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COMPLEXITY AND SOPHISTICATION

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ABSTRACT

Many financial situations present individuals with simple alternatives to solving complex problems. Are individuals sophisticated; do they know when they are better off opting out of complexity? We tested complexity's effects and evaluated sophistication in a large and diverse sample. We randomly assigned both complexity to portfolio problems and the offer of a simple alternative to portfolio choice. The less skilled opt out more often under complexity and thus earn lower returns, often from dominated choices. Estimated with a novel identification strategy, the structural parameters of a rational inattention model are, nevertheless, consistent with substantial sophistication. Substantial fractions of the money lost by opting out can be justified by attention cost savings.

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Complexity and Sophistication*

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Abstract

Many financial situations present individuals with simple alternatives to solving complex problems. Are individuals sophisticated; do they know when they are better off opting out of complexity? We tested complexity's effects and evaluated sophistication in a large and diverse sample. We randomly assigned both complexity to portfolio problems and the offer of a simple alternative to portfolio choice. The less skilled opt out more often under complexity and thus earn lower returns, often from dominated choices. Estimated with a novel identification strategy, the structural parameters of a rational inattention model are, nevertheless, consistent with substantial sophistication. Substantial fractions of the money lost by opting out can be justified by attention cost savings.

JEL Classification Numbers: D81, G02, G11

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

1 Introduction

As financial markets and instruments change, individuals are being asked to make saving, credit, and insurance choices in an increasingly complex environment. Adding options can improve consumer welfare, but the additional complexity likely makes optimization more difficult, and may thus reduce the quality of financial decisions. The 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 choose from the

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whole set of retirement saving rates and investment options, and if he feels confident in his firm's default rate and default portfolio allocation, he can accept the default and avoid both the costs of considering all his options, and the risk of making a badly suboptimal choice.

The importance of simple alternatives to solving complex financial problems, and thus sophistication, is rising. At the end of 2015, for example, 76% of new enrollees in Vanguard employer-sponsored savings plans were investing in only one target-date retirement fund; in the Australian pension system, 64% of total contributions to superannuation funds in 2015 were invested in default portfolios chosen by the employer.[1]

This paper presents the results of an experiment to study 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 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 objectives.

The results show that, when they are required to make an active portfolio decision, participants choose allocations with lower expected returns and lower risk. Because the experiment presents participants 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 as measured by violations of normative choice axioms (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 dominance principles including monotonicity with respect to first-order stochastic dominance.

Complexity has substantial and varied effects on the decision to opt out of a portfolio choice.

[1] Steve Utkus, "The End of 'Choice Overload,"' Vanguard Blog for Institutional Investors, August 2016. Australian Prudential Regulation Authority "Annual Superannuation Bulletin," August 2016.

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 problem 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 financial decision-making skills, defined in terms of numeracy, financial literacy, and consistency with utility maximization in another experiment, avoid the portfolio choice more often, even when it is simple, and are much more likely to avoid the problem when it is complex.

The availability of the outside option has a substantial negative effect on expected payoff; and this effect is especially large for those with the least decision-making skills. The reduction in expected payoff associated with complexity triples when participants have the option to avoid the portfolio problem. Among those with the least decision-making skills the option to avoid complexity reduces their expected payoff 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 especially 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 avoiding the costs of attending to a complex portfolio problem even if that implies foregoing high-return investment opportunities.

To evaluate the sophistication of the opt out decision among the low-skilled, we estimate the structural parameters of a rational inattention model. That model interprets differences in behavior as resulting either from differences in the payoffs associated with each available option, or from differences in beliefs about the payoff from each option, or from differences in the cost of acquiring and contemplating information about the payoffs from each option. In this way, the model treats all behavior as rational. We call higher rates of opting out “sophisticated” to the extent that they can be explained by higher costs of information acquisition and contemplation.

The estimates of this structural model, obtained with a novel identification strategy, fail to reject a null hypothesis of sophistication among the low-skilled. Inference from the structural estimates indicates that, relative to the higher skilled, low-skilled participants have a significantly higher cost of acquiring or contemplating information about payoffs under complexity. The low skilled are, that is, less responsive to the relative return of working through complex decision problems. Simulation of the estimated model shows, moreover, that the implied costs of information acquisition are sufficient to explain substantial fractions of the additional opting out by the low-skilled under complexity.

1.1 Related Literature

This paper joins an 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 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 of large choice sets is also motivated by a substantial experimental literature focused on the effects of increasing the number of alternatives from which a decision-maker may choose.[2] 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.[3] Related studies have examined the effects of a larger number of options on portfolio choices (Agnew and Szykman, 2005; Iyengar and Kamenica, 2010; Beshears et al., 2013), 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 complexity in reality, but it may confound the influence of complexity with more or less standard effects of a larger choice set.

