Complexity and Sophistication*

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February 15, 2017

Abstract

Complexity may overwhelm sound decisionmaking, and motivate the development of simple alternatives to solving complex financial problems. Evidence is lacking, however, on whether people who struggle with complexity are sophisticated and know when they are better off opting out. We tested the effects of complexity on financial choices in a large and diverse sample of Americans, and evaluated the sophistication of their opting out decisions. With a novel method, we randomly assigned complexity to portfolio problems. In a second treatment, we offered a simple option as an alternative to making a portfolio choice. Complexity leads those with lower skills to more often take the simple option and, as a result, earn lower returns and make more dominated choices. Structural estimates of a rational inattention model indicate that these decisions to opt out are, nevertheless, sophisticated; they are a response the higher costs of optimizing in complex settings.

*This paper benefited from many discussions with Shachar Kariv, and participants in several seminars and conferences. Special thanks to Alisdair McKay, Juan Carillo, Andrew Caplin, and Mark Dean for their thoughtful comments on earlier versions, and to Tania Gutsche, Adrian Montero, Bart Oriens, and Bas Weerman for their integral work on implementing the experiment. Francesco Agostinelli provided exemplary research assistance. This work was funded by the National Institute on Aging (NIA P30AG024962) through USC's Roybal Center for Financial Decision Making.

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JEL Classification Numbers: D81, G02, G11

Keywords: Choice under risk, Decision making quality, Rational inattention

1 Introduction

As financial instruments proliferate, individuals need to make saving, credit, and insurance choices in an increasingly complex environment. Adding options should improve welfare, but the additional complexity likely makes optimization more difficult, and may thus reduce the quality of financial decisions. These pitfalls of complexity might be avoided at low cost, however, if individuals are sophisticated and know when they should choose simple options rather than solve complex problems. If, for example, a worker knows he will struggle to make a good choice from the whole set of retirement saving rates and plans, and if he feels confident that his firm's default rate and portfolio are close to optimal, then he can accept the default and avoid both the costs of considering all his options, and the risk of making a badly suboptimal choice.

This paper presents the results of an experiment to test the effects of complexity on financial choices and to evaluate the sophistication of individuals to know when they are better off taking a simple option instead of solving a complex problem. The experiment involved 700 U.S. participants, with diverse socioeconomic characteristics, who each made 25 incentivized investment portfolio choices. The complexity of the investment problems was randomly assigned, and determined by the number of assets in which the participant could invest. Importantly, as the number of assets changed the real investment opportunities did not. The additional assets did not replicate those in the simple problem, but they were redundant; any distribution of payoffs that was feasible in a simple problem was also feasible in a complex problem, and vice versa. We therefore interpret the treatment as isolating the influence of complexity separate from other, more or less standard effects of adding options to an opportunity set.

Participants were also randomly assigned the opportunity to take a deterministic outside option rather than make an active portfolio choice. The payoff from the outside option varied randomly and was sometimes greater than the payoff associated with a "risk-free portfolio" in the investment problem, i.e. the asset allocation with a deterministic return. These outside options are meant to capture investment opportunities, such as default saving rates and portfolios, target-date retirement saving plans, or age-based college saving plans, that require less consideration or management on the part of the individual, but may not be well-tailored to her particular objectives.

The results show that, when they are required to make an active portfolio decision, respondents spend on average much more time on complex problems and choose allocations with moderately lower expected returns and lower risk. Because the experiment presents respondents with many such problems, with widely varying asset prices, we can also test whether these effects of complexity on choices are due to changes in well-behaved preferences or instead due to a decline in decision-making quality (cf. Choi et al. 2014). We find little evidence that complexity reduces decision-making quality by inducing more violations of transitivity. Other normatively appealing properties of choice are, however, eroded by complexity. We find complexity produces statistically significant increases in violations of symmetry and of monotonicity with respect to first-order dominance.

Complexity has substantial, and varied effects on the decision to opt out of a portfolio choice. When offered the opportunity to take a deterministic outside option rather than make an active portfolio choice, participants opt out 22% of the time. This decision to avoid the portfolio is correlated in expected ways with the relative value of the outside option but, on average, is uncorrelated with the complexity of the problem. This average relationship between complexity and avoidance masks heterogeneity, however. Those with the lowest levels of numeracy, financial literacy, and consistency with utility maximization in another experiment (financial decision-making skills) avoid the portfolio choice more often, even when it is simple, and are much more likely to avoid the problem when it is complex.

Especially important, we find that taking the outside option has a substantial negative effect on expected payoff; and this effect is especially large for those with the fewest decision-making skills. When they have the option to avoid the portfolio problem, on average participants' choices roughly triple the expected payoff penalty associated with complexity. This penalty associated with avoiding complexity is largest among those with the least decision-making skills. When they have the option to avoid complexity, their expected payoff declines by more than 20 percentage points. These declines in expected payoffs are almost exclusively due to the choice to opt out, and not to any effects of having the option (and not taking it) on actual portfolio choices.

While espeically low skill participants earn sharply lower returns by opting out, their decision to avoid complex portfolio problems may nevertheless be sophisticated. Those who take the outside option may know they are better off by avoiding the costs of contemplating a complex portfolio problem even if they often make a badly misguided choice.

To evaluate the sophistication of the opt out decision, we estimate the structural parameters of a rational inattention model. That model interprets systematic differences in behavior across treatments as resulting either from differences in the cost of acquiring and contemplating information about the payoffs from different choices or from differences in prior beliefs about those payoffs. We take the view that opting out in response to higher costs of information is sophisticated, while opting out because of (unfounded) changes in priors is unsophisticated avoidance. The findings support sophistication. The structural estimates indicate that complexity leads to an increase in the costs of acquiring or contemplating information about payoffs, but no discernable change in priors about those payoffs. In other words, complexity does not systematically bias participants toward opting out; instead it makes (especially the low skilled) less responsive to the relative return from dealing with it. These participants are thus more likely to avoid complexity even when doing so is especially costly.

1.1 Related Literature

This paper joins a burgeoning economics literature on the influence of complexity and the problem of evaluating large menus of choices. That literature includes several theories of complexity and models of choice from large sets. See, for example, Wilcox (1993); Al-Najjar et al. (2003); Gale and Sabourian (2005); Masatlioglu et al. (2012); Ortoleva (2013); and Caplin and Dean (2015). These theories are motivated by common sense and by a long-established tradition (cf. Simon 1957) of accounting for decision-makers' costs of obtaining relevant information and then contemplating all feasible options.

Interest in complexity and the problems caused by large choice sets is also motivated by a substantial experimental literature focused on the influence of increasing the number of alternatives from which a decision-maker may choose.[1] Iyengar and Lepper's (2000) influential field experiment in a grocery store provided evidence of a "paradox of choice," where having too many options (of jam) may demotivate buying.[2] Related studies have examined the effects of a larger number of options on portfolio choices (Agnew and Szykman 2005; Iyengar and Kamenica 2010), procrastination (Tversky and Shafir, 1992; Iyengar, Huberman and Jiang, 2004), and status quo bias (Samuelson and Zeckhauser, 1988; Kempf and Ruenzi, 2006; Dean, 2008; Ren, 2014). A common feature of these studies is that the opportunity set changes across the simple and complex conditions. This feature captures an important aspect of how complexity operates in reality, but it may confound the influence of complexity with more or less standard effects of a larger choice set.

The present paper also contributes to a small literature on the effects of more options on the quality of decision-making.[3] Using designs where some

[1] See Tse et al. (2014); Friesen and Earl (2015); Abeler and Jager (2015) for examples of other dimensions of complexity that have been studied.

[2] There are, however, many studies that find no such effect of increasing the number of choices on a menu (Scheibehenne, Greifeneder and Todd, 2010).

[3] Huck and Weizsacker (1999) find that complexity reduces the likelihood that participants maximize expected value.

(sets of) choices may violate normative axioms, a few studies find that complexity reduces the likelihood of making good choices (Caplin, Dean, and Martin, 2011; Schram and Sonnemans, 2011; Besedes et al., 2012a; Brocas et al., 2014; Kalayci and Serra-Garcia, 2015).[4] Similarly, Carlin, Kogan, and Lowery (2013) find that complexity in asset trading leads to increased price volatility, lower liquidity, and decreased trade efficiency.

