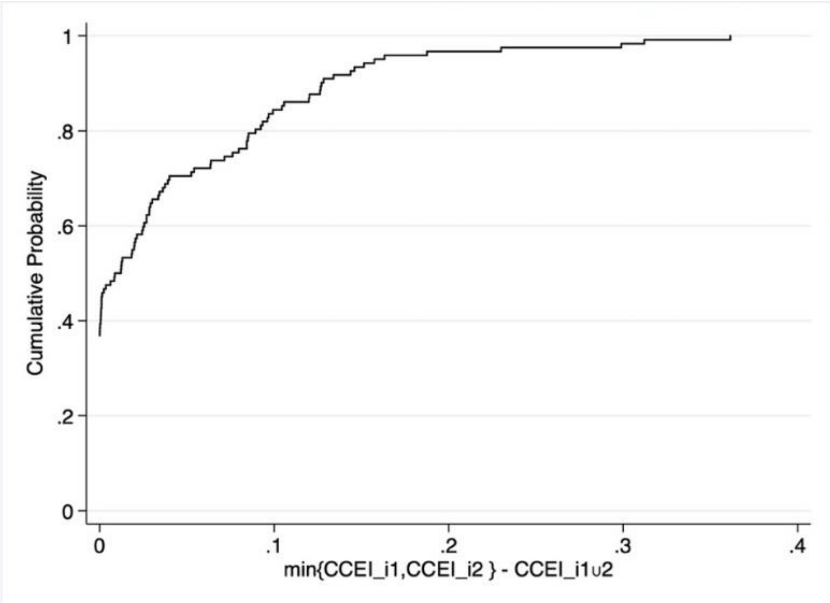

Figure 4—Cumulative distribution of inconsistency across conditions. The inconsistency is measured by $\mathrm{CCEI}_{dif} = (\min(\mathrm{CCEI}_1, \mathrm{CCEI}_2) - \mathrm{CCEI}_{1\cup 2})$ in the Main experiment. A positive CCEI difference indicates distinct preferences in the two conditions.

Given that our experiment is about choice under risk, we compute CCEIs by imposing further restrictions on the utility function: first-order stochastic dominance, expected utility, and rank-dependent utility. Figure A4 in Appendix A shows that after imposing first-order stochastic dominance, CCEIs drop significantly in both conditions—the mean CCEI is 0.89 in the full-line condition and 0.93 in the truncated-line condition. When we further test for expected utility or rank-dependent utility, CCEIs are almost unchanged. The message of these findings is in line with that of Dembo et al. (2021): A large fraction of the departure from expected utility maximization stems from dominance violation rather than a failure of the independence axiom.

In terms of the correlations among CCEIs, individual CCEIs across the two conditions are significantly correlated (Spearman's ρ = 0.282, p = 0.002), and the correlation remains significant after we impose first-order stochastic dominance (Spearman's ρ = 0.327, p < 0.001). In sum, these results suggest that subjects' local behaviors in each condition are highly rational, and individual rationality levels across conditions are moderately correlated (see also Nitsch et al., 2022). In the sequel, we examine subjects' rationality across conditions.

We compute CCEIs for the combined dataset ($\mathrm{CCEI}_{1\cup 2}$) using 44 choices in both conditions for each individual. The mean CCEI for the combined dataset is 0.89 and is significantly lower than the two within-condition CCEIs (see Figure A5 Panel A in Appendix A for the decumulative distribution).[11] We then examine consistency across conditions by comparing CCEIs of the combined dataset for the two conditions with the minimum of the two within-condition CCEIs ($\min(\mathrm{CCEI}_1, \mathrm{CCEI}_2)$). Denote the difference as CCEI_{dif}. As discussed in the theoretical analyses in Section 3, CCEI_{dif} is always non-negative and can identify whether subjects' choices are consistent across conditions. Figure 4 presents the cumulative distribution of CCEI_{dif}. Around 63 percent of subjects have a positive CCEI_{dif} with a mean of 0.07 ($p < 0.001$). These results suggest that subjects' choices appear less rational and more inconsistent when the two conditions are jointly considered.

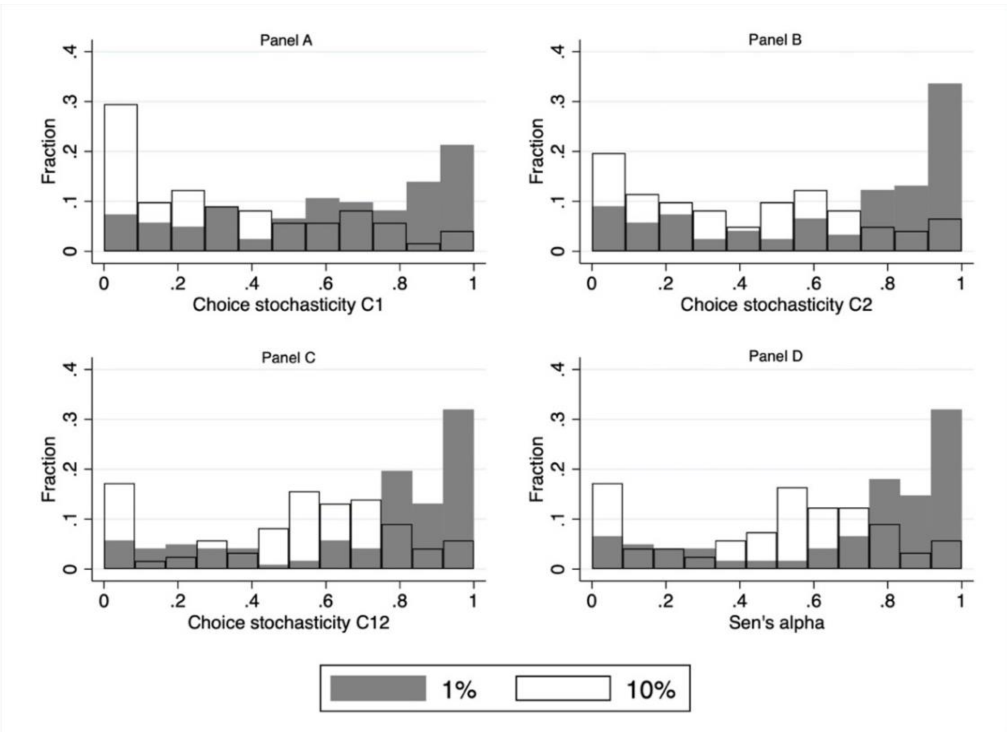

Figure 5—Distribution of choice stochasticity and violation of Sen's alpha. We plot the distribution at 1% and 10% choice error in the Main experiment. C1 refers to the full-line condition and C2 to the truncated-line condition.

[11] Panel B in Figure A5 plots the decumulative distribution of the CCEI of the half-combined dataset. We use an alternative measure by comparing the CCEIs of the half-combined dataset by randomly drawing 11 choices from each of the two conditions with the CCEI of the dataset for each of the two conditions. We find that the CCEI from the half-combined dataset is, on average, smaller than the CCEI from each of the two conditions.

We further examine consistency across the two conditions using two additional nonparametric measures: choice stochasticity and violation of Sen's alpha. As mentioned earlier, we compute the normalized distance between the two corresponding choices, and calculate for each subject the proportion of incidences in which the distance is greater than a given threshold: 1 percent or 10 percent. Moreover, given our experiment design includes symmetric budget lines within each condition, we construct two additional measures of within-condition choice stochasticity correspondingly. Panels A-C in Figure 5 plot the distributions of choice stochasticity within and across conditions. When allowing for a 1 percent choice error, 32 percent of subjects exhibit inconsistency for all 22 pairs of choices across the two conditions, while 21 percent of subjects in the full-line condition and 34 percent in the truncated-line condition exhibit inconsistency for all 10 pairs of choices. The average values of choice stochasticity are 76 percent for cross-condition comparison, 62 percent in the full-line condition, and 67 percent in the truncated-line condition. When allowing for a 10 percent choice error, the average values are 56 percent for cross-condition comparison; and 32 percent and 40 percent in the full-line and the truncated-line condition, respectively. The paired t-test shows that cross-condition stochasticity is significantly higher than the two within-condition stochasticity for both thresholds ($p < 0.001$).[12] These results suggest that cross-condition stochasticity is, in general, higher than within-condition stochasticity.

Panel D in Figure 5 presents the distribution of Sen's alpha violation. Similarly, we compute the normalized distance conditional on choices in the full-line condition satisfying first-order stochastic dominance and calculate the proportion of incidences in which the distance exceeds the same thresholds for each subject (note that the total number of choices that conform with stochastic dominance varies across subjects). We find that 32 percent of subjects violate Sen's alpha all the time when allowing for a 1 percent choice error, and 6 percent of subjects violate Sen's alpha all the time when allowing for a 10 percent choice error. The average violation rates are 75 percent and 53 percent for a 1 percent and 10 percent choice error, respectively. The message from applying these nonparametric measures is in line with those from the

[12] We compute an alternative version of cross-condition choice stochasticity in which we assume symmetry to render it directly comparable with within-condition choice stochasticity. That is, we use the distance between a full-line choice and the corresponding symmetric truncated-line choice. Figure A6 in Appendix A reports the distribution of this symmetric cross-condition choice stochasticity. We again observe a higher level of cross-condition stochasticity (the paired t-test shows that cross-condition stochasticity assuming symmetry is also significantly higher than the two within-condition stochasticity indices, with $p < 0.001$). We also compute the average cross-condition and within-condition distances for each subject. In the Main experiment, the mean normalized distance is about 18 percent of the full budget line across the two conditions. See Figure A7 in Appendix A for the distributions of the distance.

revealed preference analysis: Subjects' choices are largely consistent within conditions but inconsistent across conditions.

Finally, we check the relationship among the within- and cross-condition rationality measures, understanding test scores, and other measures elicited in our questionnaire. Regression results are summarized in Table A4 in Appendix A. Among these variables, we observe that subjects with higher CRT scores (Frederick, 2005) or lower false diversification scores (Rubinstein, 2002) tend to behave more consistently across conditions using the three measures: an indicator of CCEI_{dif} (1 if the difference is positive), choice stochasticity (1 percent choice error), and violation of Sen's alpha (1 percent choice error). More specifically, CRT scores' coefficients suggest that one standard deviation increase in CRT scores would lead to a 7 percent to 9 percent lower level of cross-condition inconsistency in terms of the three measures. The coefficients of Non-diversification suggest that one standard deviation decrease in false diversification would lead to a 7 percent to 8 percent lower level of cross-condition inconsistency. This observation suggests that inconsistency across conditions could be related to the tendency to use one's heuristic response, such as the diversification heuristic, which we will discuss in detail in the sequel.

4.3 Heuristic rules

Whereas most studies use budgetary experiments to examine the rationality of choices, others investigate the underlying heuristic rules. For instance, Choi et al. (2006) show that the portfolio choices of many subjects can be explained by not only "as if" utility maximization but also simple investment rules. For example, some subjects allocate equal number of points to the two accounts, some allocate a minimum level of points to all accounts to guarantee a secure payoff, and some respond to price ratio changes by allocating more to the cheaper account as it becomes cheaper. In Halevy and Mayraz (2022), subjects make case-by-case allocation decisions and design simple investment rules for selecting portfolios; most subjects prefer to make allocations through the rule-based interface. In our experiment, although it is difficult to differentiate rule-based decisions from utility maximization within conditions, the observed narrowly rational choice behavior is hard to rationalize with a unique utility function, and understanding the underlying heuristic rules is essential. We explore two potential heuristic rules below based on Choi et al. (2006) and Halevy and Mayraz (2022).

One heuristic rule is price responsiveness because it is cognitively simple for subjects to allocate more when the asset becomes cheaper, regardless of whether they are indeed maximizing their utility. To examine the price responsiveness heuristic, we first rescale all the budget sets (and the chosen portfolios) so that they have the same extreme point for the more expensive account, and then check whether the points allocated to the cheaper account weakly increase as its relative price decreases. If so, we say that a subject's choice satisfies price responsiveness. Within each condition, we make pairwise comparisons among the 22 budgets to see whether subjects' choices conform with price responsiveness. We have in total 231 pairwise comparisons in each condition and compute for each subject her conformity rate for price responsiveness.[13] On average, each subject conforms in 89 percent of all pairwise comparisons in the full-line condition, and the corresponding rate is also 89 percent in the truncated-line condition (see Figure A8 in Appendix A for the distribution of rates). Conformity rates in the two conditions are highly correlated (Spearman's $\rho = 0.602$, $p < 0.001$).

Moreover, conformity rates for price responsiveness are highly correlated with CCEIs in each condition (Spearman's ρ: 0.562, $p < 0.001$ for the full-line condition; 0.667, $p < 0.001$ for the truncated-line condition). We further classify subjects with conformity rates above or below the median in each condition. The group above the median has a mean CCEI of 0.99 for both conditions, whereas the group below the median has a mean CCEI of 0.93 for the full-line condition and 0.91 for the truncated-line condition. Furthermore, we find that the conformity rate does not correlate with the inconsistency represented by CCEI_{dif} (Spearman's ρ: −0.117, $p = 0.202$ for the full-line condition; −0.129, $p = 0.158$ for the truncated-line condition). Overall, these results suggest that subjects who respond to price changes tend to be more rational within conditions but not across conditions.[14]

Another heuristic rule is diversification, whereby subjects tend to choose the midpoint of the given budget line when making allocations. Consistent with this rule, Choi et al. (2006) show that a typical heuristic used by subjects is to allocate the same number of points to the two accounts, and Halevy and Mayraz (2022) observe that subjects tend to choose an equal amount

[13] Due to some overlapping prices, there are 15 comparisons in which all allocations naturally obey price responsiveness.