Motivation for studying complexity also comes from influential field evidence of the effects of retirement saving plan defaults in a literature sparked by Madrian and Shea (2001). One explanation for the important effects of defaults is that employees interpret default status as an endorsement of a plan by their employer. Accepting the default can thus reflect a sophisticated response to the costs of information acquisition and consideration in a complex environment (Beshears et al., 2009). While we study active choices rather than defaults,[4] the experiment provides systematic evidence on the plausibility of sophisticated decisions to opt out of complex financial decisions.

The present paper also contributes to a small literature on the effects of more options on the quality of decision-making.[5] Using designs where some (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;

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

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

[4]For each participant, and for each problem in the experiment, the initial asset allocation was chosen at random. If defaulting is interpreted as actively choosing this initial allocation, then participants default on 9.5% of all choices. The default rate under complexity is lower, 7.7%.

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

Kalayci and Serra-Garcia, 2015).[6] 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 combined study of three issues. First, by keeping real opportunity sets constant across treatments, the experiment separates the influence of complexity on financial choices 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 evaluation of external relevance.

Last, by offering participants a simple alternative to solving a portfolio problem and estimating, using a novel strategy, the structural parameters of a rational inattention model, 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 limited, though the question often emerges in studies of the demand for and consequences of professional advice.[7] Both our use of the structural estimates of a rational inattention model for this purpose and our method of estimating that model are, 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 and have not, to our knowledge, estimated heterogeneity in the costs of attention.[8] Our experiment allows repeated observations of individuals of the same skill level making portfolio choices with the same asset prices but varying investment amounts. We show that, under the assumption of homothetic preferences, this variation allows point estimates of heterogeneous costs of attention without having to simultaneously estimate the prior weights on each feasible portfolio or assume these prior weights are uniform. The paper thus offers a new, portable strategy for estimating the parameters of a rational inattention model.

2 Study Design

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

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

[7]See, e.g., Chalmers and Reuter (2012), Mullainathan, et al. (2012), and Egan et al. (2016). Chalmers and Reuter (2012), for example, find evidence that when the Oregon University System stopped offering retirement savings plan participants free access to advice from brokers, many new participants were more likely to take up target date retirement funds and arrive at portfolios that were superior in terms of risk and return.

[8]The closest use of structural models to draw inference about choice and belief imperfections may be those concerned with tax salience and misperceptions. Examples of these studies include Chetty, Looney, and Kroft (2007), Taubinsky and Rees-Jones (2016), and Rees-Jones and Taubinsky (2016).

2.1 Conceptual Framework

The literature offers several definitions of complexity. Here we adopt a definition based on Al-Najjar et al. (2003) that ranks the complexity of any two choice problems X and Y that are sufficiently familiar to the decision-maker. For our purposes, sufficient familiarity means that the decision maker has encountered similar problems in the past and understands that optimal choice in these problems depends on a finite set of contingencies. In these problems, that is, the decision-maker's preferred option is contingent on the realization of a discrete random variable that (indirectly) determines the underlying value of each available option.

Definition 1 *A decision maker perceives choice problem X to be* **more complex** *than Y if she thinks optimization over the choices in X requires consideration of more contingencies than optimization over the choices in Y.*

To isolate the effects of this notion of complexity on decision-making, we designed two problems – one simple, one complex – that share the same opportunity set. In the two problems participants are given an endowment 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 in the simple problem there are two assets while in the complex problem there are five assets.

Figure 1: Illustration of Simple and Complex Problems

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 illustrates with an example. In the simple problem there are two investment options: assets A and B. Each share of asset A has a price of $0.90 and the price of each share of asset B is $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 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. 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 Online Appendix for a proof).[9]

[9] By using convex combinations of assets to span the same opportunity set, our design resembles that in Eyster

According to Definition (1), the five-asset problem would be perceived as more complex than the two-asset problem if the participant thinks optimal choice requires consideration of more contingencies in the problem with more assets. This seems natural if the interpretation of contingencies includes, among other things, the relative prices of the assets.

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 demographics and socioeconomic data, and results of 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.[10] One manipulation involved varying the number of investment options: 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.[11]

and Weizsäcker (2010). In that paper, participants faced a sequence of portfolio problems, each with two assets. Each problem had a twin, with the same opportunity set but formed by assets with differently correlated returns. The paper's basic question was whether participants neglected that difference in correlation.

[10]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) whether the participant had a score in the financial literacy test above the median; 2) whether the participant had a score in the numeracy test above the median; 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 Online Appendix for more details.