This paper advances the existing literature with a combined study of three issues. First, by keeping real opportunity sets constant across treatments, the experiment separates the influence of complexity on financial choices, including decision-making quality, from other effects of increasing the number of options in a menu. Second, by implementing the experiment with a web-based panel, the experiment studies these effects of complexity on financial choices in a large and diverse sample about which much is already known. The size, heterogeneity, and existing measures of the sample allow disaggregated study and some evaluation of external validity.

Last, by offering participants a simple alternative to solving a portfolio problem, the paper evaluates the sophistication of individuals to know when they are better off opting out of a complex decision. Economics research on this form of sophistication is quite limited.[5] Our use of the structural estimates of a rational inattention for this purpose is, to our knowledge, novel. Most applications of rational inattention models have focused in macroeconomics topics (e.g., Sims 2006, or Mackowiak and Wiederholt, 2010). Microeconomic or experimental applications are less common (cites). By evaluating this form of sophistication, and its heterogeneity in the population, with a rational inattention model the paper offers new insights into the ability of different groups to make effective use of options intended to simplify their financial lives.

[4] One exception is Besedes et al. (2012b).

[5] Salgado (2006) conducted a lab experiment where participants could choose to choose from a large menu of lotteries or from a small subset of that menu.

2 Study Design

In this section, we present a conceptual framework for the study and then describe the experimental procedures.

2.1 Conceptual Framework

To isolate the effects of complexity on decision-making, we designed two problems – one simple and one complex – that share the same opportunity set. In the two problems participants are given an endowment that they have to invest in risky assets. The assets have different prices, and different payouts that depend on whether a coin comes up heads or tails. The only distinction between the simple and the complex problems is that investors in the simple problem can invest in two assets while investors in the complex problem can invest in five assets.

Simple Problem

	A	B
Prices	$0.90	$1.00
Payouts		
Heads	$0.00	$2.00
Tails	$2.00	$0.00

Complex Problem

	A	B	C	D	E
Prices	$0.90	$1.00	$0.93	$0.96	$0.99
Payouts					
Heads	$0.00	$2.00	$0.60	$1.20	$1.80
Tails	$2.00	$0.00	$1.40	$0.80	$0.20

Figure 1: Simple vs. Complex Problem

Figure 1 illustrates with an example. In the simple problem there are two investment options: assets A and B. Each share of asset A has a cost of $0.80 and each share of asset B costs $1. Each share of asset A pays $0 in the case of heads and $2 if tails. Each share of asset B pays $2 if heads and $0 if tails. The investment options in the complex problem include the two assets available in the simple problem – assets A and B – plus three additional assets – C, D, and E – each of which is a convex combination of assets A and B. In particular, asset C is composed of 70% of asset A and 30% of asset B; Asset D is composed 40% of asset A and 60% of asset B; and asset E is a combination of 10% of asset A and 90% of asset B. Because assets C, D, and E are convex combinations of assets A and B, any portfolio in the complex problem can be re-created in the simple problem, and vice versa (see the Appendix for a proof).

2.2 Sample

The study was conducted with 700 members of the University of Southern California's Understanding America Study (UAS), an Internet panel with respondents ages 18 and older living in the U.S. Respondents are recruited by address-based sampling. Those without Internet access at the time of recruitment are provided tablets and Internet access. About twice a month, respondents receive an email with a request to visit the UAS site and complete questionnaires.

The study consisted of one baseline and one follow-up survey. In the baseline survey participants were administered Choi et al.'s (2014) choice under risk experiment. As explained below, these choices can be used to construct baseline measures of decision-making skills. In the follow-up survey we administered a collection of the simple and complex problems described above.

In addition, panel members provided a variety of information collected in previous UAS modules. This information includes basic demographics and socioeconomic data. Panel members also completed numeracy and financial literacy tests.

2.3 Experimental Design

The experiment had a 2 x 2 between-subjects design, where participants were randomly assigned to one of four treatment arms as shown in the table below.[6] One manipulation involved varying the number of investment options:

[6] Study participants were randomly assigned to one of the four treatment arms using a stratified sampling and a re-randomization procedure. In particular, we stratified on: 1)

Arms I and II were assigned to the simple problem with two assets while arms III and IV were assigned to the complex problem with five assets.

	Simple Problem	Complex Problem
Forced to Invest	I	III
Option to Avoid Investment	II	IV

The other manipulation involved offering participants the option of avoiding the investment problem. In particular, participants assigned to arms II and IV were offered the choice between making the investment decision or taking an "outside option" of \$2, \$5, \$10, \$15, or \$20. The amount of the outside option was randomly varied across participants.

This experimental design addresses three different questions. The effects of complexity on decision-making are revealed by comparing treatment arms I and III. By comparing treatment arms II and IV we examine if increased complexity affects the rate at which participants avoid the portfolio decision problem. Finally, by comparing the payoffs of arms III and IV, we investigate whether those who avoid the complex investment problem end up earning higher returns than they would have otherwise.

whether the participant had a score in the financial literacy test above the median score; 2) whether the participant had a score in the numeracy test above the median score; 3) whether the participant had risk aversion above the median; and 4) the tercile in the distribution of the CCEI score (i.e., consistency with GARP). The re-randomization procedure was as follows. We chose to balance the following variables: a) age; b) whether owned stocks; c) less than high school; d) high school graduate; e) some college; f) college graduate; g) score in numeracy test; h) score in financial literacy test; i) risk aversion; and j) CCEI score. For each one of these 10 control variables and for each one of the 4 treatment arms, we ran a separate regression (i.e., 40 regressions in total) of the control variable on the treatment arm dummy (the omitted group was the other 3 treatment arms) and stratum-dummies. The randomization was re-done until the t-statistics on the treatment arm dummies in all 40 regressions were smaller than 1.4 in absolute value. See the Online Appendix for more details.

2.4 Experimental Task

The experimental task involved variations on the examples discussed in section I.A. Participants had to invest their experimental endowment in two (treatment arms I and II) or five (treatment arms III and IV) assets. They were given information about the price (per share) of assets and how much assets paid depending on the coin toss. Participants made their investment choices by indicating the number of shares they wanted to buy of each asset.

To illustrate, Online Appendix Figure 1 shows a screenshot of the interface treatment arms I and II used to make their investment choices. The table at the top of the screen shows the prices of assets A and B and their payouts. The participant was then informed about the amount available for investing and prompted to make her investment choices. The graph below the table displays two bars: the first bar shows the number of shares owned of asset A; the second bar shows the number of shares owned of asset B. Participants made their investments by either dragging the bars up and down or by clicking on the + and – buttons.[7]

Treatment arms III and IV used a similar interface to make their investment choices (see Appendix Figure 2). The only distinction is that they were shown information about 5 assets – A, B, C, D, and E – and the graph displayed 5 bars. Participants were shown a tutorial video to learn how to use the interface and had two rounds to practice – participants assigned to the simple and complex conditions were shown the same tutorial video and were administered the same practice trials; in both the tutorial video and in the practice trials the endowment could be invested in 3 assets.[8] We randomized the initial levels of the bars (see Appendix for more details).

The interfaces for treatment arms II and IV were slightly different because

[7] The interface was such that participants always invested 100% of their experimental endowment.

[8] https://www.youtube.com/watch?v=TNr3Wgakczk&feature=youtu.be We conducted cognitive interviews to make sure that participants understood the tutorial video and what they were supposed to do in the experimental task.

these groups were offered the option to avoid the investment decision-making. Online Appendix Figure 3 shows a screenshot of the interface for treatment arm II. It differs from the interface for treatment arm I (Online Appendix Figure 1) in two ways. First, the graph with the bars is not shown. Second, the sentence "How many shares of each asset do you want to buy?" is replaced by a prompt for the subject to choose between investing the experimental endowment (button "Invest $X") and taking the outside option (button "Receive $Y"). If she clicked on the first button, the bars were unveiled and she could make her investment choices using the same interface used by treatment arm I. If she clicked on the second button, she was presented with the next decision-making problem.

Participants were presented with 25 different investment problems (one of the 25 problems was randomly selected for payment; the participant was paid the outside option if in the problem selected for payment she chose to avoid). It is useful to conceive of each problem as a two-dimensional budget line, where the axes correspond to the payoffs paid in the two states of the world: heads (y-axis) and tails (x-axis). The y-axis intercept is the payoff paid if the endowment is invested all on heads (and the coin comes up heads) and the x-axis intercept is the payoff paid if the endowment is invested all on tails (and the coin comes up tails).