[14] We also examine the conformity rate of the law of demand (LOD, $(\mathbf{p}' - \mathbf{p}) \cdot (\mathbf{x}' - \mathbf{x}) < 0$, where $\mathbf{p}'$, $\mathbf{p}$ denote the price vectors in two choice tasks, and $\mathbf{x}$, $\mathbf{x}'$ are the chosen portfolios) via pairwise comparisons. The result remains robust. On average, each subject conforms with LOD in 91 percent of all pairwise comparisons in the full-line condition and 92 percent in the truncated-line condition. LOD conformity rates in the two conditions are highly correlated (Spearman's $\rho = 0.428$, $p < 0.001$) and positively related to rationality within conditions (Spearman's ρ: 0.718, $p < 0.001$ for the full-line condition; 0.671, $p < 0.001$ for the truncated-line condition).

of budget or an equal number of shares to allocate when designing their rules for investing among companies. More generally, Benartzi and Thaler (2001) and Rubinstein (2002) document that decision makers tend to split budgets/probabilities across different assets/actions equally, even though sometimes such a false diversification strategy results in strictly dominated options.

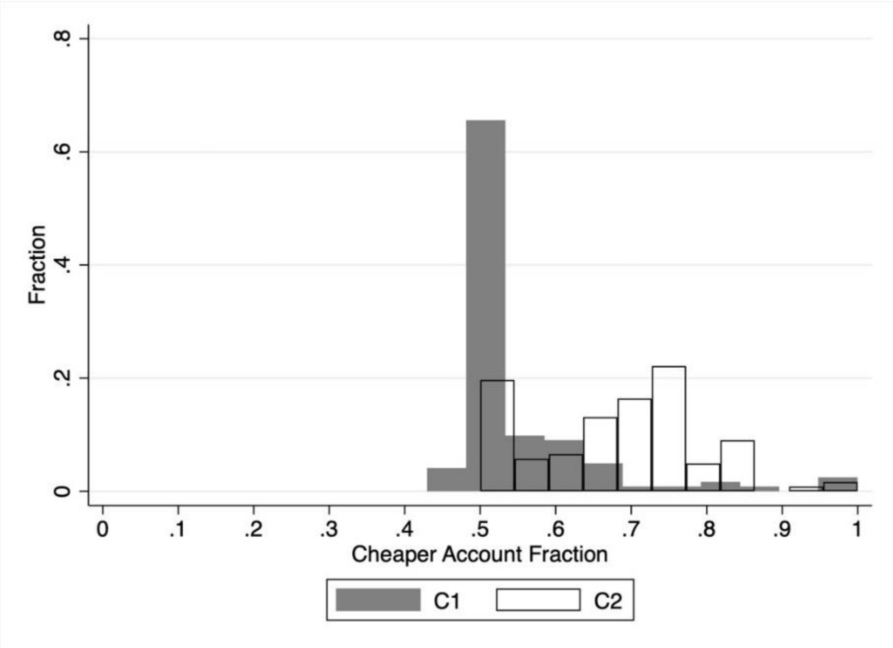

Figure 6—Proportion of allocations for price ratios around 1. We plot subjects' average cheaper account fractions across the six budgets, of which the price ratios are about 1 in the Main experiment. C1 refers to the full-line condition and C2 to the truncated-line condition. The specific order of the budgets and parameters can be found in Table A1 in Appendix A.

In our experiment, when the price ratio is close to 1, a "rational" risk-averse decision maker should choose a cheaper account fraction at 0.50 in both conditions. In contrast, a decision maker using the diversification heuristic tends to choose the midpoint of the line. Specifically, in the full-line condition, the decision maker will choose a fraction around 0.50 between the two Arrow securities, which coincides with the rational response. However, in the truncated-line condition, a decision maker using the same diversification heuristic would choose to allocate evenly between the safe and risky assets, resulting in a fraction of around 0.75 between two Arrow securities, which differs from the rational response. In general, a subject in the experiment may be attracted to either 50-50 or 25-75 between the two Arrow securities or some allocations in between, depending on the relative importance of the diversification heuristic compared with the rational response.

Figure 6 plots the distribution of average cheaper account fractions across the six budgets with price ratios of 1 and 0.95 for each subject in both conditions. We use the mean value of the six allocations to reduce individual noise. We observe that the proportion of subjects who allocate between 0.45 and 0.55 to the cheaper account is 71 percent in the full-line condition and 20 percent in the truncated-line condition (proportion test, $p < 0.001$). The proportions of boundary allocation (cheaper account fraction $\geq$ 0.95) are around 2 percent in both conditions, which do not differ between the two conditions (proportion test, $p = 0.651$). Moreover, in the truncated-line condition, there appears to be a hump around 0.75, which corresponds to the midpoint on the truncated budget line. The proportion of subjects who allocate between 0.70 and 0.80 to the cheap account is 2 percent in the full-line condition and 39 percent in the truncated-line condition (proportion test, $p < 0.001$). This observation supports the notion that subjects may use the diversification heuristic to make allocation decisions.

At individual level, 20 percent of subjects allocate between 0.45 and 0.55 in both conditions, which is consistent with having a risk-averse preference and rationally making utility-maximization decisions; 22 percent of subjects allocate between 0.45 and 0.55 in the full-line condition and between 0.70 and 0.80 in the truncated-line condition, which is in line with using the diversification heuristic to make the decisions; 20 percent of subjects allocate between 0.45 and 0.55 in the full-line condition and between 0.55 and 0.70 in the truncated-line condition, which is intermediate to making a rational (risk-averse) response and using the diversification heuristic.

We further examine how the diversification heuristic correlates with cross-condition consistency. We conduct OLS regressions with an indicator of CCEI_{dif} (1 if the difference is positive), choice stochasticity (1 percent choice error), and violation of Sen's alpha (1 percent choice error) as the dependent variables. The two independent variables are the sum of the normalized distances between the chosen allocations and the midpoints of the budget lines in the six budgets in the full-line condition and the truncated-line condition. Note that the distance in the full-line condition is not informative of the subjects' false diversification behavior. In contrast, the distance in the truncated-line condition can inform how a subject "falsely" diversifies between the two accounts. Table A5 in Appendix A presents regression results. The coefficients of the distance in the full-line condition are insignificant, while those of the distance in the truncated-line condition are significantly negative: The closer the allocation is to the midpoint in the truncated-line condition, the lower the cross-condition consistency. These results support the role of the diversification heuristic in the observed narrowly rational behavior across the two conditions.

5. Results from Two Additional Experiments

We conduct two additional experiments. These two experiments aim to reduce the inconsistency across conditions and shed light on the underlying mechanisms and robustness of the observations. Below we present results from the two experiments in comparison with those from the Main experiment.

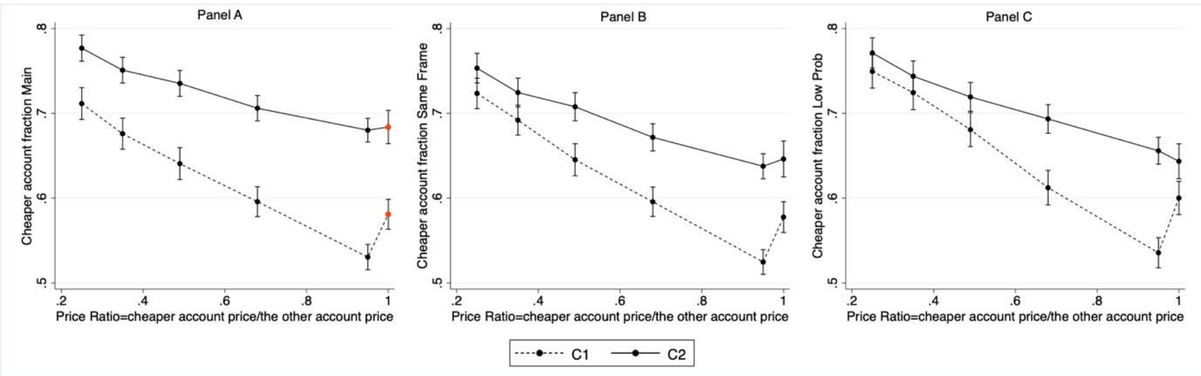

Figure 7—Mean cheaper account fractions in the three experiments. C1 refers to the full-line condition and C2 to the truncated-line condition. Compared to the Main experiment (Panel A), the gaps in the Same-frame experiment (Panel B) and the Low-probability experiment (Panel C) are smaller.

5.1 Same-frame experiment

The observed inconsistency in our Main experiment can be partly due to the diversification heuristic. In the Main experiment, allocation decisions between two accounts are framed as two Arrow securities in the full-line condition and as a safe asset and a risky asset in the truncated-line condition. To test this mechanism, we conduct the Same-frame experiment in which we change the frame in the truncated-line condition to be the same as that in the full-line condition in the Main experiment. That is, subjects are asked to allocate between the two Arrow securities in both conditions. We hypothesize that cross-condition inconsistency would be reduced when choice environments are similarly framed.

Figure 7 Panel B shows that subjects' mean allocations to the cheaper account differ across the two conditions in the Same-frame experiment (paired t-test, $p < 0.001$). On average, subjects allocate about 6 percent more points to the cheaper account in the truncated-line condition in the Same-frame experiment and 10 percent more to the cheaper account in the truncated-line condition in the Main experiment (Figure 7 Panel A). Compared with the Main experiment, the removal of the safe and risky assets frame in the truncated-line condition leads to a decrease of around 50 percent of cross-condition difference in cheaper account fraction.[15] This suggests that subjects are more consistent across the two conditions in the Same-frame experiment.

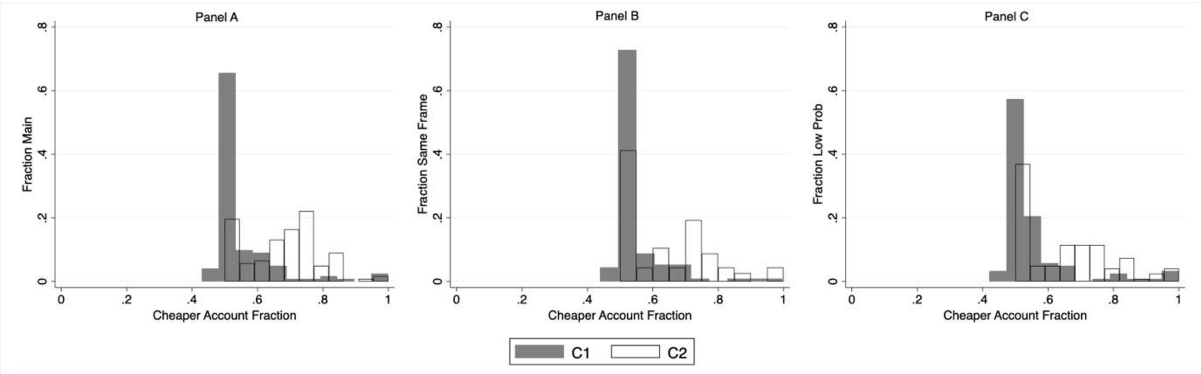

Figure 8—Proportion of subjects' allocations for price ratios around 1 in the three experiments. We plot subjects' average cheaper account fractions across the six budgets, in which the price ratios are about 1 in the two conditions. C1 refers to the full-line condition and C2 to the truncated-line condition. The allocations in C1 of the Main experiment (Panel A) and the Same-frame experiment (Panel B) are similar, as they share the same setting. The specific order of the budgets and parameters can be found in Table A1 in Appendix A.

Applying the revealed preference toolkit, we find that subjects are generally rational within conditions in the Same-frame experiment. The mean value of CCEI is 0.95 in the full-line condition and 0.96 in the truncated-line condition. This is in line with the observation in the Main experiment that subjects are generally rational within each condition. Spearman's correlation between CCEI in the two conditions is 0.596 ($p < 0.001$), which is higher than that (0.282) in the Main experiment. That is, subjects with higher rationality in one condition are

[15] We regress the cheaper account fraction difference across two conditions at individual-choice level on experiment dummy variables. We find that being in the Same-frame experiment without the safe and risky assets frame in the truncated-line condition reduces the cheaper account fraction difference by around 50 percent when we control for the price fixed effect (see Table A8 in Appendix A).

more likely to have higher rationality in another condition, especially when the conditions are similarly framed.

We use the measures of CCEI_{dif}, choice stochasticity, and violation of Sen's alpha to further examine the inconsistency across conditions in the two experiments. For CCEI_{dif}, 55 percent of subjects have a positive CCEI difference, and the mean is 0.03 in the Same-frame experiment (Figure A11 in Appendix A). The corresponding proportion is 63 percent, and the mean is 0.07 in the Main experiment. The CCEI_{dif} in the Same-frame experiment is significantly lower than that in the Main experiment (Kolmogorov-Smirnov test, p = 0.013). For choice stochasticity, when allowing for a 1 percent choice error, the proportion of subjects who are completely inconsistent across conditions is 21 percent in the Same-frame experiment (see Figure A12 in Appendix A) compared with 32 percent in the Main experiment. The mean values of choice stochasticity are 69 percent and 76 percent for the Same-frame experiment and the Main experiment (Kolmogorov-Smirnov test for the whole distribution, p = 0.097). When allowing for a 10 percent choice error, the proportion of subjects exhibiting complete cross-condition inconsistency is zero percent in the Same-frame experiment and 6 percent in the Main experiment. The mean values of choice stochasticity are 46 percent and 56 percent in the Same-frame experiment and the Main experiment (Kolmogorov-Smirnov test for the whole distribution, p = 0.019). The violation of Sen's alpha provides a similar message, whereby cross-condition inconsistency in the Main experiment is higher than that in the Same-frame experiment (Kolmogorov-Smirnov test for a 1 percent choice error, p = 0.188; 10 percent, p = 0.092). Overall, these findings suggest a lower level of inconsistency in the Same-frame experiment than that in the Main experiment.

We further examine the diversification heuristic.[16] Figure 8 Panel B plots the distribution of average individual cheaper account fractions across the six budgets with price ratios of 1 and 0.95 in both conditions in the Same-frame experiment. The proportions of the mean allocations with cheaper account fractions between 0.45 and 0.55 are 76 percent in the full-line condition and 41 percent in the truncated-line condition, compared with 71 percent and 20 percent in the Main experiment, respectively. The difference in allocating between 0.45 and 0.55 in the truncated-line condition (41 percent vs. 20 percent) is significant across the two experiments

[16] In Figure A9 in Appendix A, we plot the distribution of the price responsiveness conformity rate for the Same-frame experiment and find that most subjects respond to price changes within conditions. Conformity rates highly correlate with CCEIs (Spearman's ρ: 0.628, p < 0.001 for the full-line condition; 0.730, p < 0.001 for the truncated-line condition).