[11]A participant saw either the simple or the complex framing of problems, but not both. This would seem to make it less likely that a participant assigned to the complex frame could see the redundancy of the assets. Indeed, participants assigned to treatment arm III invested exclusively in the two Arrow securities only in 14.13% of their decisions (in 6.96% of their decisions participants invested the entire endowment in just one of the Arrow securities).

	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.

2.4 Experimental Task

The experimental task involved variations on the examples discussed in section 2.1. Participants had to allocate their experimental endowment across 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 choosing 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.[12]

Treatment arms III and IV used a similar interface to make their investment choices (see Online 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

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

assets.[13] We randomized the initial levels of the bars (see Online Appendix for more details).

The interfaces for treatment arms II and IV were slightly different because these groups were offered the option to avoid the investment decision. 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 participant to choose between investing the experimental endowment (button "Invest $26") and taking the outside option (button "Receive $5"). 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 problem.

Participants were presented with 25 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). They were not given feedback during the experiment. It is useful to conceive of each problem as a two-dimensional budget line, where the axes correspond to the payoffs paid in two states of the world: heads (y-axis) and tails (x-axis). The y-intercept is the payoff if the endowment is invested all on heads (and the coin comes up heads) and the x-intercept is the payoff paid if the endowment is invested all on tails (and the coin comes up tails).

We crafted 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.[14] The order in which the budget lines were presented to each participant was also randomized.

Each budget line was then 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). For example, a budget line with a x-intercept of $40 and a y-intercept of $80 would be converted into a simple problem with an endowment of $40 and where each share of asset 1 would cost $2. We randomized the order in which assets 1 and 2 were

[13] https://www.youtube.com/watch?v=TNr3Wgakczk&feature=youtu.be We conducted cognitive interviews to ensure participants understood the tutorial video and what they were supposed to do in the experiment.

[14] 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. If the y-axis was selected, we would randomly select the y-ntercept by drawing uniformly between $10 and $100. If the selected y-intercept was greater than $50, we would draw the x-intercept uniformly between $10 and $100. If the selected y-intercept was smaller than $50, we would draw the x-intercept uniformly between $50 and $100. For 79 participants 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-intercept uniformly between $1 and $100; and 3a) if x-intercept is greater than $50, draw y-axis intercept uniformly between $1 and $100 or 3b) if x-intercept is smaller than $50, draw y-intercept uniformly between $50 and $100. We dropped budget lines where y-intercept < 0.05 * x-axis intercept.

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-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.[15]

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.[16] 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 from money, symmetry of demand for these assets. In particular, violations of monotonicity with respect to first-order stochastic dominance (FOSD) –

[15]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.

[16]For example, consider a participant that always allocates 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, allocating the endowment to heads means allocating it to the more expensive asset, a violation of monotonicity with respect to first-order stochastic dominance.

that is, the failure to recognize that some allocations yield payoff distributions with unambiguously lower returns – may be 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 evidence of lower quality decision-making.

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.[17]

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 a value of 1. If the selected allocation was dominated, we calculated the FOSD score as $\frac{x+y}{z+y}$, which equals the expected return of the selected allocation as a fraction of the maximal expected return. For participants assigned to treatment arms II and IV, we used the same procedure to calculate the FOSD when participants 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, of monotonicity with respect to FOSD, and symmetry of demand, we combine the 25 choices for a given participant 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 chosen from the budget defined by $(p_1, p_2; m)$ where $p_1x_1 + p_2x_2 = m$, then we assume (x_2, x_1) would have been chosen subject to the mirror-image budget $(p_2, p_1; m)$. We then compute the CCEI for the data set consisting of 50 observations that combines the 25 actual choices with their 25 mirror images. Violations of GARP in this combined dataset result from violations in the actual choice data and from violations of monotonicity with respect to FOSD. This measure can also detect violations of symmetry, as the combined data would induce no more violations if the actual demand were consistent with GARP and symmetric. Cf. Choi et al. (2014).

3 Descriptive Results

3.1 Summary Statistics

Summary statistics of the sample show that the controls are balanced across the treatment arms. The first four columns of Table 1 show means, separately by treatment arm (for continuous

[17] We drop choice sets where the price of asset 1 equals $1 and thus all portfolios have the same expected return.

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.

Table 1: Summary Statistics

	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
Observations	178	181	158	183				

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

3.2 Portfolio Choices

Table 2 investigates if complexity affects portfolio choices by comparing the expected return and the 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).[18] 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 expected return as a fraction of the endowment) multiplied by 100, and the standard deviation of the portfolio – on an indicator for being assigned to treatment arm III and a constant. 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 outside 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), interprets 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 his choice when the same decision problem is framed in a complex manner. Choices in the simple frame are interpreted as benchmarks; the larger the gap between simple and complex framed choices, the lower the individual's financial competence.