We selected the investment problems by randomly selecting 10 sets of budgets, each consisting of 25 budget lines. The lines were chosen at random to generate substantial variation in the relative prices of the assets and in the endowment available for investment.[9] The order in which the budget lines

[9] We used a procedure similar to the one used by Choi et al. (2014) to draw budget lines. First we randomly selected between the x-axis and y-axis. Say the y-axis was selected. We would then randomly select the y-axis intercept by drawing uniformly between $10 and $100. If the selected y-axis intercept was greater than $50, we would draw the x-axis intercept uniformly between $10 and $100. If the selected y-axis intercept was smaller than $50, we would draw the x-axis intercept uniformly between $10 and $50. For 79 participants (about 11% of the sample) the budget line was randomized at the individual level using a procedure similar to the described above: 1) randomly select x- or y-axis; 2) if x is selected, draw x-axis intercept uniformly between $1 and $100; and 3a) if x-axis intercept is greater than $50, draw y-axis intercept uniformly between $1 and $100 or 3b) if x-axis intercept is smaller

were presented to each subject was also randomized.

Each budget line was converted into a simple problem using the following procedure. Let asset 1 be the asset that pays \$2 if the coin comes up tails and \$0 otherwise and let asset 2 be the asset that pays \$2 if the coin comes up heads and \$0 otherwise. We normalized the price of asset 2 to \$1 such that the endowment was equal to the y-axis intercept divided by 2 (rounded to closest integer for convenience). The price of asset 1 was equal to the y-axis intercept divided by the x-axis intercept (rounded to closest multiple of 0.1). We randomized the order in which assets 1 and 2 were shown on the screen (that is, asset 1 could be shown on the first column and first bar or on the second column and second bar).

To construct a complex analogue of a simple problem, we created assets 3, 4, and 5 by taking convex combinations of the prices and payouts of assets 1 and 2. In particular, the price of asset 3 was equal to 0.7 times the price of asset 1 plus 0.3 times the price of asset 2. Similarly, the payout of asset 3 was \$0.60 (= 0.7 * \$0 + 0.3 * \$2) when the coin came up heads and \$1.40 (= 0.7 * \$2 + 0.3 * \$0) when it came up tails. Asset 4 was composed 40% of asset 1 and 60% of asset 2; and asset 5 was a combination of 10% of asset 1 and 90% of asset 2. We randomized the order in which assets 1, 2, 3, 4, and 5 were shown, from left to right, on the screen.

2.5 Measuring the Quality of Decision-making

We exploit the within-subject variation in the endowment and in asset prices to construct individual-specific measures of decision-making quality. We examine four measures of the quality of decision-making. First, we study whether choices violate the General Axiom of Revealed Preference (GARP). Choi et al. (2014) and Kariv and Silverman (2013) argue that consistency with GARP is a necessary but not sufficient condition for high quality decision-

than \$50, draw y-axis intercept uniformly between \$50 and \$100. We dropped budget lines where y-axis intercept $<$ 0.05 * x-axis intercept.

making.This view draws on Afriat (1967), which shows that if an individual's choices satisfy GARP in a setting like the one we study, then those choices can be rationalized by a well-behaved utility function. Consistency with GARP thus implies that the choices can be reconciled with a single, stable objective. Here we will assess how nearly individual choice behavior complies with GARP using Afriat's (1972) Critical Cost Efficiency Index (CCEI). The CCEI is a number between zero and one, where one indicates perfect consistency with GARP. The degree to which the index falls below one may be viewed as a measure of the severity of the GARP violations.[10]

Consistency with GARP may be viewed as too low a standard of decision-making quality because it treats all stable objectives of choice as equally high quality.[11] A more stringent requirement would also require monotonicity of preferences and, because the realization of the state (heads or tales) should not influence the utility function from money, symmetry of demand for these assets. In particular, violations of monotonicity with respect first-order stochastic dominance (FOSD) – that is, the failure to recognize that some allocations yield payoff distributions with unambiguously lower returns – may be reasonably regarded as errors and provide a compelling criterion for decision-making quality. Similarly, asymmetries of demand with respect to the state of the world might also be regarded as eveidence of lower quality decision-making.

[10]Formally, the CCEI measures the fraction by which all budget lines described above must be shifted in order to remove *all* violations of GARP. Put precisely, suppose the choice data for individual i are given by $\mathbf{p}^i, \mathbf{x}^i$ where the vector $\mathbf{p}^i$ describes the relative prices (budget sets) i faced, and $\mathbf{x}^i$ describes the choices made from those budget sets. Then for any number $0 \leq e \leq 1$, define the direct revealed preference relation

$$\mathbf{x}^i R^D(e) \mathbf{x}^j \Leftrightarrow e\mathbf{p}^i \cdot \mathbf{x}^i \geq \mathbf{p}^i \cdot \mathbf{x}^j,$$

and define $R(e)$ to be the transitive closure of $R^D(e)$. Let e^* be the largest value of e such that the relation $R(e)$ satisfies GARP. The CCEI is the e^* associated with the data set.

[11]For example, consider a participant that always allocates all her endowment to heads. This behavior is consistent with maximizing the utility function $U(x_{heads}, x_{tails}) = x_{heads}$ and would generate a CCEI score of one. However, these choices are hard to justify because for some of the budget lines that a subject may face, allocating all the endowment to heads means allocating all the endowment to the more expensive asset, a violation of monotonicity with respect to first-order stochastic dominance.

We use the distribution of possible payoffs to assess how closely individual choice behavior complies with the dominance principle. To illustrate a violation of first-order stochastic dominance, suppose that the y-axis intercept is larger than the x-axis intercept (such that the price of tails is higher than the price of heads) and that a participant chooses an allocation (x,y) that is on the "shorter side" of the 45 degree line. It is possible to show that there is an allocation (y,z) on the "longer side" of the 45 degree line that yields an unambiguously higher payoff distribution than (x,y) – i.e., z > x. The third measure of decision-making quality is the fraction of times in which participants selected a dominated portfolio.[12]

Following Choi et al. (2014), we calculated a FOSD score as follows. If there was no feasible allocation that dominated the selected allocation, then the FOSD score was assigned the highest value of 1. If the selected allocation was dominated, then we calculated the FOSD score as $\frac{x+y}{z+y}$, which is equal to the expected return of the selected allocation as a fraction of the maximal expected return. We also calculated the FOSD score for participants assigned to treatment arms II and IV. We used the same procedure described above to calculate the FOSD when subject chose to make investment decisions. However, when they chose to avoid decision-making, we calculated the FOSD score as $\min\left\{1, \frac{\text{outside option}}{\text{risk free return}}\right\}$.

To provide a unified measure of violations of GARP, monotonicity with respect to first order stochastic dominance, and of symmetry of demand, we combine the 25 choices for a given subject with the mirror image of these data obtained by reversing the prices for heads and tails and the actual choices. More specifically, if (x_1, x_2) were actually chosen subject to the budget constraint $p_1x_1 + p_2x_2 = m$, then we assume (x_2, x_1) would have been chosen subject to the mirror-image budget constraint $p_2x_1 + p_1x_2 = m$. We then compute the CCEI for the data set that combines the actual choice data with their mirror images. (Cf. Choi et al., 2014.)

[12] We drop choice sets where the price of asset 1 is equal to \$1. In these cases all portfolios yield the same expected return.

3 Descriptive Results

3.1 Summary Statistics

We begin with summary statistics of the sample showing that the controls are balanced across the treatment arms. The first four columns of Table 1 show means, separately by treatment arm (for continuous variables the standard deviation is displayed in parentheses). Participants ranged in age from 18 to 90 with an average and median age of 48. There is also substantial variation in schooling (21% had a high school diploma or less while 57% graduated from college) and in annual household income (with 25% making $30,000 or less and 20% making $100,000 or more). About half of the sample owned stocks with varying degrees of numeracy and financial literacy (the standard deviation of these variables, which corresponds to the fraction of correct answers in numeracy and financial literacy tests, is respectively 0.25 and 0.24).