(proportion test, $p < 0.001$). We also run a regression to check the relation between the diversification heuristic and cross-condition inconsistency in the Same-frame experiment. Results are summarized in Table A6 in Appendix A. Similar to that in the Main experiment, subjects whose allocations are closer to the midpoint in the truncated-line condition tend to have a low level of cross-condition consistency using either the measure of CCEI_{dif}, choice stochasticity, or violation of Sen's alpha.

5.2 Low-probability experiment

Cross-condition inconsistency is reduced, yet not eliminated, in the Same-frame experiment. In the Low-probability experiment, we keep the frame of Arrow securities and lower the probabilities of both accounts from 50 percent to 5 percent. We hypothesize that subjects could become more risk-seeking when the probability is low (Kahneman and Tversky, 1979), so they are less likely to adopt the diversification heuristic. To examine whether this further reduces cross-condition inconsistency, we mainly compare the Same-frame and Low-probability experiments below.

Figure 7 Panel C shows that subjects' mean allocations to the cheaper account again differ across the two conditions in the Low-probability experiment (paired t-test, $p < 0.001$). On average, subjects allocate around 6 percent more points to the cheaper account in the truncated-line condition in the Low-probability experiment, which is similar to that in the Same-frame experiment (see Table A8 in Appendix A for details). Despite the cross-condition difference not being further reduced, we do observe more risk-seeking choices in the Low-probability experiment. Specifically, compared with the Same-frame experiment, subjects allocate 2.4 percent more points to the cheaper account in the full-line condition and 1.6 percent more points to the cheaper account in the truncated-line condition (see Table A9 in Appendix A).

Applying the revealed preference toolkit, the mean value of CCEI is 0.92 in the full-line condition and 0.96 in the truncated-line condition, which suggests that subjects are, on average, rational in the Low-probability experiment. CCEIs across the two conditions are positively correlated (Spearman's $\rho = 0.400$, $p < 0.001$). For CCEI_{dif}, 43 percent of subjects have a positive CCEI_{dif} with a mean of 0.04 in the Low-probability experiment (Figure A11 in Appendix A). The CCEI_{dif} comparison is insignificant between the Low-probability and Same-frame experiments (Kolmogorov-Smirnov test, $p = 0.263$). Moreover, we do not observe significant differences between the Low-probability experiment and the Same-frame experiment in terms of choice stochasticity (Kolmogorov-Smirnov test for a 1 percent choice error, p = 0.990; 10 percent, p = 0.974) or violation of Sen's alpha (Kolmogorov-Smirnov test for a 1 percent choice error, p = 0.991; 10 percent, p = 0.660).

As for the diversification heuristic, Figure 8 Panel C plots the distribution of average cheaper account fractions across the six budgets with price ratios of 1 and 0.95 for each subject in the two conditions in the Low-probability experiment. The proportions of the mean allocations with cheaper account fractions between 0.45 and 0.55 are 72 percent in the full-line condition and 36 percent in the truncated-line condition. The proportion in the truncated-line condition is significantly higher than the corresponding proportion in the Main experiment (36 percent vs. 20 percent, proportion test, p = 0.002), but not significantly different from that in the Same-frame experiment (36 percent vs. 41 percent, proportion test, p = 0.494). Moreover, we continue to observe a positive correlation between the diversification heuristic and cross-condition inconsistency in the Low-probability experiment (Table A7 in Appendix A).

6. Discussion

We observe that subjects' choices are consistent within conditions and inconsistent across conditions. The former is in line with the revealed preference literature and the latter is in agreement with behavioral economics literature. We first recognize that subjects with stable preferences respecting dominance should make identical choices across the two conditions, since we remove only dominated portfolios when comparing the full-line and truncated-line conditions. It remains possible that the subjects change their preferences after removing dominated options from their choice sets. In a recent study differentiating preferences and mistakes, Nielsen and Rehbeck (2022) find that most subjects would like to follow the independence of irrelevant alternatives axiom (Sen's alpha) and revise their choices to be consistent with the axiom. Their evidence supports that the observed cross-condition inconsistency in our study, violation of Sen's alpha in specific, is unlikely to be driven by fundamental (context-dependent) preferences.[17]

[17] The other related axiom is first-order stochastic dominance. In the Main experiment, on average, subjects choose a dominated portfolio in 23 percent of the allocation problems in the full-line condition, and the mean cheaper account fraction of these dominated allocations is 0.43. The corresponding mean fraction for the same choice tasks in the truncated-line condition is 0.68. Preference for "mix" may account for a violation of dominance (Agranov et al., 2020). As we continue to observe inconsistency across the two conditions when the choices in the full-line condition are not dominated (i.e., violation of Sen's alpha), dominance violation is not likely to be the core drive behind the observed narrowly rational behavior.

We further show that cross-condition inconsistency is higher for subjects with lower CRT scores (Frederick, 2005), a stronger tendency to exhibit false diversification in the choice setting of Rubinstein (2002), and to diversify between the two assets in each condition. In two additional experiments, we show that framing the two conditions similarly reduces cross-condition inconsistency by 50 percent while changing the underlying probability from 50 percent to 5 percent has no further effect.[18] Overall, these results support the role of the diversification heuristic underlying our main observation. Below, we briefly discuss alternative models to incorporate heuristics to account for our observations.

Cognitive noise and default. One possibility is to adopt an approach used in the recently developed cognitive noise literature (Khaw et al., 2021; Woodford, 2020; Frydman and Jin, 2021; Heng et al., 2020; Enke and Graeber, 2022). Specifically, given the budget $p_x x + p_y y = w$, a decision maker's true optimal decision is denoted as (x^*, y^*). But she only has access to a (unbiased) noisy signal (x^s, y^s) of her optimal decision, and the noise partly depends on the complexity of the choice problem. In the meantime, the decision maker is influenced by her cognitive default decision (x^0, y^0). Under certain specifications on the noise distribution, the decision maker ends up choosing an allocation that is a weighted average of her cognitive default decision (x^0, y^0) and the noisy signal (x^s, y^s). That is, her actual decision is given by $\delta(x^s, y^s) + (1-\delta)(x^0, y^0)$, where the weight δ positively correlates with the precision of her signal. Whereas identifying the cognitive default choice (x^0, y^0) can be difficult, we follow the literature and assume that the midpoints of the budget lines are subjects' cognitive default.[19]

Under this cognitive noise model, a subject's allocation locates between her true optimal and the midpoint (i.e., cognitive default) in each condition. Given that the cognitive default in the truncated-line condition is riskier than that in the full-line condition, subjects can appear more risk-seeking in the truncated-line condition, as shown in Figure 2. For example, when the relative price is close to 1, the true optimal decision for a risk-averse subject is the same in both conditions: close to the midpoint of the full budget line. However, the cognitive defaults—the

[18] Following Nielsen and Rehbeck (2022), we could consider alternative ways to reduce cross-condition inconsistency. For example, if we show subjects that cross-condition inconsistency violates the axiom, they may seek to be consistent by revising their choices. Alternatively, if subjects were to make choices for the full-line and the truncated-line conditions side by side on the same screen, they would most likely realize that cross-condition inconsistency violates the axiom and thus make consistent choices.

[19] It is possible that a risk-averse decision maker actively uses the diversification heuristic and treats the midpoint as the cognitive default. It is also possible that a decision maker, regardless of her risk preferences, sees the midpoint as the cognitive default because the visual saliency of the midpoint is likely to be the highest (Li and Camerer, 2022).

midpoints of the budget lines—differ between the two conditions. Consequently, as shown in Figure 6, subjects choose the midpoint of the full budget line in the full-line condition, since the optimal decision and cognitive default coincide; they choose allocations between the midpoints of the full budget line and the truncated budget line in the truncated-line condition, as the optimal decision and cognitive default differ. Moreover, subjects' allocations within each condition (in terms of cheaper account fractions) respond to price changes—because their true optimal decisions respond to price changes—although the responsiveness is attenuated due to cognitive noise. Finally, note that the weight δ may differ across experiments, so the model could account for the observed differences across experiments.[20]

Reference dependence. An alternative and related approach is to consider reference dependence (e.g., Kahneman and Tversky, 1979; Köszegi and Rabin, 2006), under which subjects may have different reference points and hence behave differently across the two conditions. For example, similar to cognitive default, consider subjects take the midpoints (x^0, y^0) in each condition as their reference points and evaluate an allocation (x, y) using the following reference-dependent utility à la Köszegi and Rabin (2006):

$$U(x, y|x^0, y^0) = 0.5u(x) + 0.5u(y) + 0.5\mu(x, x^0) + 0.5\mu(y, y^0).$$

The first component, $0.5u(x) + 0.5u(y)$, captures monetary utility, whereas the second component, $0.5\mu(x, x^0) + 0.5\mu(y, y^0)$, is a gain-loss utility. Notice that any allocation (x, y) relative to (x^0, y^0) entails both gain and loss. In the presence of loss aversion, a subject gets "penalized" from the gain-loss utility when deviating from her reference point, which could drive the subject's choice toward the reference point/midpoint in each condition. On the other hand, as the relative price decreases, the model allows the subjects to respond to price changes as the marginal gain from the monetary utility of deviating from the reference point increases, while the marginal loss from the gain-loss utility of deviating from the reference point decreases. Overall, it suggests that reference dependence may also account for the observed difference across conditions.[21]

[20] We run linear regressions between the cheaper account fraction and the price ratios to compare price responsiveness in the truncated-line condition across the three experiments. Table A10 in Appendix A reports the results. Responsiveness to price in the Main experiment is relatively lower than in the additional two experiments.

[21] A related model is regret theory (Loomes and Sugden, 1987; Quiggin, 1994). In our setting, regret can be induced by either the midpoint allocation or the extreme portfolios along the horizontal and vertical axes. In the former case, the prediction of regret theory would be in line with our specification of reference dependence. In the latter case, if the regret function is convex, the incentive for minimizing total regret over not obtaining the maximum payoffs in each state will again drive subjects to choose intermediate allocations. Specifically, the maximum possible payoffs in each state are determined by the two extreme points of the budget lines in each

Mental accounting. Another possibility is mental accounting (Thaler, 1980; Read et al., 1999; Köszegi and Matějka, 2020; Lian, 2021; Zhang, 2021; Ellis and Freeman, 2020). In the full-line condition, given a portfolio (x, y), a subject mentally evaluates the two accounts using $U(x, y)$, which could adopt either expected utility or non-expected utility form. In the truncated-line condition, portfolio (x, y) is obtained by summing the payoffs from the safe account (x, x) and the risky account $(0, y - x)$ (assume $x < y$ without loss of generality). A subject may mentally evaluate the two accounts separately: $V\big(U(x, x), U(0, y - x)\big)$, where U is the same utility function for even-chance risks as in the full-line condition, and V is an "aggregator" function for the two accounts. When V is concave, the subject would like to diversify between the two accounts, which generates an additional incentive to invest in the risky asset in the truncated-line condition.[22] Moreover, it is also possible for the subject to respond properly to a price change in both conditions. In this regard, mental accounting can also align with the observed aggregate patterns.

To sum up, these three approaches can give rise to more risk taking in the truncated-line condition than in the full-line condition, and thereby generate inconsistency between the two conditions. In the meantime, each approach allows for proper responsiveness to price changes and hence maintains internal consistency within conditions. We suggest these alternative approaches incorporating heuristic rules and leave differentiating these approaches to future research.

7. Conclusion

While revealed preference analysis of both laboratory and consumer data suggests that individual choice behavior is largely rational, studies in behavioral economics provide ample evidence in support of choice inconsistency across settings. We integrate two classic experiments in decision-making under risk—Choi et al. (2007) and Gneezy and Potters (1997)—in the same experimental framework. We find that choice behavior is rational within each condition but not across the two conditions. Cross-condition inconsistency is in part due

condition. As such, the convex regret function predicts that the subject will tend to choose allocations close to the midpoint in the respective budget line in each condition.

[22] Consider the case in which the price ratio equals 1 and income equals w. Without mental accounting, a risk-averse subject should stay on the 45° line to maximize their utility $u(w, w)$. Meanwhile, with mental accounting, the subject could invest a strictly positive amount a in the risky asset even if she is risk-averse, since the resulting utility $V\big(u(w - a, w - a), u(0, 2a)\big)$ can be higher than $V\big(u(w, w), u(0,0)\big)$.

to the use of the diversification heuristic and can be reduced by framing the choice environments similarly.

Revealed preference analysis provides a powerful tool to make inferences about individual preferences, errors, and rationality from observable choices, but heuristics can systematically bias the inferences. Whereas the high-level within-condition rationality and the relatively lower cross-condition rationality offer the illusion of as-if distinct preferences, subjects are unlikely to apply different risk preferences with only the removal of dominated options. It can be misleading to infer a subject's preference solely based on her midpoint choice in the full-line condition. If the same subject also chooses the midpoint of the full budget line in the truncated-line condition, we can be reassured that this subject is likely to be risk-averse. However, if the same subject chooses the midpoint of the truncated budget line in the truncated-line condition, the subject most likely uses the diversification heuristic to make decisions instead of making decisions according to stable preferences in separate conditions. Relatedly, the inferred rationality in each setting may capture not only the general ability to make good decisions, but also the adoption of heuristic rules that may be more useful in some settings than others. In this regard, our study suggests the need to incorporate heuristics in revealed preference analysis and to develop a more encompassing notion of rationality.