[18]Separate from portfolio choice, participants assigned to the complex problem appear to encounter more difficulties. Comparing the 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 the 1% level.

Table 2: Effects of Complexity on Portfolio Choices

	Expected Return	*Ln(Expected Return)*	*Rate of Return * 100*	*Standard Deviation*
{Complexity}	-$1.27	-0.05	-7.99	-$2.08
	[0.40]***	[0.02]***	[2.32]***	[0.86]**
Constant	$28.25	3.28	19.75	$12.09
	[0.29]***	[0.01]***	[1.69]***	[0.64]***

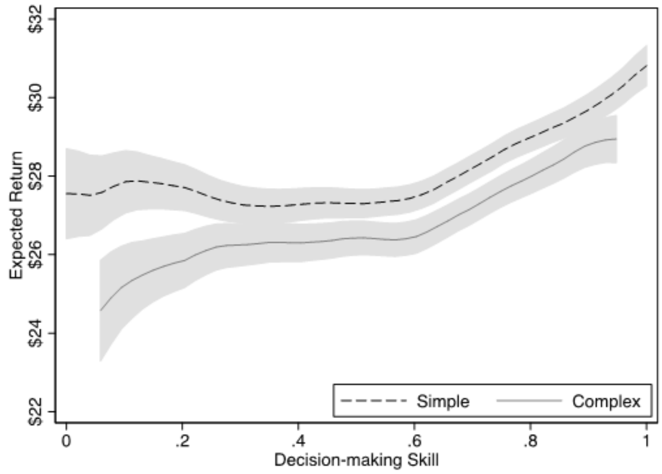
Notes: This table compares the portfolio choices in treatment arm III (complex without outside option) to the portfolio choices in treatment arm I (simple without outside option). Curly brackets indicate dichotomous variables. Standard errors clustered at the individual level are in brackets. The analysis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

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 face greater challenges dealing with 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 of 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.[19] The measure was re-scaled to range from 0 to 1.

Figure 2 shows non-parametric regressions of expected return conditional on decision-making skills, separately for treatment arm I (simple without outside option) and treatment arm III (complex without 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 are 95% confidence bands. The difference between the two curves is the effect of complexity on expected return at any given level of decision-making skills.

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

Figure 2: Effect 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 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 Decision-making Quality

The evidence that complexity affects portfolio choices in a similar way across the skill distribution suggests that the reaction to complexity may not reflect an erosion of decision-making quality. It is possible that the change in the average risk and return of portfolios reflects a change in well-behaved risk preferences. To further evaluate the effects complexity on decision-making quality, Table 3 compares four measures of the quality of the choices made in treatment arm III (complex without outside option) to those of 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.

Table 3: Effects of Complexity on Decision-Making Quality

	GARP *CCEI*	GARP+FOSD *CCEI*	*% Dominated* *Portfolio*	FOSD *FOSD Score*
{Complexity}	0.03	-0.03	0.09	-0.01
	[0.02]	[0.03]	[0.02]***	[0.01]**
Constant	0.86	0.69	0.28	0.94
	[0.02]***	[0.02]***	[0.02]***	[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 are in brackets. The last two columns exclude choice sets where all portfolios yielded the same expected return. N Participants = 336.

The results show 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.[20] As discussed in section I.E, compliance with GARP may be viewed as a necessary but not sufficient condition for high-quality decision-making. Violations of symmetry in demand, or of monotonicity with respect to first-order stochastic dominance (FOSD), also provide compelling criteria for decision-making quality.

Analysis of a unified measure of violations of GARP, FOSD and symmetry of demand via an evaluation of both the actual choices and their mirror image (second column), shows that complexity modestly reduces this measure of decision-making quality. 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 average lower ranks (i.e., lower decision-making quality) in the distribution of the unified measure of violations of GARP, FOSD and symmetry of demand, than participants assigned to the simple condition.[21]

[20] Online 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.