The last four columns of Table 1, which present the p-values of tests of differences in means, show that the observable characteristics are orthogonal to treatment assignment. Out of 84 comparisons, 4 are significant at 10% and one is significant at 5%. Notice that some of these variables – in particular male and the income categories – were not used in the re-randomization procedure.

	Means by Treatment Arm (Std. deviation in parenthesis)				*P-value Test*			
	I	II	III	IV	I = III	I = IV	II = IV	III = IV
Individual Characteristics								
Age*	48.7	47.8	48.4	47.2	0.82	0.30	0.70	0.48
	(13.74)	(14.74)	(16.35)	(14.71)				
{Male}	0.48	0.45	0.47	0.51	0.96	0.56	0.29	0.54
Numeracy*	0.49	0.46	0.49	0.49	0.90	0.80	0.39	0.91
	(0.27)	(0.24)	(0.24)	(0.25)				
Financial Literacy*	0.71	0.67	0.68	0.72	0.15	0.87	0.08	0.10
	(0.24)	(0.23)	(0.24)	(0.23)				
{Own Stocks*}	0.49	0.52	0.49	0.51	0.97	0.75	0.83	0.79
CCEI at Baseline*	0.88	0.90	0.88	0.90	0.97	0.31	0.94	0.39
	(0.14)	(0.13)	(0.16)	(0.13)				
Risk Aversion at Baseline*	0.67	0.67	0.68	0.68	0.42	0.52	0.75	0.83
	(0.13)	(0.13)	(0.14)	(0.13)				
Education								
{Less than High School*}	0.03	0.07	0.05	0.03	0.44	0.73	0.08	0.26
{High School Graduate*}	0.17	0.20	0.16	0.16	0.70	0.69	0.32	1.00
{Some College*}	0.20	0.22	0.24	0.21	0.33	0.80	0.86	0.47
{College Graduate*}	0.60	0.52	0.55	0.61	0.41	0.83	0.09	0.30
Annual Household Income								
{Less than $10,000}	0.07	0.07	0.06	0.04	0.75	0.14	0.22	0.27
{Between $10,000 and $20,000}	0.10	0.04	0.08	0.07	0.70	0.28	0.39	0.51
{Between $20,000 and $30,000}	0.10	0.12	0.12	0.13	0.55	0.49	0.95	0.95
{Between $30,000 and $40,000}	0.06	0.12	0.10	0.10	0.11	0.10	0.67	1.00
{Between $40,000 and $50,000}	0.09	0.10	0.10	0.06	0.84	0.27	0.15	0.20
{Between $50,000 and $60,000}	0.07	0.08	0.06	0.08	0.58	0.78	0.91	0.40
{Between $60,000 and $75,000}	0.10	0.16	0.17	0.15	0.08	0.20	0.80	0.59
{Between $75,000 and $100,000}	0.18	0.12	0.16	0.15	0.62	0.46	0.51	0.83
{Between $100,000 and $150,000}	0.11	0.13	0.07	0.15	0.19	0.34	0.62	0.03
{More than $150,000}	0.11	0.06	0.07	0.08	0.19	0.31	0.34	0.72
N	178	181	158	183				

Notes: This table reports summary statistics and test whether controls are balanced across the different treatment arms. The first four columns report means for each treatment arm. The standard deviations of continuous variables are reported between parentheses. The last four columns report p-values of tests of the differences in means. Curly brackets indicate dichotomous variables. Asterisks indicate the 10 variables that were used in the re-randomization procedure.

Table 1: Summary Statistics

3.2 Effect of Complexity on Portfolio Choices

Table 2 investigates if complexity affects portfolio choices by comparing the return and risk of the portfolios selected in treatment arm III (complex without outside option) to those of the portfolios selected in treatment arm I (simple without outside option).[13] It presents results from OLS regressions of the dependent variables listed in the columns – namely the expected return in U.S. dollars, the log of expected return, the rate of return (i.e., the net expected return as a fraction of the endowment) multiplied by 100, and the standard deviation of the portfolio. Standard errors are clustered at the individual level.

Complexity leads participants to select portfolios with lower return and lower risk. The portfolios selected by participants in the complex condition have an expected return \$1.27 lower than the portfolios selected by participants in the simple condition, corresponding to a 4%-5% decrease. The reduction in the rate of return is even larger. The portfolios selected by participants in the complex condition have a rate of return 8 percentage points lower than the portfolios selected by those in the simple condition. All of these differences are statistically significant at 1%. Finally, the standard deviation of the portfolios selected in treatment arm III is \$2.08 lower than of the portfolios selected in treatment arm I.

To put these estimates into perspective, Online Appendix Table 1 estimates the cross-sectional relationship between having a college degree and portfolio choices (the sample is restricted to treatment arm I – simple without oustide option). The effect of complexity corresponds approximately to one-half of the "returns to a college degree."

The theory of "financial competence," introduced by Ambuehl, Bernheim and Lusardi (2014), inteprets these effects of complexity on returns and risk as the result of lower quality of decision-making. Financial competence compares the choices an individual makes when a decision problem is framed simply to

[13] Before showing the effects of complexity, we note evidence that participants assigned to the complex problem encountered more difficulties. Comparing the amount of time spent making choices in treatment arm III versus treatment arm I, we find that the typical participant assigned to the simple condition spent 10 minutes and 40 seconds making choices, and the typical participant assigned to the complex condition spent 19 minutes and 56 seconds. That is, participants in treatment arm III spent typically 87% more time on the choices than those in treatment arm I. This difference is statistically significant at 1% confidence level.

his choice when the same decision problem is framed in a complex manner. Choices in the simple frame are interpreted as normative benchmarks; the larger the gap between simple and complex framed choices, the lower the individual's financial competence.

	Expected Return	*Ln(Expected Return)*	*Rate of Return * 100*	*Standard Deviation*
{Complexity}	-$1.27	-0.05	-7.98	-$2.08
	[0.40]***	[0.02]***	[2.32]***	[0.86]**
Constant	$28.25	3.28	19.76	$12.09
	[0.29]***	[0.01]***	[1.69]***	[0.64]***

Notes: This table compares the portfolio choices in treatment arm III (complex without outside option) to the portfolio choices in treatment arm I (simple without outside option). Curly brackets indicate dichotomous variables. Standard errors clustered at the individual level in brackets. The analysis excludes 275 choice sets where all portfolios yield the same expected return. N Choices = 8,125. N Participants = 336.

Table 2: Effects of Complexity on Portfolio Choices

Consistent with Ambuehl, et al. (2014), a primary motivation for our study is the hypothesis that individuals differ in their financial competence or decision-making skills, and that those with fewer skills are affected differently by complexity. Different from Ambuehl et al. (2014), we evaluate this hypothesis by formulating a measure of decision-making skills separate from the reaction to complexity. Specifically we identify decision-making skills with the first component from a principal component analysis of three variables: the score in a numeracy test, the score in a financial literacy test, and consistency with GARP measured at baseline.[14] The measure was re-scaled to range from 0 to 1. Figure 2 shows non-parametric regressions of expected return conditional on decision-making abilities, separately for treatment arm I (simple without outside option) and treatment arm III (complex without

[14] We stratified the randomization on these three variables in anticipation of investigating whether the effects of complexity vary by these skills.

outside option). The dashed black curve shows the expected return for those assigned to the simple condition. The grey solid curve shows the expected return for those assigned to the complex condition. The shaded areas show 95% confidence bands. The difference between the two curves gives the effect of complexity on the expected return at any given level of decision-making skills.