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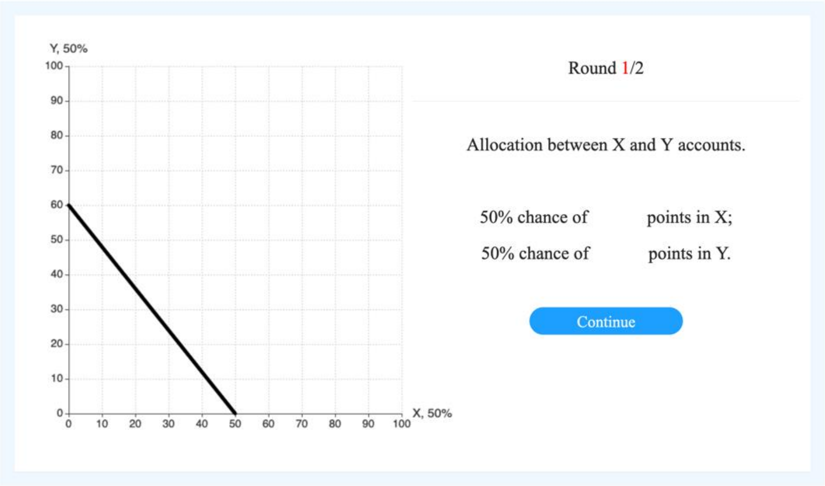
Online Appendix A. Figures and Tables

Panel A. Full-line Condition



Panel B. Truncated-line Condition

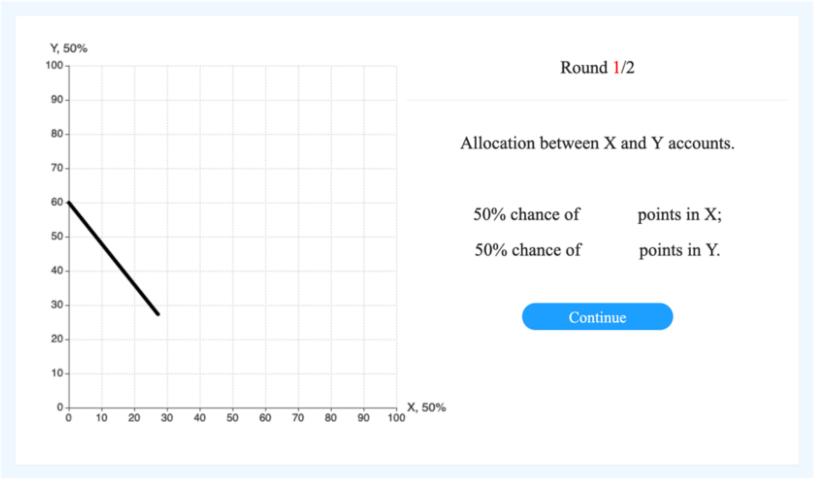
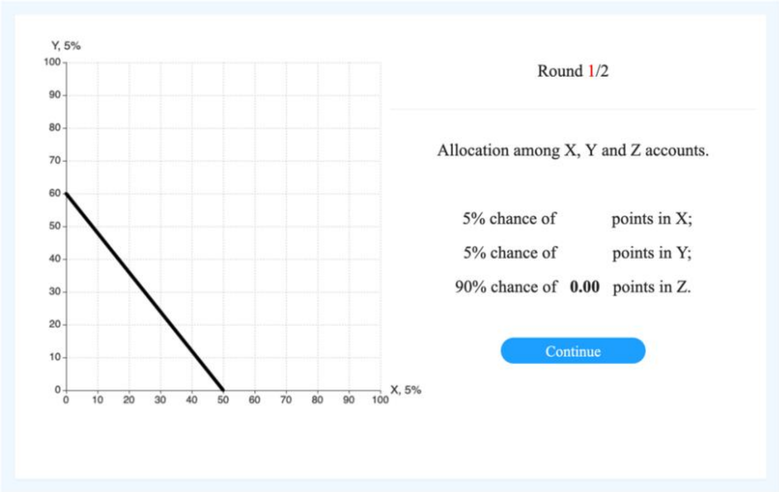


Figure A1—Experimental interfaces in the Same-frame experiment. We present the interfaces of the first practice round in each condition. We randomly truncated the lines in the two budget lines with a price ratio of 1.

Panel A. Full-line Condition



Panel B. Truncated-line Condition

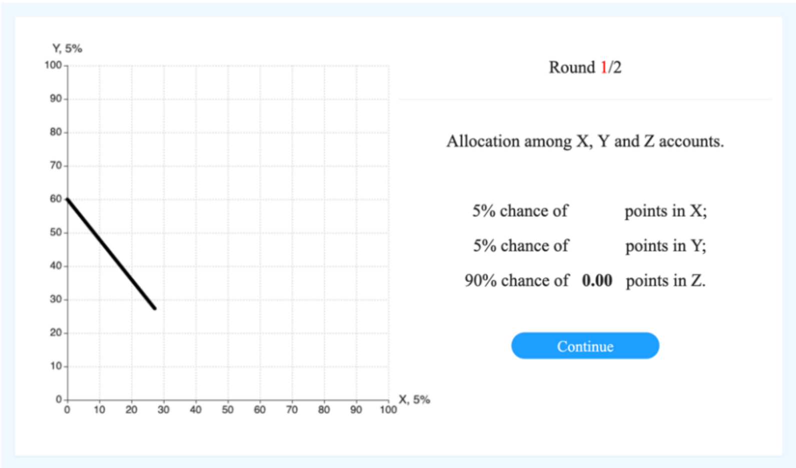


Figure A2—Experimental interfaces in the Low-probability experiment. We present the interfaces of the first practice round in each condition. We randomly truncated the lines in the two budget lines with a price ratio of 1.

Panel A. Bronars test

Panel B. Mixed choices dataset

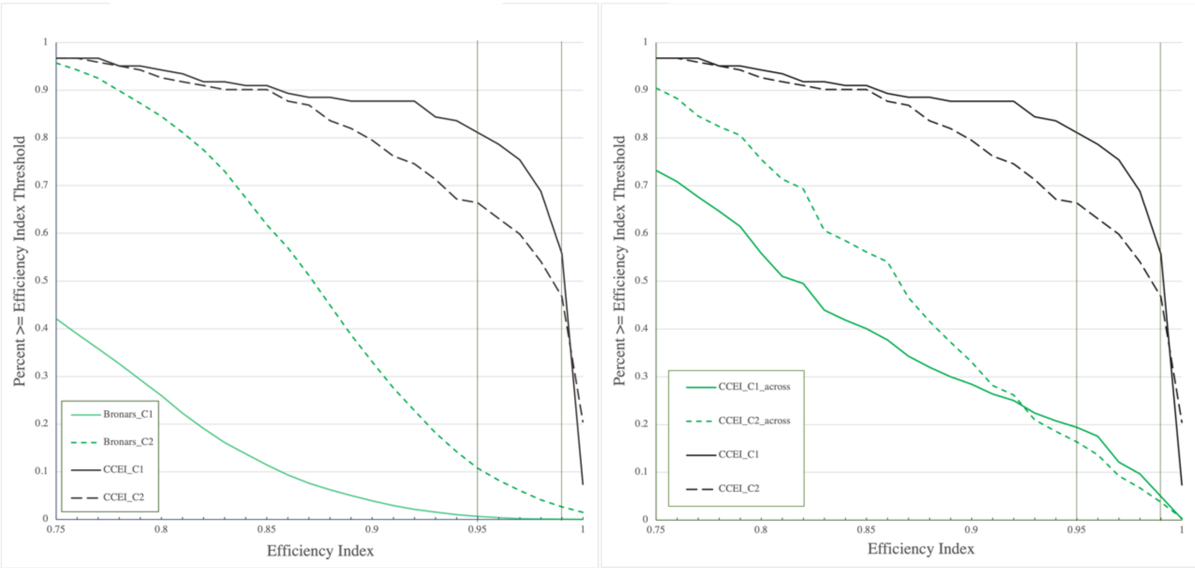


Figure A3—Decumulative distribution of the simulated CCEIs. Panel A: Decumulative distribution of the CCEIs using the power test in Bronars (1987) with 10,000 hypothetical subjects. Panel B: Decumulative distribution of the CCEIs of the mixed dataset with 22 choices from 22 subjects in each condition of the Main experiment. C1 refers to the full-line condition and C2 to the truncated-line condition.

Panel A. Full-line condition Panel B. Truncated-line

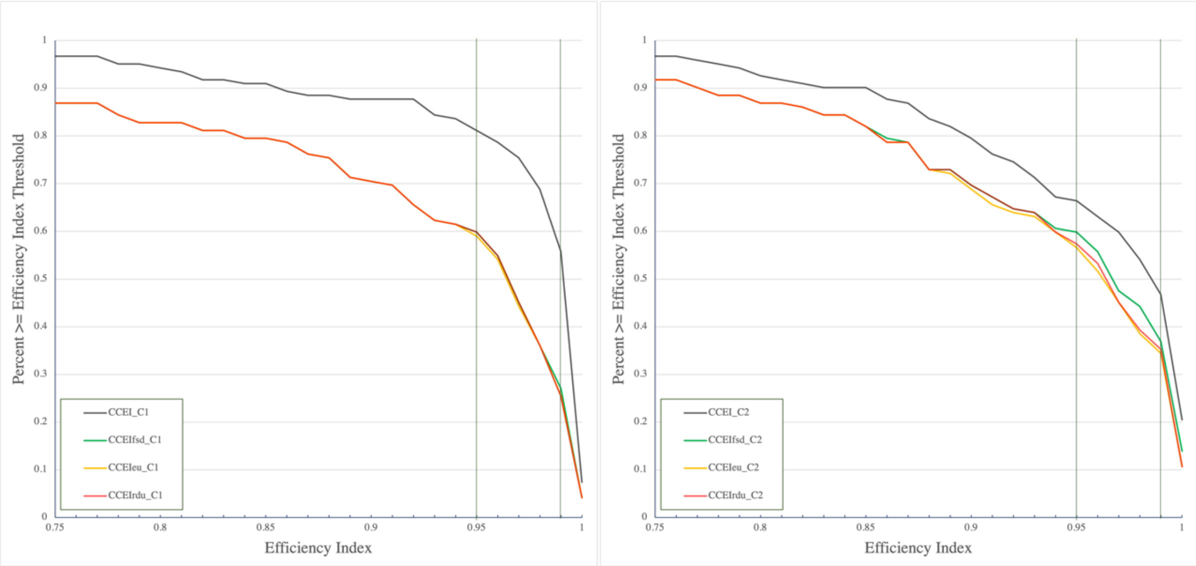


Figure A4—Decumulative distribution of the CCEIs with further restrictions of the Main experiment: first-order stochasticity dominance (FOSD), expected utility (EU), and rank-dependent utility (RDU) for each condition. For the computation of RDU, we apply the probability distortion from 0.4 to 0.5 (Polisson et al., 2020). Panel A: C1 refers to the full-line condition. Panel B: C2 refers to the truncated-line condition.

Panel A. Combined dataset Panel B. Half-combined dataset

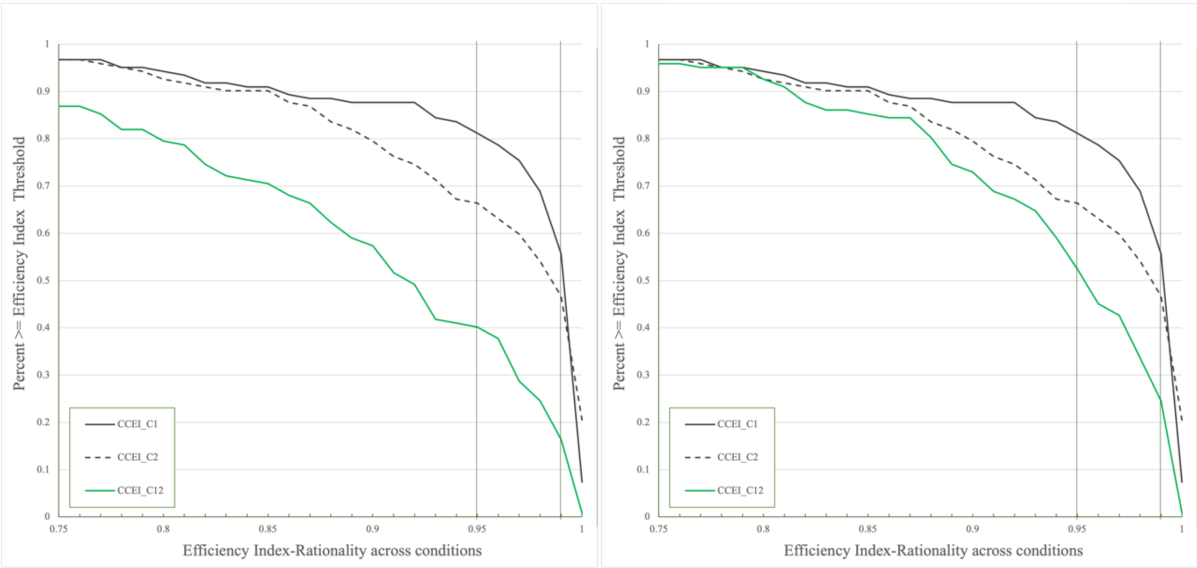


Figure A5—Decumulative distribution of the within- and cross-condition CCEIs. Panel A: Decumulative distribution of the CCEIs of the combined dataset using all 44 choices in both conditions for every subject in the Main experiment. Panel B: Decumulative distribution of the CCEIs of the half-combined dataset using 11 randomly selected choices in the full-line condition and the remaining 11 choices in the truncated-line condition for each subject in the Main experiment. C1 refers to the full-line condition and C2 to the truncated-line condition.