[21] 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

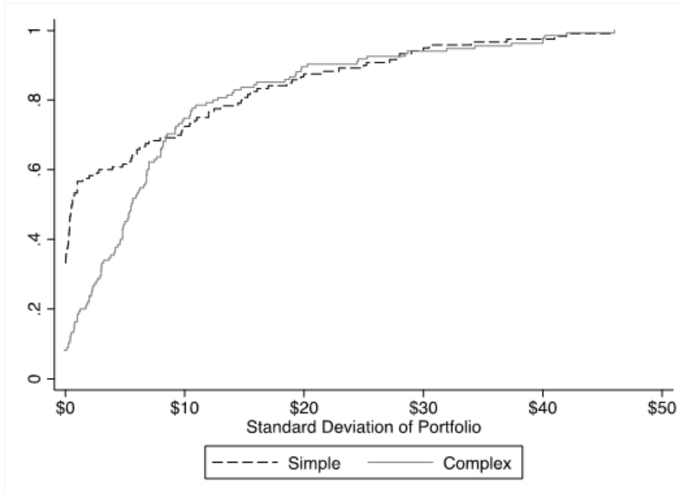
Isolated analysis of violations of monotonicity with respect to first-order stochastic dominance shows more definitively the effects of complexity on decision-making quality. The third column of Table 3 shows that participants assigned to the complex condition are 9 percentage points more likely to pick 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, Online Appendix Table 2 shows that participants with a college degree are 14 percentage points less likely to pick a dominated portfolio than their peers.

Especially clear evidence that complexity degrades decision-making quality appears in Figure 3 where 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 – any other portfolio involves more risk but no additional return. Figure 3 shows 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.[22]

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)

[22]Some of the degredation in decision-making quality might be attributed to additional reliance on heuristics or rules of thumb for making decisions. An especially important rule is the "1/n strategy," in which individuals divide their wealth equally among n investment options (Benartzi and Thaler, 2001). Because participants choose a number of shares rather than a direct dollar allocation, this heuristic may not be as compelling in this setting. Nevertheless, we find no evidence that complexity led to increases in the tendency to equate either the amount of money invested in each asset or to equate the number of shares purchased of each asset. Both of these behaviors are rare, representing less than 5% of choices.

Figure 3: Distribution of Portfolio Risk (when all Portfolios Have Same Expected Return)



Notes: This figure investigates if participants assigned to the complex condition take more risk, even when there is no return to it. 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 negative effects on the quality of decision-making, especially on the tendency to pick dominated portfolios. We now consider the decision to avoid complexity by choosing a simple alternative over solving a complex problem. In treatment arms II and IV participants were given the opportunity to take an outside option rather than making 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 participants had the outside option but were assigned to the simple condition.

The first column of Table 4 shows 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 in 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.

Table 4: Effects of Complexity on Avoidance

	{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.

While the effect of complexity on portfolio returns does not much vary with decision-making skills (see Figure 2), the effect of complexity on choice avoidance may still depend on those skills. We would expect, in particular, higher rates of avoidance for those who, due to lower decision-making skills, face higher costs of attending to 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 point estimates of column 3 indicate, first, that the low-skilled tend to opt out more often, even in the simple condition. While somewhat imprecise, the point estimate indicates an average 13 percentage points difference in rates of opting out in the simple condition between the highest and lowest skilled. Complexity expands that difference expands importantly. Complexity increases the difference in avoidance rates between the least and highest skilled by 21 percentage points. This expanded gap in avoidance rates derives in part from the fact that complexity leads to a 14 percentage points increase in opting out by the lowest skilled and in part from the surprising fact the very highest skilled avoid a simple problem, on average, somewhat more often than a complex one.

3.5 Consequences of Avoidance

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 lowest 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 participant 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 participant 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 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 treatment arm III (complexity without outside option); it estimates the effect of having the outside option in the complex condition.[23]

[23]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.

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

	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 treatment arm IV (complex with outside option) to the payoffs of treament 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 participant 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 the 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 are in brackets. N Choices = 12,558. N Participants = 519. We exclude choice sets where all portfolios yielded the same expected return.

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 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 degrades the quality of decision-making, reducing compliance with monotonicity with respect to FOSD. The effect is large, four times larger than the effect of complexity when there is no outside option. This effect is driven mostly by the fact that participants sometimes opt out when the outside option pays less than the risk-free portfolio.[24]

Table 6 shows the penalty associated with the option to avoid complexity is especially large for those with the least decision-making skills. It compares the choices of treatment arm IV (complexity with outside option) to the choices of treatment arm III (complexity without outside option), allowing 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 an expected payoff 40 percent lower than they would have otherwise. They also exhibit a large reduction in compliance with a dominance principle. In contrast, those with high decision-making skills guard themselves 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.

[24] In Online 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.

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

	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 treament 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 participant 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 the 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 are in brackets. N Choices = 8,203. N Participants = 340. We exclude choice sets where all portfolios yielded the same expected return and dropped 1 participant for whom numeracy or financial literacy scores were missing.