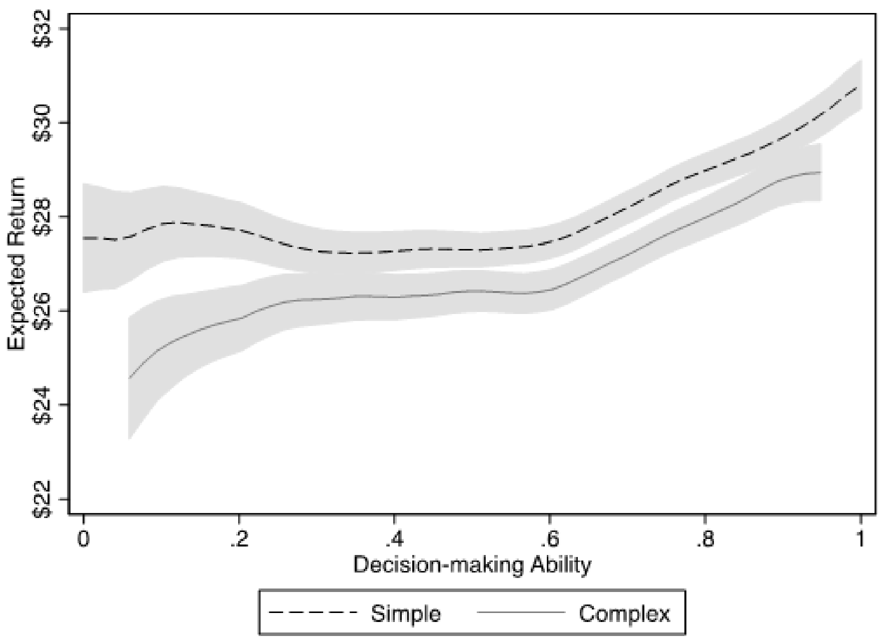

Figure 2: Effects of Complexity on Portfolio Choice, By Decision-making Skill

Notes: This figure investigates if the effect of complexity differs by decision-making skills. It plots non-parametric regressions of the expected return conditional on decision-making skills, separately for treatment arm III (complex without outside option) and treatment arm I (simple without outside option). The non-parametric regressions are estimated using kernel-weighted local-mean polynomial regressions (the rule-of-thumb bandwidth estimator and the epanechnikov kernel function are used). The shaded areas show 95% confidence bands. N Choices = 4,400 (simple) and 3,950 (complex). N Participants = 176 (simple) and 158 (complex). We excluded choice sets where all portfolios yielded the same expected return and dropped 2 participants for whom numeracy and/or financial literacy was missing.

Figure 2 shows little evidence that complexity has a stronger effect on those with low decision-making skills. The dashed black curve is always above the solid gray curve, indicating that complexity reduces expected returns at any level of decision-making skills, but the two curves are parallel for most levels of decision-making skills. It is only for decision-making skills levels below 0.3 that the gap between the two curves starts to widen, but fewer than 10% of participants have such low levels of decision-making skills.

3.3 Complexity and Decision-making

Though we have shown that complexity affects portfolio choices, it is unclear whether participants exhibit different risk preferences in the two conditions or if instead complexity errodes the quality of decision-making which results in lower risk. Table 3 compares the quality of the choices made in treatment arm III (complex without outside option) to the choices made in treatment arm I (simple without outside option). See section 2.5 for a discussion of how these measures of decision-making quality are constructed. With the exception of the fraction of choices in which participants picked a dominated portfolio (third column), the measures are such that higher values correspond to higher quality of decision-making.

	GARP *CCEI*	GARP+FOSD *CCEI*	*% Dominated* *Portfolio*	FOSD *FOSD Score*
{Complexity}	0.03 [0.02]	-0.03 [0.03]	0.09 [0.02]***	-0.01 [0.01]**
Constant	0.86 [0.02]***	0.69 [0.02]***	0.28 [0.02]***	0.94 [0.01]***
P-value Wilcoxon	0.62	0.02	0.00	0.00

Notes: This table investigates if complexity affects the quality of decision-making. It compares measures of the decision-making quality of treatment arm III (complex without outside option) to the decision-making quality of treatment arm I (simple without outside option). Curly brackets indicate dichotomous variables. Robust standard errors in brackets. N Participants = 336. The last two columns exclude choice sets where all portfolios yielded the same expected return

Table 3: The Effect of Complexity on Decision-making Quality

There is no evidence that complexity induces more violations of transitivity. The difference in means indicates that the choices of participants in treatment arm III comply a bit more closely with GARP than treatment arm I, but this difference is not statistically significant.[15] As discussed in section I.E, compliance with GARP is a necessary but not sufficient condition for high-quality decision-making. Violations of monotonicity with respect to first-order stochastic dominance (FOSD) provide a compelling criterion for decision-making quality.

When we look at a unified measure of violations of FOSD and GARP via an evaluation of the symmetry of choices (second column), the coefficient on the complexity indicator variable changes from positive to negative, indicating that complexity increases violations of symmetry. The difference in means is not statistically significant, but we can reject the null of a Wilcoxon rank-sum test at 5%. That is, participants assigned to the complex condition have on

[15] Appendix Figure 4 shows the cumulative distribution of the CCEI score, separately for treatment arms I and III. It illustrates that this result is mostly driven by a difference in mass at lower levels of CCEI.

average lower ranks (i.e., lower decision-making quality) in the distribution of the unified measure of violations of GARP and FOSD than participants assigned to the simple condition.[16]

Complexity also increases violations of monotonicity with respect to first-order stochastic dominance. The third column of Table 3 shows that participants assigned to the complex condition are 9 percentage points more likely to pick a dominated portfolio than participants assigned to the simple condition. The difference in means in the FOSD score (last column), which is statistically significant at 5%, confirms this result. To put into perspective, Appendix Table 2 shows that participants with a college degree are 14 percentage points less likely to pick a dominated portfolio than their peers.

Finally, we provide evidence against the hypothesis that complexity reduces portfolio returns strictly because participants exhibit reveal well-defined preferences with greater risk aversion in the complex condition. In Figure 3 we plot the cumulative distribution of portfolio risk, separately for the simple and complex conditions, for choice sets in which all portfolios yielded the same expected return. In these cases, the optimal choice of any risk averse agent is the risk free portfolio since any other portfolio involves more risk but no additional return. Figure 3 suggests that participants assigned to the complex condition (treatment arm III) pick portfolios with greater risk than participants assigned to the simple condition (treatment arm I). We can reject the null of a Wilcoxon test at 1%, indicating that participants assigned to the complex condition have on average higher ranks in the distribution of portfolio risk than participants assigned to the simple condition.

[16] Angrist and Imbens (2009) argue that "[i]f the focus is on establishing whether the treatment has some effect on the outcomes, rather than on estimating the average size of the effect, such rank tests [as the Wilcoxon] are much more likely to provide informative conclusions than standard Wald tests based differences in averages by treatment status... As a general matter it would be useful in randomized experiments to include such results for rank-based p-values, as a generally applicable way of establishing whether the treatment has any effect." (pp. 22-23)

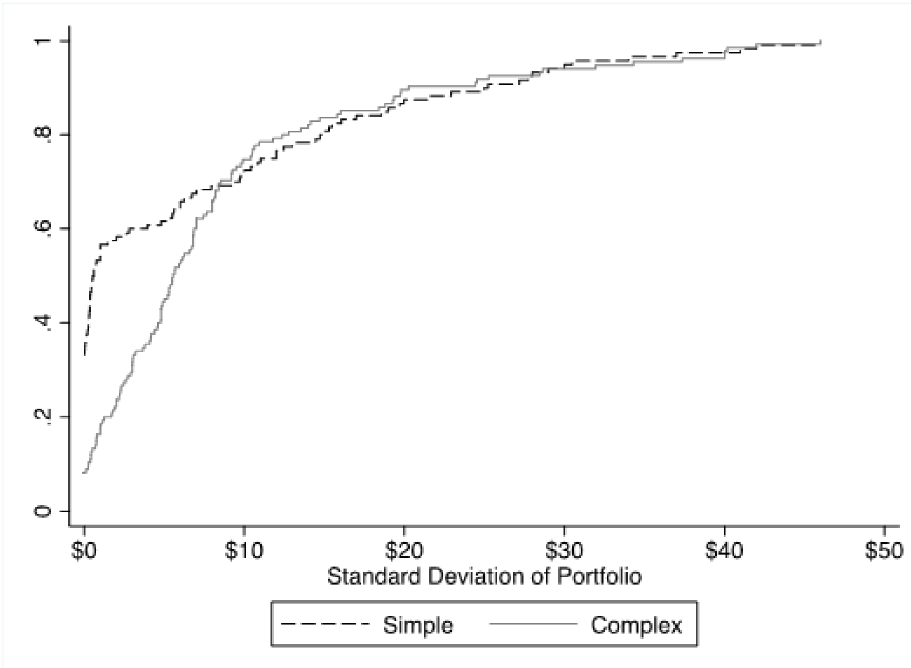

Figure 3: Cumulative Distribution of Portfolio Risk (in Choice Sets where all Portfolios Yield the Same Expected Return)

Notes: This figure investigates if participants assigned to the complex condition exhibit greater risk aversion. It compares the risk of portfolios picked by treatment arm III (complex without outside option) to the risk of portfolios picked by treatment arm I (simple without outside option) in choice sets where all portfolios yielded the same expected return. N Choices = 255. N Participants = 137.