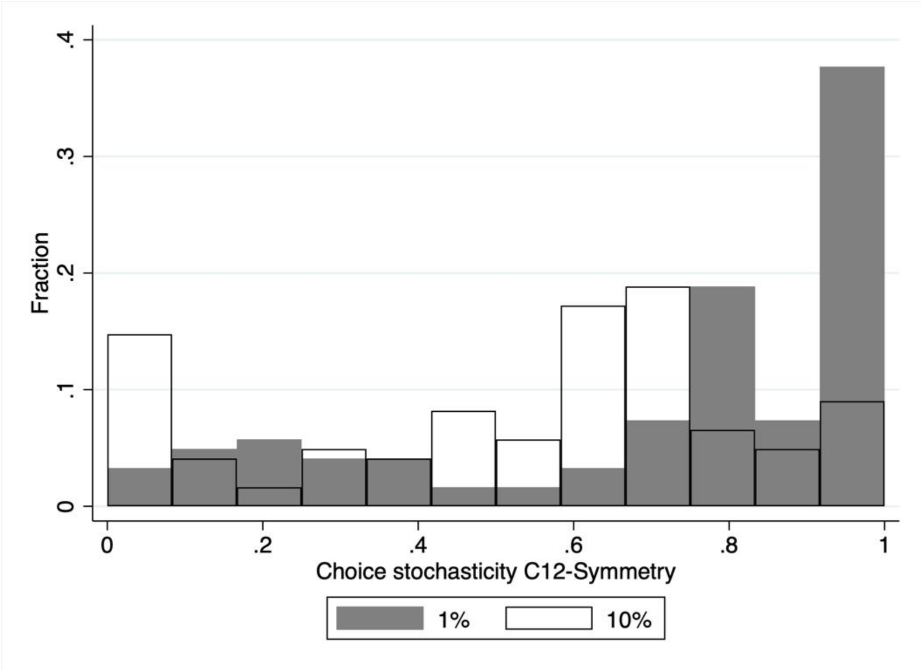


Figure A6—Distribution of symmetric cross-condition choice stochasticity in the Main experiment.

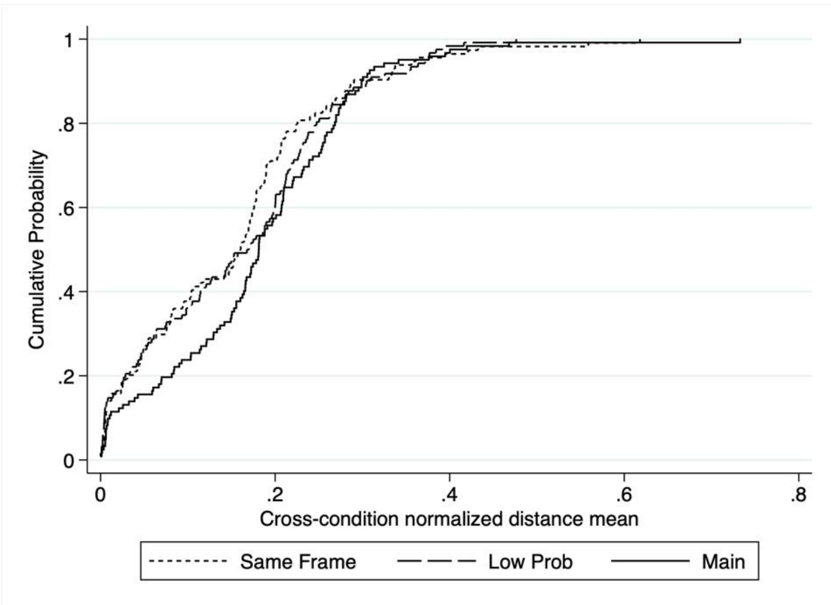


Figure A7—Cumulative distribution of the averaged cross-condition normalized distance for corresponding choices at individual level for the three experiments.

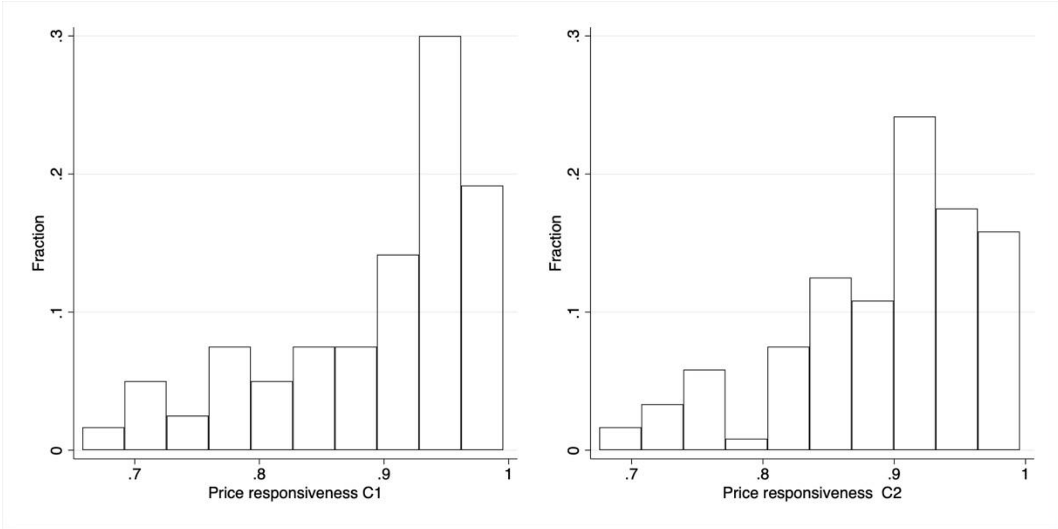


Figure A8—Distribution of price responsiveness conformity rates in the Main experiment. We drop two subjects with conformity rates lower than 0.649 for a better demonstration. C1 refers to the full-line condition and C2 to the truncated-line condition.

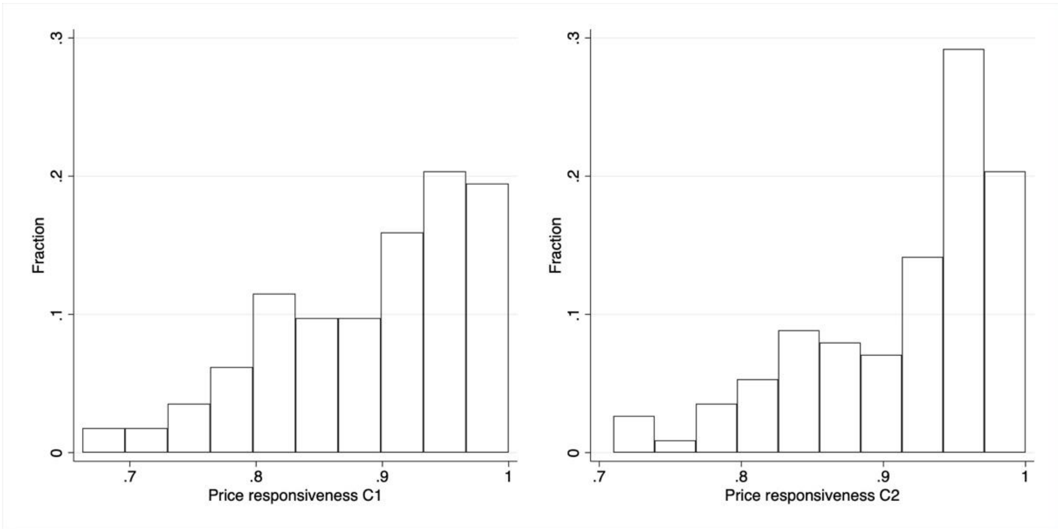


Figure A9—Distribution of price responsiveness conformity rates in the Same-frame experiment. We drop one subject with conformity rate lower than 0.649 for a better demonstration. C1 refers to the full-line condition and C2 to the truncated-line condition.

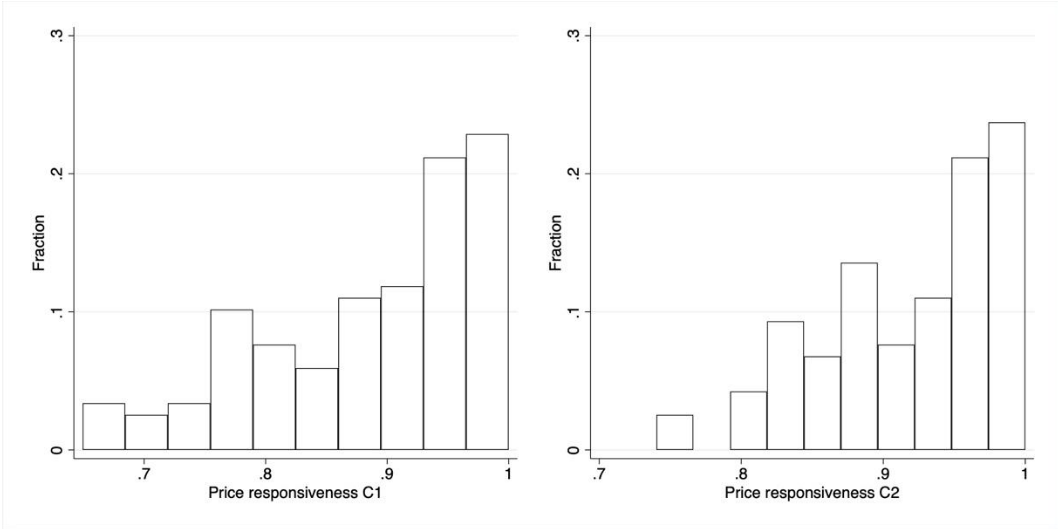


Figure A10—Distribution of price responsiveness conformity rates in the Low-probability experiment. We drop four subjects with conformity rates lower than 0.649 for a better demonstration. C1 refers to the full-line condition and C2 to the truncated-line condition.

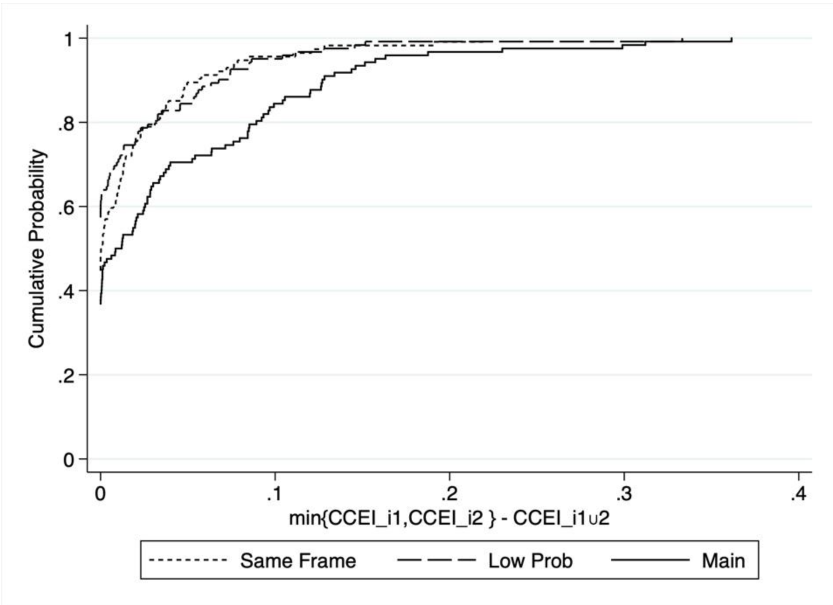


Figure A11—Cumulative distribution of inconsistency across conditions for the three experiments. The inconsistency is measured by $\mathrm{CCEI}_{dif} = (\min(\mathrm{CCEI}_1, \mathrm{CCEI}_2) - \mathrm{CCEI}_{1\cup 2})$. The distribution for the Main experiment is the same as that in Figure 4. A positive CCEI difference value represents the distinct preferences in the two conditions.

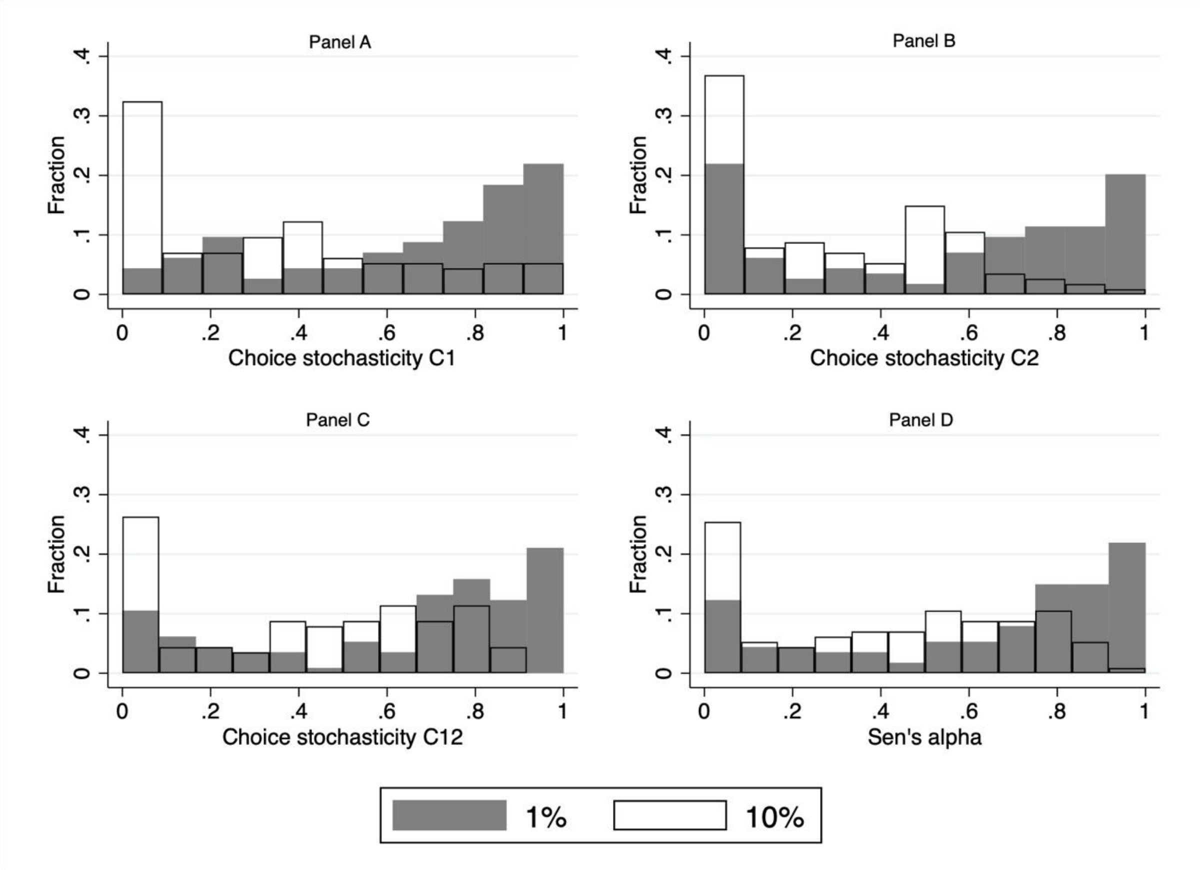


Figure A12—Distribution of choice stochasticity and violation of Sen's alpha. We plot the distribution at 1% and 10% choice error in the Same-frame experiment. C1 refers to the full-line condition and C2 to the truncated-line condition.