4 Sophistication – Structural Estimates

When facing a complex problem, the availability of a simple alternative to solving a portfolio problem results in much lower returns and more often dominated choices for the lower-skilled. These negative consequences of the simple alternative for the lower-skilled derive from the fact that they more often take the simple alternative even when it pays relatively little. In one view, these results imply a lack of sophistication; the lower-skilled appear not to know when they are better off taking a simple alternative to solving a 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. Based on this fact alone, it seems that a sophisticated but low-skilled participant should not take the outside option more often than her high-skilled counterpart when facing a complex choice environment.

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. 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 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 opting out, we 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. It also accommodates random choice, and thus offers a theory of why participants might sometimes make dominated or intransitive choices.

In this model, a participant is uncertain about the value of each of the options she faces (the state), 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. Our inference does not require that the information acquisition and contemplation strategy be specified. A strategy might 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. A 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 her options, the participant chooses the one with the highest expected utility.

Formally, we follow 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 N options indexed by i. Option $i = N$ is to opt out and take the simple alternative. The remaining $N - 1$ options are the elements of the set of feasible portfolios. The value to the participant of each option i, denoted v_i, is uncertain. Let $\mathbf{v} = (v_1, ..., v_N) \in \mathbb{R}^N$ denote this uncertain state. We assume the participant is endowed with a prior belief about the distribution of $\mathbf{v}$, $G \in \Delta\left(\mathbb{R}^N\right)$, where $\Delta\left(\mathbb{R}^N\right)$ is the set of all probability distributions on $\mathbb{R}^N$.

The participant knows her information about the distribution of the state is imperfect. Before choosing an option, therefore, the participant may select a costly information acquisition and contemplation strategy to refine her prior. As noted above, we need not specify the strategy except to assume that strategies reduce uncertainty about the state ($\mathbf{v}$) and result in a posterior belief $F \in \Delta\left(\mathbb{R}^N\right)$. The uncertainty of beliefs is described in terms of entropy. Specifically, if $H(G)$ is the entropy of the prior G, if the state distribution is discrete, and if p_k is the probability of state k, then $H(G)$ satisfies

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

Entropy thus gives the average log likelihood of each state. If, for example, there were just two states then entropy would rise 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. Starting with prior G and associated uncertainty $H(G)$, to arrive at posterior beliefs F with associated uncertainty $H(F)$ involves a cost $c(F)$ that satisfies

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

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 conditional probability a participant chooses option $i, P(i, \mathbf{v})$, satisfies

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

where α_i is the prior weight assigned to option i.[25] 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 optimal conditional choice probabilities in (1) imply that when information acquisition and contemplation costs λ are high, the prior weights α_i dominate the true values v_i. This is perhaps easiest to see in the ratio of the conditional probabilities of choosing any two options i and j. This ratio is given by

$$\frac{P(i, \mathbf{v})}{P(j, \mathbf{v})} = \frac{e^{(v_i+\alpha_i)/\lambda}}{e^{(v_j+\alpha_j)/\lambda}} = \frac{P(i)}{P(j)} * e^{(v_i-v_j)/\lambda} \tag{2}$$

where the unconditional probability of choosing option i, $P(i) \equiv \int_{\mathbf{v}} P(i, \mathbf{v}) G(d\mathbf{v}) = e^{\alpha_i/\lambda}$.

Equation 2 shows that when the costs of information acquisition are very high, the difference in the realized values of different options, $(v_i - v_j)$, has little influence on the relative probabilities of choosing those options. Instead, the relative likelihood of choosing option i instead of j is driven by the unconditional probabilities. Choices are driven, that is, by the average probabilities of making either choice before any information is acquired. Conversely, when contemplation costs are low, true values dominate 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 differences in rates of opting out in the experiment. Specifically, and other things equal, if lower-skilled participants are less responsive to the true value of each option, this would be captured by a higher cost of information acquisition λ.

[25] As Caplin, Dean, and Leahy (2016) emphasize, this conditional choice probability formula holds only for those options the individual believes worth considering at all. It holds, that is, only for those options with a positive unconditional choice probability. Our estimation strategy is sufficiently flexible to allow some options to have zero unconditional choice probabilities. All that we require is that the unconditional probability of opting out is not zero or one.

4.2 Identification, Estimation, and Interpretation

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, given a cost of information acquisition and contemplation (λ), the realized value of option i (v_i) and the prior weight on that option (α_i) have similar influence on the probability of choosing that option. In the controlled experimental setting, however, we can make progress by exploiting random variation in the contingent payoffs that determine the fundamental value of an option, v_i.