3.4 The Decision to Avoid

The preceding analysis shows that complexity has modest, negative effects on the quality of decision-making. We now consider the consequences of allowing individuals to avoid complexity by choosing a simple alternative to solving a complex problem. In teatment arms II and IV participants were given the opportunity to take an outside option rather than make active portfolio choices. In Table 4 we compare the avoidance behavior in treatment arm IV, where participants were assigned to the complex condition and had the outside option, to the avoidance behavior in treatment arm II, where particpants had the outside option but were assigned to the simple condition.

The first column of Table 4 shows that participants assigned to the simple condition opt out in 22% of choices. The first column also shows that on average there is no effect of complexity on choice avoidance. Complexity increases choice avoidance by 1 percentage point, but this effect is not statistically significant. In the second column we add controls for other factors that may influence the avoidance decision, namely the amount available for investing (i.e., the endowment), the price of the asset that pays $2 if the coin comes up tails, and the dollar amount of the outside option. The avoidance behavior responds in expected ways to incentives: Participants are 2.5 percentage points less likely to avoid when the endowment increases 10 percent; 0.4 percentage points more likely to avoid when the price of tails increases in 10 percent; and 1.1 percentage points more likely to avoid when the outside option increases in 10 percent.

	{Avoid Investment Decision}		
{Complexity}	0.01 [0.03]	0.00 [0.02]	0.14 [0.08]*
Decision-making Skill * {Complexity}	-	-	-0.21 [0.12]*
Decision-making Skill	-	-	-0.13 [0.09]
Ln(Endowment)	-	-0.25 [0.02]***	-0.25 [0.02]***
Ln(Price of Tails)	-	0.04 [0.01]***	0.04 [0.01]***
Ln(Outside Option)	-	0.11 [0.02]***	0.11 [0.02]***
Constant	0.22 [0.02]***	0.81 [0.06]***	0.88 [0.08]***

Notes: This table investigates if complexity leads to decision-making avoidance. It compares the avoidance behavior of treatment arm IV (complex with outside option) to the avoidance behavior of treatment arm II (simple with outside option). Curly brackets indicate dichotomous variables. Decision-making skills is the first component of a principal component analysis using the score in a numeracy test, the score in a financial literacy test, and Afriat's Critical Cost Efficiency Index (CCEI) measured at baseline; the measure of decision-making skills is normalized to range from 0 to 1. Standard errors clustered at the individual level in brackets. N Choices = 9,050. N Participants = 362. We dropped 2 participants for whom numeracy and/or financial literacy was missing.

Table 4: The Effects of Complexity on Decision-Making Avoidance

We showed in Figure 2 that the effect of complexity on portfolio returns does not much vary with decision-making skills, but the effect of complexity on choice avoidance may nevertheless vary with participants' skills. Indeed, we would expect higher rates of avoidance for those who, due to lower decision-making skills, incur higher costs of obtaining information about and contemplating a complex problem. In the third column we re-estimate the results including the measure of decision-making skills and interacting it with the complexity indicator.

The results of column 3 show that complexity leads to more choice avoidance among the low skilled. Participants with the lowest level of decision-making skills are 14 percentage points more likely to avoid complex decision-making. The coefficient on the interaction term is negative, indicating that participants with higher decision-making skills are less likely to avoid in response to increased complexity. Indeed, the point estimate of this interaction term indicates that the highest skilled are more likely to avoid a simple problem than a complex one.[17]

3.5 Consequences of Avoidance

The preceding results indicate that, when given the option, participants often avoid portfolio choice and prefer to take a simple outside option. This opting out is especially common among the low skilled when facing a complex portfolio problem. Here we consider consequences for outcomes of giving participants the option to avoid (complex) portfolio problems. We describe both the effects on expected returns and on an aspect of decision-making quality.

In Table 5 we study the effects of offering the option to avoid the portfolio problem on the expected payoff, the log of the expected payoff, the rate of return (i.e., the expected payoff as a fraction of the endowment) multiplied by 100, and compliance with FOSD (measured by the FOSD score). If a subject chose to invest, the expected payoff is equal to the expected return and the FOSD score is as defined above (Section 2.5). If a subject chose to avoid, the expected payoff is equal to the outside option and the FOSD score is equal to $\min\{1, (\text{outside option})/(\text{risk free return})\}$.

Table 5 shows 3 sets of coefficients. The coefficient on the complexity indicator compares the choices of treatment arm III (complexity without outside option) to the choices of treatment arm I (simple without outside option); it

[17] This attraction to complex problems by the highest skilled may reflect a (mistaken) belief that, with more assets available, complex problems allow for higher returns.

estimates the effect of complexity when no outside option is available, reproducing some of the results shown in tables 2 and 3. The coefficient on the interaction between the complexity indicator and the outside option indicator compares the choices of treatment arm IV (complexity with outside option) to the choices of III (complexity without outside option); it estimates the effect of having the outside option in the complex condition.[18]

	Expected Payoff	*Ln(Expected Payoff)*	*Rate of Return * 100*	*FOSD Score*
{Complexity} * {Outside Option}	-$2.21	-0.15	-8.99	-0.06
	[0.47]***	[0.03]***	[2.48]***	[0.01]***
{Complexity}	-$1.27	-0.05	-7.99	-0.01
	[0.40]***	[0.02]***	[2.32]***	[0.01]**
Constant	$28.25	3.28	19.75	0.94
	[0.29]***	[0.01]***	[1.68]***	[0.01]***

Notes: This table investigates if having the option to avoid complexity mitigates its effects. It compares the payoffs of treatment arms III (complex without outside option) and IV (complex with outside option) to the payoffs of treatment arm I (simple without outside option). The payoff is equal to the outside option if the participant chose to avoid the investment decision-making and equal to the portfolio return if the subject chose to invest. Curly brackets indicate dichotomous variables. For participants in treatment arm IV who chose to avoid complexity the FOSD score is equal to outside option divided by the return of the risk-free portfolio if outside option < return of risk free-portfolio and equal to 1 otherwise. Standard errors clustered at the individual level. N Choices = 12,558. N Participants = 519. We exclude choice sets where all portfolios yielded the same expected return.

Table 5: The Effects of Having the Option to Avoid Complex Decision-Making

We find no evidence that the possibility of opting out helps participants avoid suboptimal choices in the complex portfolio problem. To the contrary, the availability of the outside option amplifies the effects of complexity. The outside option lowers the portfolio returns even further, reducing the expected return by 15 percent and the rate of return by 9 percentage points (relative to the complex condition with no outside option). The outside option also

[18] Note, for ease of exposition, this is not a difference-in-difference specification, which would include observations from treatment arm II. This simpler specification avoids the need to sum four coefficients to obtain the point estimate of interest.

deteriorates the quality of decision-making, reducing compliance with FOSD. The effect is large, four times larger than the effect of complexity when there is no outside option. This effect is largely driven by the fact that participants sometimes opt out when the outside option pays less than the risk-free portfolio.[19]

Table 6 shows that the penalty associated with avoiding complexity is especially large for those with the least decision-making skills, who are more likely to avoid in the face of increased complexity. It compares the choices of treatment arm IV (complexity with outside option) to the choices of treatment arm III (complexity without outside option), allowing for the effect of the outside option to vary with decision-making skills. When offered the outside option, participants with the lowest level of decision-making skills have a payoff 40 percent lower than they would have otherwise. There is also a large reduction in compliance with a FOSD principle. High decision-making skills protect against the negative effects of having the outside option. The coefficient on the interaction term is positive and the point estimates indicate that the effect of the outside option for someone with the highest level of decision-making skills is close to zero.

[19] In Appendix Table 3 we estimate an upper bound of the effect on portfolio choices of having the option to opt out by replacing – in those opportunity sets in which the participant exercised this option – the outside option by the lowest expected return.