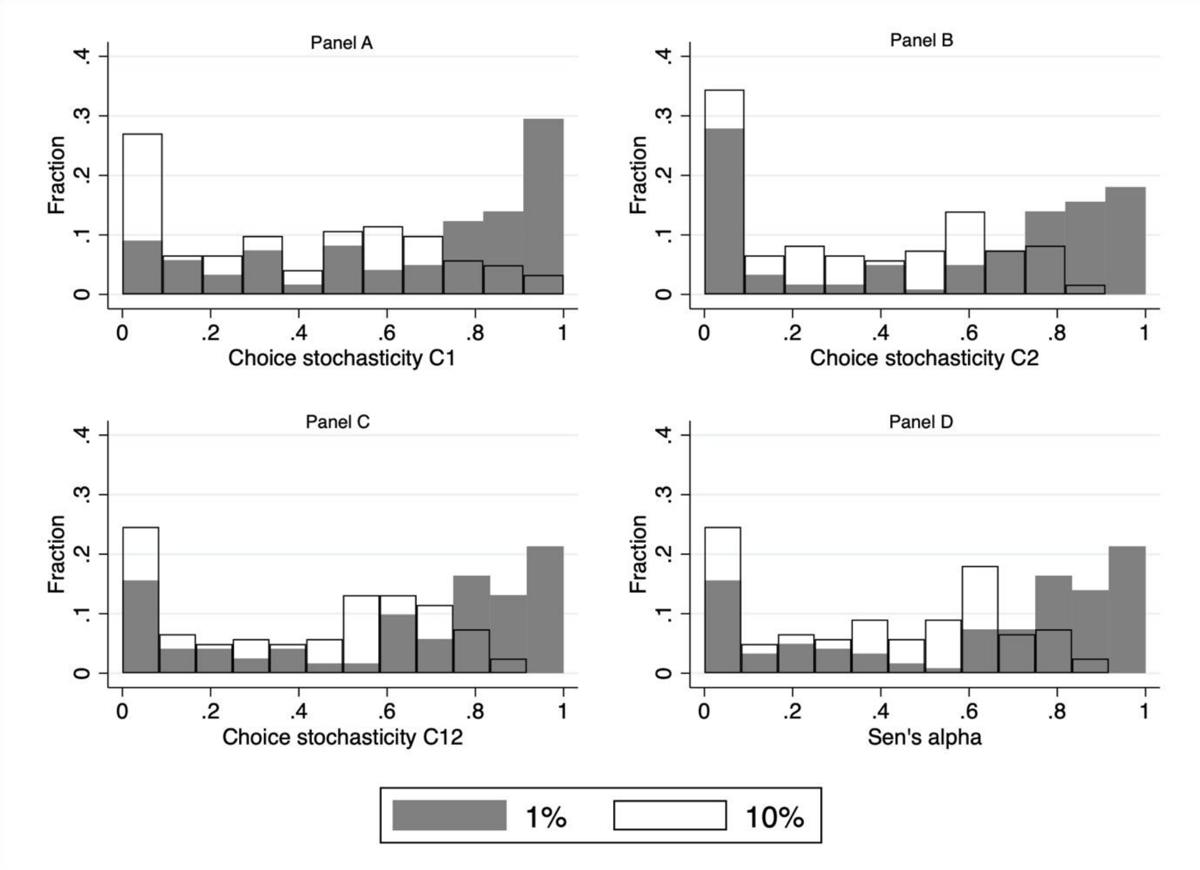


Figure A13—Distribution of choice stochasticity and violation of Sen's alpha. We plot the distribution at 1% and 10% choice error in the Low-probability experiment. C1 refers to the full-line condition and C2 to the truncated-line condition.

X Intercept	Y Intercept	Budget Order	Price Ratio
100	34.92	1	0.35
20	80	2	0.25
61.57	58.5	3	0.95
98.67	67.26	4	0.68
80	80	5	1
100	25	6	0.25
60	60	7	1
39.03	80	8	0.49
80	39.03	9	0.49
34.92	100	10	0.35
74	50.45	11	0.68
25	100	12	0.25
78	82.1	13	0.95
50.45	74	14	0.68
100	48.79	15	0.49
48.79	100	16	0.49
80	27.94	17	0.35
67.26	98.67	18	0.68
80	20	19	0.25
58.5	61.57	20	0.95
82.1	78	21	0.95
27.94	80	22	0.35

Table A1—The parameters and the corresponding budget orders of the 22 budgetary decisions. Budgets 3, 5, 7, 13, 20, and 21 are the six budgets with price ratios around 1.

	Main	Same-F	Low-P
Female	0.484	0.561	0.549
Age			
18-29	0.254	0.175	0.23
30-49	0.369	0.289	0.336
50-69	0.32	0.518	0.369
70+	0.057	0.018	0.066
Education			
Low	0.369	0.316	0.254
Medium	0.451	0.439	0.525
High	0.18	0.246	0.221
Income			
$0-24,999	0.197	0.254	0.156
$25,000-49,999	0.303	0.237	0.221
$50,000-99,999	0.303	0.307	0.451
$100,000+	0.197	0.202	0.172
Occupation			
Paid work	0.68	0.667	0.689
House work	0.033	0.079	0.049
Retired	0.098	0.158	0.148
Others	0.189	0.096	0.115
Household composition			
Partner	0.443	0.439	0.516
Number of Children	0.713	1.061	0.943
Observations	122	114	122

Table A2—Subjects' demographic information in the three experiments.

Panel A	C1 CCEI	C1 MPI	C1 HMI	C1 MCI
C1 CCEI	1.000			
C1 MPI	-0.902	1.000		
C1 HMI	0.652	-0.516	1.000	
C1 MCI	-0.988	0.884	-0.675	1.000

Panel B	C2 CCEI	C2 MPI	C2 HMI	C2 MCI
C2 CCEI	1.000			
C2 MPI	-0.919	1.000		
C2 HMI	0.769	-0.717	1.000	
C2 MCI	-0.985	0.913	-0.771	1.000

Table A3—Spearman's rank correlation across CCEI, MPI, HMI, and MCI in the Main experiment for each condition. We compute MPI for cyclic sequences of allocations of length two. We normalize MCI by each subject's total budget. Panel A/C1 refers to the full-line condition, and Panel B/C2 to the truncated-line condition.

	C1 CCEI	C2 CCEI	CCEI Diff	Choice Stochasticity 1%	Sen's Alpha 1%
	(1)	(2)	(3)	(4)	(5)
Understanding	0.0108	0.00761	-0.0924*	-0.0607	-0.0506
	(0.00939)	(0.00725)	(0.0544)	(0.0370)	(0.0383)
Constant	0.949***	0.940***	0.721***	0.821***	0.800***
	(0.0135)	(0.0104)	(0.0657)	(0.0411)	(0.0435)
R-squared	0.010	0.006	0.023	0.024	0.016
CRT	0.00664	0.00868	-0.0605*	-0.0732***	-0.0729***
	(0.00549)	(0.00588)	(0.0362)	(0.0203)	(0.0211)
Constant	0.947***	0.931***	0.751***	0.906***	0.895***
	(0.0150)	(0.0146)	(0.0802)	(0.0357)	(0.0368)
R-squared	0.008	0.018	0.022	0.075	0.071
ChoiceConfidence	0.00448	0.00317	0.00555	-0.0225***	-0.0235***
	(0.00272)	(0.00204)	(0.0130)	(0.00697)	(0.00722)
Constant	0.914***	0.916***	0.575***	0.989***	0.988***
	(0.0306)	(0.0223)	(0.140)	(0.0648)	(0.0660)
R-squared	0.030	0.019	0.001	0.057	0.060
FinancialScore	0.0212	0.0133	0.0607	-0.0862***	-0.0866***
	(0.0132)	(0.00944)	(0.0540)	(0.0230)	(0.0234)
Constant	0.907***	0.914***	0.480***	0.976***	0.967***
	(0.0372)	(0.0257)	(0.143)	(0.0510)	(0.0521)
R-squared	0.043	0.022	0.011	0.053	0.051
Non-diversification	0.0155	0.00825	-0.100*	-0.110***	-0.108***
	(0.0108)	(0.00885)	(0.0587)	(0.0381)	(0.0387)
Constant	0.946***	0.940***	0.721***	0.860***	0.848***
	(0.0157)	(0.0102)	(0.0657)	(0.0369)	(0.0379)
R-squared	0.018	0.007	0.024	0.068	0.064
Diversify-prob	0.00974	0.0104	0.107	-0.0416	-0.0493
	(0.0238)	(0.0123)	(0.0782)	(0.0528)	(0.0540)
Constant	0.949***	0.936***	0.511***	0.808***	0.806***
	(0.0284)	(0.0162)	(0.103)	(0.0615)	(0.0623)
R-squared	0.004	0.005	0.013	0.005	0.006
Observations	122	122	122	122	122

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A4—OLS regression among within- and cross-condition rationality measures, understanding test scores, and all questionnaire measures in the Main experiment. Understanding represents the sum scores of correct answers to the second and third understanding tests. CRT represents the sum scores of correct answers to the CRT (Frederick, 2005). ChoiceConfidence represents the sum scores of the two choice confidence questions regarding subjects' choices. FinancialScore represents the sum scores of correct answers to the questions on financial literacy (Lusardi and Mitchell, 2011). Non-diversification represents the frequency that a subject chooses the correct answers to the two questions on false diversification (Rubinstein, 2002). And Diversify-prob represents the frequency with that a subject chooses probability-matching answers to the two questions on false diversification.

	CCEI Diff	Choice Stochasticity 1%	Sen's Alpha 1%	Normalized Distance Mean
	(1)	(3)	(2)	(4)
DistanceMid_C1	0.0466	0.00328	-0.00531	0.0339
	(0.0611)	(0.0340)	(0.0343)	(0.0229)
DistanceMid_C2	-0.375***	-0.525***	-0.536***	-0.108***
	(0.0806)	(0.0401)	(0.0414)	(0.0181)
Constant	0.935***	1.220***	1.223***	0.258***
	(0.0735)	(0.0340)	(0.0341)	(0.0201)
Observations	122	122	122	122
R-squared	0.133	0.626	0.627	0.222

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A5—Regressions between cross-condition inconsistency and diversification heuristic. We run the OLS regression for all four columns using the individual-level data of the Main experiment. The dependent variables are defined as 1 if $(\min(\mathrm{CCEI}_1, \mathrm{CCEI}_2) - \mathrm{CCEI}_{1\cup 2}) > 0$ and 0 otherwise in column 1, choice stochasticity (1 percent choice error) in column 2, violation of Sen's alpha (1 percent choice error) in column 3, and the averaged cross-condition normalized distances for corresponding choices in column 4. A higher value of Choice Stochasticity 1%, Sen's Alpha 1%, and Normalized Distance Mean represent a higher inconsistency across the two conditions. The independent variables are the sum of the distance between the choices and the midpoints of the six budgets, of which the price ratio equals 1 or 0.95. C1 refers to the full-line condition and C2 to the truncated-line condition.

	CCEI Diff	Choice Stochasticity 1%	Sen's Alpha 1%	Normalized Distance Mean
	(1)	(2)	(3)	(4)
DistanceMid_C1	-0.0435	0.0466	0.0392	0.0791***
	(0.0702)	(0.0509)	(0.0549)	(0.0250)
DistanceMid_C2	-0.239***	-0.441***	-0.441***	-0.0757***
	(0.0859)	(0.0423)	(0.0431)	(0.0179)
Constant	0.824***	1.129***	1.120***	0.193***
	(0.0995)	(0.0421)	(0.0418)	(0.0210)
Observations	114	114	114	114
R-squared	0.057	0.445	0.420	0.304

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A6—Regressions between cross-condition inconsistency and diversification heuristic. We run the OLS regression for all four columns using the individual-level data of the Same-frame experiment. The dependent variables are defined as 1 if $(\min(\mathrm{CCEI}_1, \mathrm{CCEI}_2) - \mathrm{CCEI}_{1\cup 2}) > 0$ and 0 otherwise in column 1, choice stochasticity (1 percent choice error) in column 2, violation of Sen's alpha (1 percent choice error) in column 3, and the averaged cross-condition normalized distances for corresponding choices in column 4. A higher value of Choice Stochasticity 1%, Sen's Alpha 1%, and Normalized Distance Mean represent a higher inconsistency across the two conditions. The independent variables are the sum of the distance between the choices and the midpoints of the six budgets, of which the price ratio equals 1 or 0.95. C1 refers to the full-line condition and C2 to the truncated-line condition.