The logic for identification is, again, evident in the ratio of the conditional probabilities of choosing any two options i and j:

$$\frac{P(i,\mathbf{v})}{P(j,\mathbf{v})} = \frac{P(i)}{P(j)} * e^{(v_i - v_j)/\lambda} \tag{3}$$

where the unconditional probability of choosing option i, $P(i) = e^{\alpha_i/\lambda}$. Taking logs of both sides of equation (3) we obtain

$$\ln\left(\frac{P(i,\mathbf{v})}{P(j,\mathbf{v})}\right) = \ln\left(\frac{P(i)}{P(j)}\right) + \frac{v_i - v_j}{\lambda} \tag{4}$$

As equation (4) makes clear, the change in the log likelihood ratio of choosing option i versus j caused by a change in the difference in their values is given by the inverse of λ. Thus, random variation in the contingent payoffs that determine v_i in $v_1, ..., v_N$ can be used to identify the cost of information acquisition and contemplation. If λ is thus identified, then the prior weights α_i could be backed out from the average log likelihood ratios.

This method of identification relies, however, on several strong assumptions and imposes substantial data demands. These assumptions and data demands include

1. A precise specification of the available options i in each problem. In our context this means a specific partition of the portfolio space.

2. Functional form assumptions for the utility function that maps the contingent payoffs of each option i into its value v_i.

3. Sufficiently large samples to estimate $N - 1$, parameters: $\alpha_1, ..., \alpha_{N-1}$.

We avoid these assumptions and data demands by exploiting the fact that, if preferences are homothetic, $v_1, ..., v_{N-1}$ are proportional to the dollar amount of the endowment while v_N is proportional to the dollar amount of the outside option. As detailed in the Appendix, this assumption allows identification of λ without further functional form assumptions on the utility function. It also allows us to avoid any assumptions on how individuals perceive the size or elements of the option set. All that is required is that individuals view opting out of the portfolio problem, option

N, as one of the available options and that it is distinct from options involving portfolio choice. We can then estimate the parameters via maximum likelihood allowing the parameters to vary with decision-making skill.

For purposes of evaluating sophistication we will interpret the structural estimates as follows. In the model, there are three reasons why lower-skilled participants may opt out more often than those with higher skills, even when opting out is dominated. It is either because the low-skilled derive a different relative value from opting out (v_N), or because they place a different relative prior weight on opting out (α_N), or because they have higher costs of information acquisition and contemplation (λ). Any of these reasons for costly opting out is, by construction, rational. But we will classify the higher rates of costly opting out by the lower skilled as sophisticated only to the extent they are driven by higher costs of information acquisition and contemplation. In this view, sophistication means opting out at monetary cost in order to save the utility costs of becoming more certain about which is the best option.

4.3 Results

Table 7 presents estimates of the cost of information acquisition and contemplation, λ, by skill, in complex problems. Here high- and low-skilled are defined simply as above or below the median level of the decision-making skill index. The first column shows both the point estimate of λ for low-skilled participants and the point estimate of the difference in λ by skill. The last two columns show the bounds of 95% confidence intervals for these estimates, calculated by bootstrapping. The point estimates indicate that lower-skilled participants have a cost of contemplation that is more than two times higher than that of higher-skilled participants. The confidence intervals around these point estimates indicate, as expected, that we can reject a null hypothesis of costless information acquisition ($\lambda = 0$), and a null hypothesis of equal costs of information acquisition between skill groups.

Table 7: Structural Estimates of Information Costs, by Skill (Complex Problems)

	Point Estimate	Bounds of bootstrapped 95% confidence interval	
		Lower	*Upper*
High Skilled - Low Skilled	-0.900	-2.957	-0.017
Low Skilled	1.660	0.888	3.644

Notes: This table presents maximum likelihood estimates of the costs of information acquisition parameter, λ, for low-skilled participants and the difference in this parameter between high- and low-skilled participants. Attention is restricted to complex treatments in which the outside option is available. N Choices = 8,203. N Participants = 340.

We interpret the results in Table 7 as consistent with the hypothesis that the higher rates of costly opting out among lower skill participants in complex problems is, to some extent, sophisticated. Viewed through a rational inattention model, the estimates in Table 7 indicate that, relative to higher-skilled participants, the increased avoidance by lower-skill participants is driven at least in part by their higher costs of acquiring and contemplating information.

4.4 Quantifying the Importance of Contemplation Costs for Opting Out

The point estimates in Table 7 show statistically significant differences in the costs of information acquisition and contemplation between participants of different skills. Because these differences in λ are measured in terms of utility, however, it is not immediately clear whether they are economically important. In particular, it is not clear that even large level differences in λ translate into large differences in the rates of costly opting out.