	Expected Payoff	*Ln(Expected Payoff)*	*Rate of Return * 100*	*FOSD Score*
Decision-making Skill * {Outside Option}	$4.12	0.38	24.33	0.13
	[2.25]*	[0.16]**	[12.18]**	[0.06]**
{Outside Option}	-$4.86	-0.39	-24.47	-0.15
	[1.41]***	[0.11]***	[7.19]***	[0.04]***
Decision-making Skill	$4.88	0.21	24.23	0.12
	[1.27]***	[0.05]***	[6.68]***	[0.03]***
Constant	$24.11	3.10	-2.45	0.86
	[0.69]***	[0.03]***	[3.48]	[0.02]***

Notes: This table investigates if the effects of having the option to avoid complexity differ by decision-making skills. It compares the payoffs of treatment arm IV (complex with outside option) to the payoffs of treatment arm III (complex without outside option). The payoff is equal to the outside option if the participant chose to avoid the investment decision-making and equal to the portfolio return if the subject chose to invest. For participants in treatment arm IV who chose to avoid complexity the FOSD score is equal to outside option divided by the return of the risk-free portfolio if outside option < return of risk free-portfolio and equal to 1 otherwise. Standard errors clustered at the individual level. N Choices = 8,203. N Participants = 340. We excluded choice sets where all portfolios yield the same expected return and dropped 1 subject for whom numeracy and/or financial literacy was missing.

Table 6: The Effects of Having the Option to Avoid by Decision-making Skill (Complex Condition)

4 Sophistication – Structural Estimates

We find that low-skilled participants, especially, earn much lower returns and more often make dominated choices when offered a simple alternative to solving a (complex) portfolio problem. In one view, these results imply a lack of sophistication; the low-skilled appear not to know when they are better off taking a simple alternative to solving a more complex problem. This view is bolstered by Figure 2 which showed that, when participants were forced to solve the portfolio problem, the effects of complexity on expected returns do not much differ by decision-making skills. Thus, a sophisticated but low-skilled participant should not take the outside option more often than her high-skilled counterpart.

This interpretation of the evidence does not, however, account for the costs of attending to the portfolio problem. A plausible hypothesis is that lower-skilled participants face higher costs of processing information about and evaluating the portfolio problem in a complex choice environment. Thus, even though their performance would not suffer differentially if they actually attended to and solved the complex portfolio problem, they rationally opt out and thus trade attention costs for lower returns.

4.1 Rational Inattention Model

Attention costs are not observable. To draw inference about their importance and evaluate the hypothesis of sophisticated, though costly, opting out we will therefore structure our analysis with a rational inattention model based on Sims (2003) and formulated by Matějka and McKay (2015). Information acquisition and contemplation costs are central to this model. The model also has the advantage of accommodating random choice, and can therefore make sense of participants sometimes making dominated or intransitive choices.

In this model, a participant is uncertain about the value of the options she faces, but has a prior belief about those values. The participant adopts an optimal information acquisition and contemplation strategy by which she accumulates knowledge about those values and updates her prior. Knowledge accumulation is costly. Inference does not require that the information acquisition and contemplation strategy be specified. That strategy may include a decision about which aspects of the problem to attend to. A participant might attend to the number of assets in the choice set, the relative prices of assets, the payoffs of each asset, the endowment she has to spend, the level of the outside option level, etc. The strategy may also include a decision about *how* to attend to different aspects of the problem. A participant might decide about each option whether to calculate its expected value, and whether to rank its value against some set of other options, etc. Regardless of strategy, the model assumes that, based on her posterior belief about the value of his options, the participant chooses the one with the highest expected utility.

Formally, we follow closely the structure and notation of Matějka and McKay (2015). We restrict attention to treatment arms of the experiment that include the alternative to opt out and model each decision problem as presenting the participant with just two options indexed by i. Option $i = 1$, is to opt in and invest in a portfolio; option $i = 2$ is to opt out and take the simple alternative.[20] The value to the participant of each option i, denoted v_i, is uncertain. Let $v = (v_1, v_2) \in \mathbb{R}^2$ denote this uncertain state. We assume the participant has a prior belief about the distribution of v, $G \in \Delta(\mathbb{R}^2)$, where $\Delta(\mathbb{R}^2)$ is the set of all probability distributions on $\mathbb{R}^2$.

Before choosing whether to opt out, the participant selects a costly information acquisition and contemplation strategy. As noted above, we need not specify the strategy space except to assume that strategies reduce uncertainty about the state (v) and result in a posterior belief $F \in \Delta(\mathbb{R}^2)$. Drawing on information theory (Shannon 1948), the uncertainty of beliefs is described in terms of entropy. If $H(G)$ is the entropy of the prior G then, if the state distribution is discrete and p_k is the probability of state k, $H(G)$ satisfies

$$H(G) = -\sum_k p_k \log(p_k).$$

Entropy thus describes the average likelihood of each state. If, for example, there were just two states then entropy rises with variance and is maximized when each state is equally likely.

Following the rational inattention literature, we assume the costs of information acquisition and contemplation are linear in entropy reduction. Thus, arriving at posterior beliefs F with associated uncertainty $H(F)$ involves a

[20] In principal this option space could be further partitioned to distinguish between a finite number of distinct portfolios within the investment problem. In practice, the modest size of the relevant sample, and the need to allow for within-person corrleation of errors in the choice function, limits our ability to estimate with precision the structrual parameters of a meaningfully larger option space.

cost $c(F)$ that satisfies

$$c(F) = \lambda \left[H(G) - H(F) \right].$$

We assume the participant chooses an information acquisition and contemplation strategy to maximize the expected utility of her choice net of the costs of that strategy $c(F)$.

Matějka and McKay (2015) show that optimal behavior in this model implies the probability a participant chooses option $i, P(i)$, satisfies

$$P(i) = \frac{e^{(v_i+\alpha_i)/\lambda}}{\sum_{j=1}^{N} e^{(v_j+\alpha_j)/\lambda}} \tag{1}$$

where α_i is the prior weight assigned to option i. The prior weight α_i describes the relative tendency to choose option i in the absence of additional information about its actual value v_i. The "logit" form of (1) implies that when contemplation costs λ are high, the prior weights α_i dominate the true values v_i because the participant optimally chooses not to pursue much information about the decision problem. Conversely, when contemplation costs are low, true values dominate priors and as λ gets arbitrarily small the probability of choosing the option with the highest true value goes to 1.

The model thus offers an interpretation of alternative patterns of behavior in experiment. Specifically, if the primary consequence of complexity is to cause the distribution of choices to shift toward opting out, this is interpreted as a shift in the relative weight of priors on opting out (α_1, α_2). Alternatively, if the primary consquence of complexity is to make choices less responsive to the relative value of each option, this would be interpreted as an increase in the costs of information acquisition λ.

4.2 Identification, Estimation, and Interpretation

In many settings, it is difficult to identify separately v_i, α_i, and λ from choice data alone. Separate identification is challenging because none of these parameters is observed directly and both the fundamental value v_i and the prior weight α_i enter into the probability of choosing option i in the same way. In the controlled experimental setting, however, we have direct information about the fundamental value of an option v_i; we can calculate its (expected) value or, given an assumption on functional form, its expected utility. We can use these assumptions, and the additional information which is often hard to measure in the field, to separately identify the prior weights and the cost of information λ.

Specifically, we assume the fundamental value of investing v_1 is given by the expected utility of the utility-maximizing portfolio while the the fundamental value of opting out v_2 is equal to the utility of the outside option. Notice that, as usual with the logit specification, we can only identify the difference between α_1 and α_2.

We estimate the parameters of this rational inattention model, allowing the parameters to vary with decision-making skill and complexity. Details of the estimation procedure are provided in the appendix. To summarize, the unit of observation is the respondent-decision problem. In each problem, the respondent chooses between investing (opting in) and avoiding ("opting out"). The parameters of equation (1) are estimated via maximum likelihood.

For purposes of evaluating the sophistication of, especially, low-skilled participants we will interpret the structural estimates as follows. If complexity primarily causes (low skilled) participants to change their priors $\alpha_1 - \alpha_2$ regarding the fundamental value of investing, we will interpret the resulting rise in opting out as unsophisticated. There is no fundamental reason for priors to be different in the complex setting; opting out for that reason thus appears naive or superstitious. If, however, complexity primarily causes (low skilled) participants to experience higher costs of information acquisition and contemplation,

λ, we will interpret the resulting increase in opting out as sophisticated. In this view, even though prior beliefs are little changed, participants are making optimal decisions to opt out more often rather than face the higher costs of becoming more sure that is fundamentally the best option.