	CCEI Diff	Choice Stochasticity 1%	Sen's Alpha 1%	Normalized Distance Mean
	(1)	(2)	(3)	(4)
DistanceMid_C1	-0.0388	-0.0156	-0.0179	0.0256*
	(0.0531)	(0.0336)	(0.0333)	(0.0130)
DistanceMid_C2	-0.159	-0.557***	-0.561***	-0.123***
	(0.0972)	(0.0464)	(0.0466)	(0.0178)
Constant	0.625***	1.283***	1.277***	0.274***
	(0.124)	(0.0517)	(0.0518)	(0.0209)
Observations	122	122	122	122
R-squared	0.023	0.499	0.496	0.292

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A7—Regressions between cross-condition inconsistency and diversification heuristic. We run the OLS regression for all four columns using the individual-level data of the Low-probability experiment. The dependent variables are defined as 1 if $(\min(\mathrm{CCEI}_1, \mathrm{CCEI}_2) - \mathrm{CCEI}_{1\cup 2}) > 0$ and 0 otherwise in column 1, choice stochasticity (1 percent choice error) in column 2, violation of Sen's alpha (1 percent choice error) in column 3, and the averaged cross-condition normalized distances for corresponding choices in column 4. A higher value of Choice Stochasticity 1%, Sen's Alpha 1%, and Normalized Distance Mean represent a higher inconsistency across the two conditions. The independent variables are the sum of the distance between the choices and the midpoints of the six budgets, of which the price ratio equals 1 or 0.95. C1 refers to the full-line condition and C2 to the truncated-line condition.

	Cheaper Account Fraction Difference					
	(1)	(2)	(3)	(4)	(5)	(6)
Same-F vs. Main	-0.0361***			-0.0361***		
	(0.00562)			(0.00557)		
Low-P vs. Main		-0.0443***			-0.0443***	
		(0.00572)			(0.00566)	
Low-P vs. Same-F			-0.00821			-0.00821
			(0.00564)			(0.00557)
Price Fixed Effect	N	N	N	Y	Y	Y
Constant	0.0993***	0.0993***	0.0633***	0.0656***	0.0657***	0.0299***
	(0.00403)	(0.00403)	(0.00391)	(0.00697)	(0.00722)	(0.00674)
Observations	5,192	5,368	5,192	5,192	5,368	5,192
R-squared	0.008	0.011	0.000	0.028	0.035	0.027

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A8—Cheaper account fraction difference across the three experiments. We run the OLS regression for all six columns. The dependent variables are the difference between the cheaper account fractions across two conditions at individual-choice level ($\text{cheaper account fraction}_{truncated} - \text{cheaper account fraction}_{full}$). The independent variables are dummy variables with the indicator = 1 for the first-listed experiment. We control the price fixed effect in columns 4 to 6.

	Cheaper Account Fraction					
	(1)	(2)	(3)	(4)	(5)	(6)
Same-F vs. Main	0.00457			-0.0315***		
	(0.00526)			(0.00478)		
Low-P vs. Main		0.0287***			-0.0156***	
		(0.00560)			(0.00488)	
Low-P vs. Same-F			0.0241***			0.0159***
			(0.00554)			(0.00508)
Condition	1	1	1	2	2	2
Price Fixed Effect	Y	Y	Y	Y	Y	Y
Constant	0.715***	0.716***	0.724***	0.781***	0.782***	0.754***
	(0.00716)	(0.00739)	(0.00724)	(0.00625)	(0.00632)	(0.00681)
Observations	5,192	5,368	5,192	5,192	5,368	5,192
R-squared	0.107	0.106	0.119	0.054	0.047	0.052

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A9—Cheaper account fraction across the three experiments. We run the OLS regression for all six columns. The dependent variables are the cheaper account fractions at individual-choice level. The independent variables are dummy variables with the indicator = 1 for the first-listed experiment. We control the price fixed effect in all the columns. Condition 1 refers to the full-line condition and Condition 2 to the truncated-line condition.

	Cheaper Account Fraction in C2	
	(1)	(2)
Price Ratio	-0.126***	-0.126***
	(0.0116)	(0.0116)
Price Ratio*Same-F vs. Main	-0.0242	
	(0.0173)	
Same-F vs. Main	-0.0173	
	(0.0116)	
Price Ratio* Low-P vs. Main		-0.0329*
		(0.0176)
Low-P vs. Main		0.00362
		(0.0118)
Constant	0.800***	0.800***
	(0.00776)	(0.00776)
Observations	5,192	5,368
R-squared	0.053	0.047

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table A10—Price responsiveness across the three experiments. We run the OLS regression for both columns. The dependent variable is the cheaper account fraction at individual-choice level in the truncated-line condition (C2). The independent variables are price ratios, dummy variables with the indicator = 1 for the first-listed experiment, and the interaction terms.

Online Appendix B. Experimental Instructions

This appendix offers the experimental instructions of the Main experiment. The instructions in the Same-frame and Low-probability experiments are similar to that in the Main experiment. The interfaces for these two experiments can be found in Appendix A. As mentioned in the paper, we randomize the two conditions in the experiment. Below, we show the instructions for the full-line condition first, followed by the truncated-line condition, and finally, the questions and survey part.

Experimental Instructions

This is an experiment on decision making. National University of Singapore, Economics department has made funding available to conduct this research. The study has three parts and requires about 25 minutes. In this experiment, you can earn real money, which shall be paid out in Prolific. **Please read the instructions at the start of each part carefully since a considerable amount of money is involved depending partly on your decisions and partly on chance.** During the experiment, we will refer to points instead of dollars. Your bonus earnings will be calculated in points and later paid to you in money: **10 points = $1**.

Your payment consists of the following three parts:

- You will receive a basic payment ($3.34) based on the hourly rate for completing the experiment.
- There will be 3 questions testing your understanding of the instructions in the first two parts. **You would be screened out of this experiment if you failed to answer the first question.** You will receive $0.5 for each correct answer to the remaining questions.
- At the end of the experiment, one of the decision rounds in the first two parts will be randomly selected for the bonus payment based on your choice. All rounds have the same probability of being chosen.

Information in the study will be kept confidential and be used for research purposes only. If you have any questions, please ask our experimenter via Prolific messages or the email: experimentcontact01@gmail.com.

Condition 1

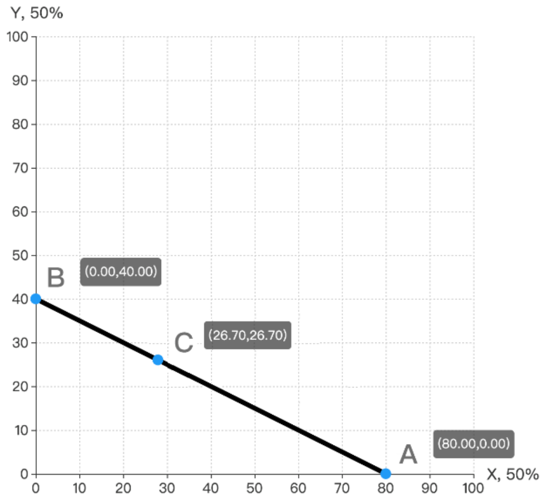
In this part, you will make 22 independent decisions that share a common form. In each decision, you will be given a certain number of points, and your task is to distribute points between two accounts—X account and Y account. At the start of each round, you will receive a set of possible distributions of points illustrated by a line, and you choose one distribution of points on the line.

The computer will randomly draw a number from 100 numbers: 1, 2, 3, …, 100. If the number falls between 1 and 50, you will receive the points in the X account. If the number falls between 51 and 100, you will receive the points in the Y account. That is, both X and Y accounts have the same probability of 50% being selected.

Examples

To make your decision in each round, you will use an interface as in the following examples. The X account corresponds to the horizontal axis (indicated as **"X, 50%"**), and the Y account corresponds to the vertical axis (indicated as **"Y, 50%"**). In each decision round, you will see a line which shows the possible distributions of points between the two accounts. In each decision round, you choose one point on the line.

For the round that is selected for payment at the end of the experiment, your payment is determined by the number of points allocated to one account and the chance. To help you understand, we explain some possible distributions of points along the line below.



- Option A: you allocate **80.00** points to the X account and **0.00** points to the Y account. That is, you allocate all to the X account. You will receive:

    80.00 points in the X account (50% chance);

    0.00 points in the Y account (50% chance).

    In sum, Option A is indicated as (80.00, 0.00).

- Option B: you allocate **0.00** points to the X account and **40.00** points to the Y account. That is, you allocate all to the Y account. You will receive:

    0.00 points in the X account (50% chance);

    40.00 points in the Y account (50% chance).

    In sum, Option B is indicated as (0.00, 40.00).

- Option C: you allocate **26.70** points to the X account and **26.70** points to the Y account. That is, you will receive:

    26.70 points in the X account (50% chance);

26.70 points in the Y account (50% chance).

In sum, Option C is indicated as (26.70, 26.70).

Please note that these points are for illustrative purposes, and you are allowed to choose any point on the line in each decision round.

Understanding Tests

This is the first understanding test. Please select the correct answer.

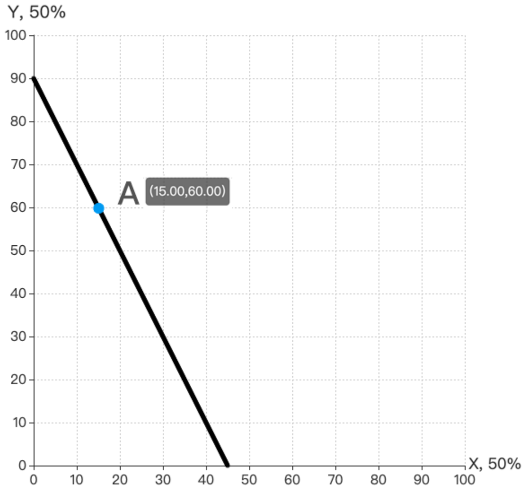
Please note that you will be screened out of this experiment if you fail to answer this question correctly.

What is the probability of receiving the points in the X account?

100% 90% 50% 10% 5% 0%

Suppose you choose **option A** on this line. Please select all that apply.

Please note that you will receive an additional $0.5 for answering this question correctly.



A. You allocate **60.00** points to the X account and **15.00** points to the Y account. That is, you will receive:

60.00 points in the X account (50% chance);

15.00 points in the Y account (50% chance).

B. You allocate **0.00** points to the X account and **45.00** points to the Y account. That is, you will receive:

0.00 points in the X account (50% chance);

45.00 points in the Y account (50% chance).

C. You allocate **90.00** points to the X account and **0.00** points to the Y account. That is, you will receive:

90.00 points in the X account (50% chance);

0.00 points in the Y account (50% chance).

D. You allocate **15.00** points to the X account and **60.00** points to the Y account. That is, you will receive:

15.00 points in the X account (50% chance);

60.00 points in the Y account (50% chance).

E. X and Y accounts are equally likely to be chosen for payment.

F. X account is more likely to be chosen for payment than Y account.

Practice

In this screen you can practice for two rounds. You'll see a line with the possible distributions in each practice round. To make a choice, use the mouse to move the cursor on the screen along the line towards your choice. When you move the cursor close to the line, there will be a small hand-shaped pointer with corresponding values of choice. You can only choose one distribution located on the line. When you know which decision you would like to make, click on the left button on your mouse to select your choice. You will see the number of points that you may receive in the X and Y accounts. On the right-hand side of the interface, you will see:

50% chance of [ ] points in X;

50% chance of [ ] points in Y.

To confirm your decision and move to the next round, click the 'Continue' button. If you want to change your mind, click the 'Back' button. The practice decisions you make will not be recorded.

Payment

At the end of the experiment, the computer will randomly select one decision round in the first two parts for payment. If one of the 22 rounds in this part is chosen, X and Y accounts in that round have the same probability of 50% being selected. If the X account is chosen, you will receive the points in the X account. If the Y account is chosen, you will receive the points in the Y account. The points in the other account are not used. **Since all decisions are equally likely to be chosen, you should make each decision carefully as if it will be the decision that counts.** Please note that you can only change your mind within each part. That is, once you finish this part, you cannot move back to change your decisions.

This is the end of the instructions for this part. If you have any questions, you can ask the experimenter via Prolific messages or email. If you have no further questions, please click 'Continue' to start. Thanks.

Condition 2

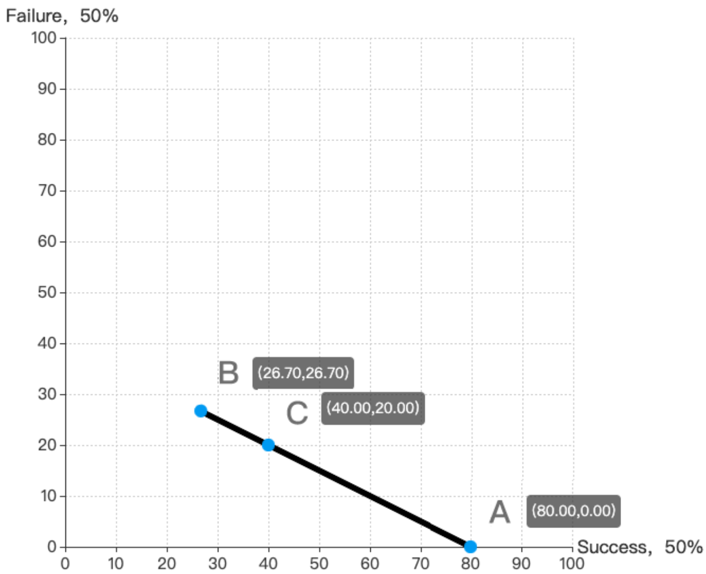
In this part, you will make 22 independent decisions that share a common form. In each decision, you will be given a certain number of points, and your task is to distribute points between two accounts—Safe account and Risky account. At the start of each round, you will receive a set of possible distributions of points illustrated by a truncated line, and you choose one distribution of points on the line.

The computer will randomly draw a number from 100 numbers:1, 2, 3, …, 100. If the number falls between 1 and 50, the investment in the Risky account is a Success. That is, you will receive some extra points from what you allocated to the Risky account and the points you allocated to the Safe account. If the number falls between 51 and 100, the investment in the Risky account is a Failure. That is, you will lose all the points you allocated to the Risky account and only receive the points you allocated to the Safe account.

Examples

To make your decision in each round, you will use an interface as in the following examples. The Success and Failure correspond to the two axes separately (indicated as **"Success, 50%"** and **"Failure, 50%"**). The Success may correspond to the horizontal axis or vertical axis in different decision rounds. In each decision round, you will see a line which shows the possible distributions of points between the Safe and the Risky accounts. In each decision round, you choose one point on the line.