4.3 Results

Table 7 presents the structural estimates of the cost of information acquisition and contemplation, λ, and the relative prior weight on opting in, $\alpha_1 - \alpha_2$. The estimates indicate that in the simple setting there are no statistically significant differences in costs of contemplation or in prior weights on opting in, by skill. The only exception is for the prior weight on investing, which is higher for those with higher decision-making skills in the CRRA specification (but not in the linear specification).

The consequences of complexity are, however, quite different depending on one's decision-making skills. For the "baseline group" with the lowest decision-making skills, the point estimates indicate that the cost of information acquisition and contemplation in the complex environment more than doubles. In contrast, the point estimates suggest that the effects of complexity on the costs of contemplation are attenuated for those with higher decision-making skills.

There are no statistically significant effects of complexity on the relative prior weight on opting in. The coefficient on the complexity indicator variable is positive, suggesting that complexity increases the prior weight on opting in for those with the lowest decision-making skills, but the effect is not statistically significant at the 10% confidence level. The coefficient on the interaction of decision-making skills and complexity is negative, which would suggest that the effect of complexity on the prior weight on opting in is attenuated for those with higher decision-making skills, but again this effect is not statistically significant at the 10% confidence level.

	Linear		*CRRA with ρ = 2*	
	Invest Prior Weight	Contemplation Cost	Invest Prior Weight	Contemplation Cost
Decision-making Skill * {Complexity}	-22.2	-29.5	-0.69	-0.73
	(21.34)	(11.80)**	(0.62)	(0.33)**
{Complexity}	9.4	16.2	0.26	0.35
	(11.65)	(7.17)**	(0.32)	(0.18)**
Decision-making Skill	24.8	7.3	0.62	0.35
	(15.78)	(9.08)	(0.29)**	(0.22)
Constant	-19.3	12.9	-0.08	0.10
	(6.50)***	(3.72)***	(0.06)	(0.07)

Notes: This table shows rational inattention investigates if the cost of information acquisition and contemplation, λ, and the relative prior weight on option in, α_1-α_2, differ by decision-making skills and complexity. The sample is restricted to treatment arm II (simple with outside option) and IV (complex with outside option). Standard errors clustered at the individual level. N Choices = 9,050. N Participants = 362.

Table 7: Structural Estimates of Information Costs and Prior Weights on Opting In, by Skill and Complexity of Problem

We interpret the results in Table 7 to indicate that, despite its negative effects on expected payoffs, the response by lower skill participants to complexity is sophisticated. Viewed through the lens of a rational inattention model, the increased avoidance by lower skill participants is driven by higher costs of acquiring and contemplating information and not by unfounded differences in prior beliefs about the fundamental value of different options.

5 Conclusion

Evolving financial products and investment opportunities have the potential to provide more people greater autonomy and access to the benefits of financial markets. This potential may be limited, however, if consumers are poorly equipped to handle the increased complexity associated with the new choices. Providing such consumers with simple alternatives, like target-date retirement saving plans, or age-based college saving plans, is a sensible way to guard against some negative effects of increasingly complex financial markets. The benefits of these simple alternatives may depend, however, on consumer sophistication. If they can now avoid complex financial decisions, it becomes important for consumers to know when they are better off choosing simple options instead of solving complex problems. Are consumers sufficiently self-aware to see when they ought to avoid complexity in favor of a simple, perhaps imperfect, alternative?

This paper describes an experiment, conducted with a large and diverse population of Americans, that evaluates the effects of complexity on financial choices and assesses the sophistication of individuals to know when they are better off taking a simple option instead of solving a complex problem. The results show that, when they are required to make an active portfolio decision, participants spend more time on complex problems and make choices with somewhat lower expected payoffs and lower risk. On average, complexity also reduces some desirable properties of choice; it leads to more violations of symmetry and more violations of monotonicity with respect to first-order dominance.

When offered a simple alternative to the portfolio choice, complexity has substantial, and varied effects on choice. Participants opt out, on average, about a quarter of the time, but the rate at which the portfolio problem is avoided depends on the decision-making skills of the participant. Those with the lowest levels of financial decision-making skill avoid the portfolio choice more often, even when it is simple, and are much more likely to avoid the problem when it is complex. Especially important, when participants take the outside option, it often has a substantial negative effect on expected payoffs, and this effect is especially large for those with the fewest decision-making skills.

Because low-skilled participants, especially, earn much lower returns and more often make dominated choices when offered a simple alternative to solving a (complex) portfolio problem they appear unsophisticated. They appear, that is, not to know when they are better off opting out. It could be, however, that lower-skilled participants face higher costs of considering and evaluating the portfolio problem and thus rationally trade contemplation costs for lower returns. In this view, they are making sophisticated, if costly, decisions to opt out.

Because such contemplation costs are not observable, we draw inference about their importance and about sophistication by estimating the structural parameters of rational inattention model based on Sims (2003) and formulated by Matějka and McKay (2015). In this model, a participant is uncertain about the value of each option he faces, but has a prior belief about those values. The participant adopts an optimal information acquisition and contemplation strategy by which she accumulates costly knowledge about those values and updates her prior. Based on her posterior belief about the value of her options, the participant chooses the one with the highest expected utility.

We interpret the structural estimates as follows. If complexity primarily caused participants to change their priors regarding the fundamental values of different options, we view the resulting increase in opting out as unsophisticated. We adopt this interpretation because there is no fundamental reason for priors to be different in the complex setting, thus opting out for that reason appears naive or superstitious. If, however, complexity primarily caused (lower skilled) participants to experience higher costs of information acquisition and contemplation we interpret the resulting increase in opting out as sophisticated. In this view, particpants are making optimal decisions to opt out rather than incur the higher costs of learning more about what, fundamentally, is the best option.

The structural estimates point to sophisticated opting out. Complexity causes substantial increases in information acquisition and contemplation costs for low-skilled participants, while leaving their priors little changed. We therefore interpret the increase in avoidance that comes with complexity as a sophisticated response to higher costs of determining the optimal choice.

Future work should evaluate the robustness of these results in other settings. It will be especially important to understand if, as predicted by the rational inattention model, the opting out rate declines as the stakes of the problem rise. In the interim, the results of this experiment underscore the importance of taking selection into account when designing simple alternatives to solving complex problems. If lower-skilled people find contemplation of complex problems too costly, they are more likely to take simple options regardless of their fundamental value. Plan designers should therefore take special care to ensure the simple alternatives are well-suited to the least skilled who are most likely to take them.

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6 Appendix - Structural Estimation

We consider the decision problems in which the participant's choice y is either to invest ($y = 1$) or to opt out ($y = 2$). Equation (1) from above, due to Matejka and McKay (2015), states:

$$\Pr(y = i) = \frac{e^{(v_i + \alpha_i)/\lambda}}{\sum_{j=1}^{N} e^{(v_j + \alpha_j)/\lambda}}$$

We rewrite (1) by dividing both the numerator and denominator by $e^{(v_2+\alpha_2)/\lambda}$:

$$\Pr(y = 1) = \frac{e^{(v_1 - v_2 + \alpha_1 - \alpha_2)/\lambda}}{1 + e^{(v_1 - v_2 + \alpha_1 - \alpha_2)/\lambda}}, \tag{2'}$$

where v_1 is the maximum utility the participant can achieve if she invests and v_2 is the utility of the outside option.

To allow for lambda to vary with decision-making skill, we parametrize λ as:

$$\lambda = \gamma_0 + \gamma_1 Complexity + \gamma_2 Skill + \gamma_3 Complexity * Skill \tag{2}$$

γ_3 is one of our coefficient of interest. It gives the derivative of λ with respect to $Complexity * Skill$. It permits testing whether the effect of complexity on λ is greater for those with lower decision-making skills.

We parametrize $\alpha_2 - \alpha_1$ as:

$$\alpha_2 - \alpha_1 = \phi_0 + \phi_1 Complexity + \phi_2 Skill + \phi_3 Complexity * Skill \qquad (3)$$

ϕ_3 is one of our coefficient of interest. It gives the derivative of $\alpha_2 - \alpha_1$ with respect to $Complexity * Skill$. It permits testing whether the effect of complexity on $\alpha_2 - \alpha_1$ is greater for those with lower decision-making skills.