For the round that is selected for payment at the end of the experiment, your payment is determined by the number of points allocated to one account and the chance. To help you understand, we explain some possible distributions of points along the line below.



- Option A: you allocate **0.00** points to the Safe account and **80.00** points to the Risky account. That is, you allocate all to the Risky account. You will receive:

0.00 + **80.00** points if the investment is a Success (50% chance);

0.00 + **0.00** points if the investment is a Failure (50% chance).

In sum, Option A is indicated as (80.00, 0.00).

- Option B: you allocate 26.70 points to the Safe account and **0.00** points to the Risky account. That is, you allocate all to the Safe account. You will receive:

26.70 + **0.00** points if the investment is a Success (50% chance);

26.70 + **0.00** points if the investment is a Failure (50% chance).

In sum, Option B is indicated as (26.70, 26.70).

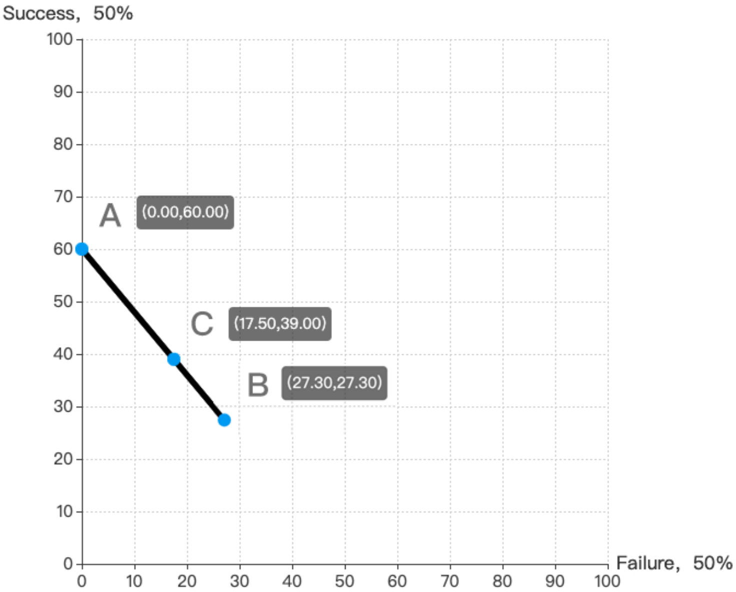
- Option C: you allocate 20.00 points to the Safe account and **20.00** points to the Risky account. That is, You will receive:

20.00 + **20.00** points if the investment is a Success (50% chance);

20.00 + **0.00** points if the investment is a Failure (50% chance).

In sum, Option C is indicated as (40.00, 20.00).

Another example of the lines is shown below.



- Option A: you allocate 0.00 points to the Safe account and **60.00** points to the Risky account. That is, you allocate all to the Risky account. You will receive:

0.00 + **0.00** points if the investment is a Failure (50% chance);

0.00 + **60.00** points if the investment is a Success (50% chance).

In sum, Option A is indicated as (0.00, 60.00).

- Option B: you allocate 27.30 points to the Safe account and **0.00** points to the Risky account. That is, you allocate all to the Safe account. You will receive:

27.30 + **0.00** points if the investment is a Failure (50% chance);

27.30 + **0.00** points if the investment is a Success (50% chance).

In sum, Option B is indicated as (27.30, 27.30).

- Option C: you allocate **17.50** points to the Safe account and **21.50** points to the Risky account. That is, you will receive:

 17.50 + **0.00** points if the investment is a Failure (50% chance);

 17.50 + **21.50** points if the investment is a Success (50% chance).

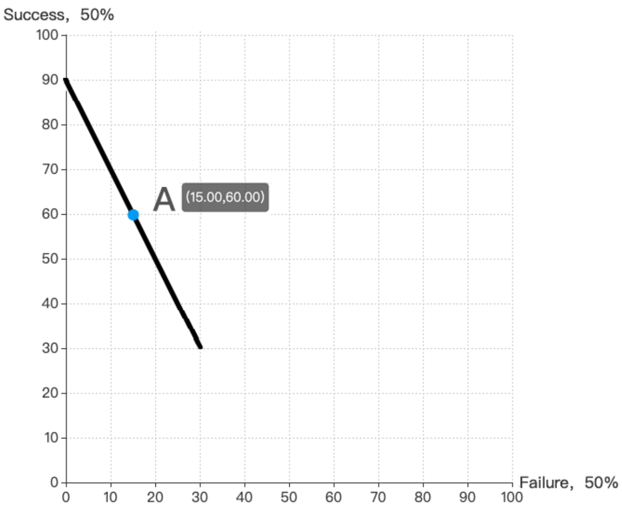
 In sum, Option C is indicated as (17.50, 39.00).

Please note that these points are for illustrative purposes, and you are allowed to choose any point on the line in each decision round.

Understanding Tests

Suppose you choose **option A** on this line. Please select all that apply.

Please note that you will receive an additional $0.5 for answering this question correctly.



A. You allocate **0.00** points to the Safe account and **90.00** points to the Risky account. You will receive:

 0.00 + **0.00** points if the investment is a Failure (50% chance);

 0.00 + **90.00** points if the investment is a Success (50% chance).

B. You allocate **15.00** points to the Safe account and **45.00** points to the Risky account. You will receive:

 15.00 + **0.00** points if the investment is a Failure (50% chance);

 15.00 + **45.00** points if the investment is a Success (50% chance).

C. You allocate **0.00** points to the Safe account and **30.00** points to the Risky account. You will receive:

 0.00 + **0.00** points if the investment is a Failure (50% chance);

 0.00 + **30.00** points if the investment is a Success (50% chance).

D. You allocate **30.00** points to the Safe account and **0.00** points to the Risky account. You will receive:

 30.00 + **0.00** points if the investment is a Failure (50% chance);

30.00 + **0.00** points if the investment is a Success (50% chance).

E. You can receive the points in the Safe account no matter Success or Failure in the Risky account.

F. Failure is more likely to happen than Success.

Practice

In this screen you can practice for two rounds. You'll see a line with the possible distributions in each practice round. To make a choice, use the mouse to move the cursor on the screen along the line towards your choice. When you move the cursor close to the line, there will be a small hand-shaped pointer with corresponding values of choice. You can only choose one distribution located on the line. When you know which decision you would like to make, click on the left button on your mouse to select your choice. You will see the number of points that you may receive in the Success and Failure states. On the right-hand side of the interface, you will see:

50% chance of [ ] points if Success;

50% chance of [ ] points if Failure.

To confirm your decision and move to the next round, click the 'Continue' button. If you want to change your mind, click the 'Back' button. The practice decisions you make will not be recorded.

Payment

At the end of the experiment, the computer will randomly select one decision round in the first two parts for payment. If one of the 22 rounds in this part is chosen, Success and Failure in that round have the same probability of 50% being selected. If the Risky investment is a Success, you will receive the points in both the Safe and the Risky accounts. If the Risky investment is a Failure, you will only receive the points in the Safe account. The points in the Risky account will be lost. **Since all decisions are equally likely to be chosen, you should make each decision carefully as if it will be the decision that counts.** Please note that you can only change your mind within each part. That is, once you finish this part, you cannot move back to change your decisions.

This is the end of the instructions for this part. If you have any questions, you can ask the experimenter via Prolific messages or email. If you have no further questions, please click 'Continue' to start. Thanks.

Questions and Survey

This is the final part of the experiment. You will first see some questions and then a survey in this part. The experiment will end by showing you first your payment and then the completion code for you to use in the Prolific. Thank you!

1. A bat and a ball cost £1.10 in total. The bat costs £1.00 more than the ball. How much does the ball cost?

A. 9 pence B. 10 pence C. 1 pence D. 5 pence

2. If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?

A. 100 minutes B. 20 minutes C. 500 minutes D. 5 minutes

3. In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?

A. 47 days B. 12 days C. 36 days D. 24 days

(Note: The choices for the first three questions are in random order.)

4. The mall where you wish to meet your friend has four gates. According to a statistical survey, visitors entering the mall choose their gates with the following probabilities:

North 21%; East 27%; South 32%; West 20%.

You need to meet your friend at one of the gates, but you do not know which gate he is going to use. What are you going to do? (Choose one of the two options and fill in the appropriate details.)

I will wait at gate: [ ].

I will choose the gate randomly according to the following probabilities:

North:[ ]%; East:[ ]%; South:[ ]%; West:[ ]%. [Need to sum up to 100%]

5. Imagine you are a detective at a mall. Every day at noon, a messenger arrives with an envelope. The identity of the messenger is unknown; he is one of the dozens of messengers who work for a delivery company. The mall has four gates and you have only one video camera, which you have to install on one of the four gates each morning. Your aim is to take photos of the maximum number of all messengers as they enter the mall. You need a plan for where to install the camera every morning. You have the results of reliable statistics on the entry of messengers according to gates:

North 36%, East 25%, South 22% and West 17%.

What are you going to do?

My plan is:

Sunday: A. North B. East C. South D. West

Monday:	A. North	B. East	C. South	D. West
Tuesday:	A. North	B. East	C. South	D. West
Wednesday:	A. North	B. East	C. South	D. West
Thursday:	A. North	B. East	C. South	D. West
Friday:	A. North	B. East	C. South	D. West
Saturday:	A. North	B. East	C. South	D. West

6. Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?

A. More than $102

B. Exactly $102

C. Less than $102

D. Don't know

E. Refused to answer

7. Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy more than today, exactly the same as today, or less than today with the money in this account?

A. More than today

B. Exactly the same as today

C. Less than today

D. Don't know

E. Refused to answer

8. Do you think that the following statement is true or false: Buying a single company stock usually provides a safer return than a stock mutual fund?

A. True

B. False

C. Don't know

D. Refused to answer

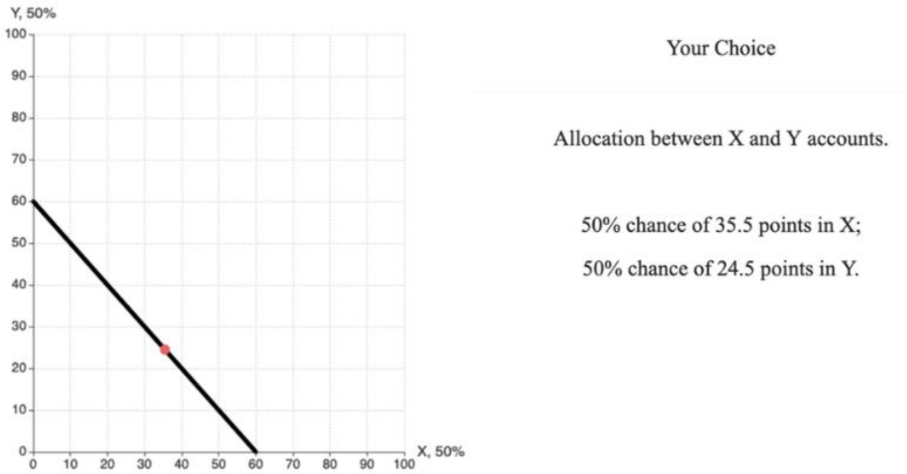
9. Please indicate, in general, how willing or unwilling you are to take risks.

Please use a scale from 0 to 10, where 0 means "completely unwilling to take risks" and 10 means you are "very willing to take risks".

You can choose any numbers between 0 and 10 to indicate where you fall on the scale:

0 1 2 3 4 5 6 7 8 9 10

10. In the figure, you can see your previous choice for one decision round (red point). You can check other possible choices on the budget line. Please check and indicate how certain you want to choose your previous choice with the scale below.

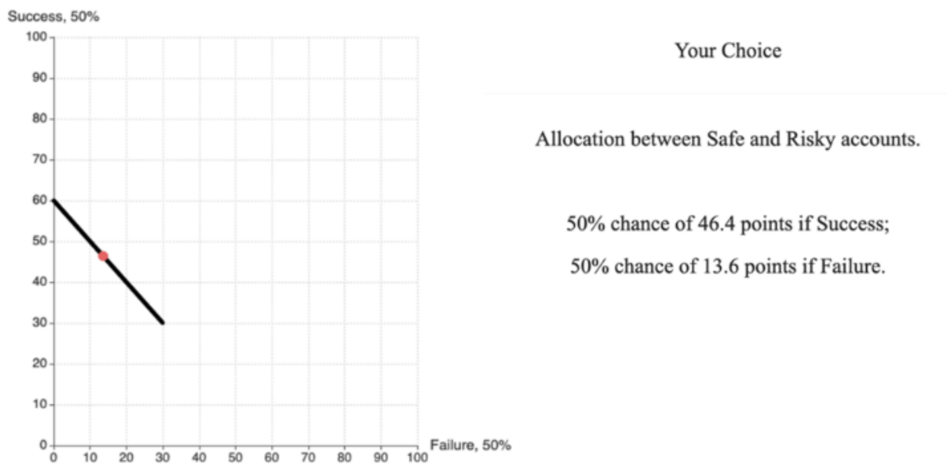


Please use a scale from 0 to 7, where 0 means "very uncertain", and 7 means you are "completely certain".

You can choose any numbers between 0 and 7 to indicate where you fall on the scale:

0 1 2 3 4 5 6 7

11. In the figure, you can see your previous choice for **another decision round** (red point). You can check other possible choices on the budget line. Please check and indicate how certain you want to choose your previous choice with the scale below.



Please use a scale from 0 to 7, where 0 means "very uncertain", and 7 means you are "completely certain".

You can choose any numbers between 0 and 7 to indicate where you fall on the scale:

0 1 2 3 4 5 6 7

(Note: The two red points in questions 10 and 11 are for illustrative purposes. Subjects will see their own choices corresponding to these two budget lines in the two conditions of the experiment.)

In the final part of the experiment, subjects complete the demographic survey (including gender, age, annual household income, education level, occupation, partner, and the number of children. We will show her final payment, including the information about which decision round is selected randomly and her corresponding choice for the bonus part in that round.