To evaluate the quantitative importance of these differences in contemplation costs for rates of costly opting out, we can calculate how much of the difference in opting out rates between skill groups can be explained by the estimated differences in λ. To do that requires that we impose some assumptions we avoided in estimation. It requires, in particular, a specific partition of the option space inside the portfolio, and an assumption on the functional form of utility. In the results that follow, we assume the option space for each problem is partitioned according to the fraction of the endowment allocated to heads versus tails, and we assess the sensitivity of the results to alternative assumptions about the functional form of utility.

In addition, the cost of acquiring and contemplating information (λ) influences both the conditional probability of choosing option i, $P(i, \mathbf{v})$, and the unconditional probability of choosing option i, $P(i) \equiv \int_{\mathbf{v}} P(i, \mathbf{v})\, G(d\mathbf{v})$. To our knowledge, the latter, which depends on prior beliefs $G(\mathbf{v})$ has no closed form. For the calculations reported below, therefore, we assume that priors are such that, despite their different λs, the unconditional probabilities are the same for the high- and low-skilled. The calculations below thus isolate the $ex-post$ effect of costs of information acquisition on conditional choice probabilities, separate from their influence on the probability of making a choice before any information is acquired.

More precisely, we consider one element of the option space, a choice to opt in and invest 60% of the endowment in heads and 40% in tails. Aggregating over all complex problems, the low-skilled are eight times more likely to take the outside option than to opt in and make this choice of 60-40 in favor of heads. The same relative probability is 1.1 for the high-skilled. We then ask the question, if the only thing determining the difference in these relative choice probabilities were the ex-post effects of costly information acquisition (utilities and unconditional probabilities are the same), what fraction of that difference could the differences in λ explain?

The results in Table 8 show that this fraction of the opting out behavior that can be explained by ex-post differences in costs of information acquisition depends on the specification of utility. We consider four examples of homothetic utility functions and find, for linear utility, the ex-post effects of differences in contemplation costs alone could explain 34% of the average difference in rates of opting out. At the other extreme of risk aversion, Leontieff utility, differences in λ can explain 26.5% of the difference in rates of opting out.

Table 8: Additional Opting Out Explained by Ex-post Effects Information Costs

Linear Utility	Log Utility	CES $\rho = 3$	Leontieff
34.5%	15.7%	32.3%	26.5%

Notes: This table evaluates what percentage of the difference in rates of opting out between low- and high-skilled participants can be explained by the ex-post effects of differences in their costs of acquiring information (λ). It assumes the utility of a given option, and the unconditional probability of choosing a given option, are the same for low- and high-skilled groups. It then calculates, for four different assumptions about the functional form of utility, the extent to which the point estimates of λ from Table 7 can explain the average difference between low- and high-skilled groups in their rates of opting out versus selecting a portfolio that invests 60% of the endowment in heads and 40% in tails.

The results of Table 8 indicate that the estimated differences in costs of information acquisition may explain economically substantial differences in the rates of costly opting out by decision-making skill. These results suggest, therefore, that the low-skilled may often be sophisticated in their decision to take a simple alternative to solving a complex problem. The estimated model implies that they may opt out more often, even when that choice is dominated, because doing so saves the costly effort of attending to the problem more thoroughly.

5 Conclusion

Evolving financial products and investment opportunities can 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. Consistent with concerns about the influence of complexity, the results show that, when they are required to make an active portfolio decision, participants facing complex problems make choices with lower expected payoffs and lower risk. On average, complexity also reduces some desirable properties of choice; it leads especially to more violations of monotonicity with respect to first-order stochastic dominance.

When offered a simple alternative to the portfolio choice, complexity has substantial, and varied effects on behavior. 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 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 have the outside option, it often has a substantial negative effect on expected payoffs, and this effect is especially large for those with the least 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. If, however, lower-skilled participants face higher costs of gathering information about and evaluating the portfolio problem they may rationally trade these costs for lower returns.

Information acquisition and contemplation costs are not observable, so we draw inference about their importance and about sophistication by estimating the structural parameters of a 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 accumulates costly knowledge about those values and updates her prior. Based on her posterior belief, the participant chooses the option with the highest expected utility.

In our interpretation, if the lower-skilled experience higher costs of information acquisition and contemplation, we treat the resulting increase in opting out as sophisticated. In this view, participants 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 are consistent with sophistication. We find a positive, statistically significant, and economically substantial difference between the attention costs of low-skilled and high-skilled participants. The ex-post effects of the estimated differences in these attention costs, alone, can explain sizeable fractions of the differences in the rates of costly opting out between these groups.

Future work should evaluate the robustness of these results in other settings. 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 decision problems in which the participant's choice y is either to invest in a portfolio $(y = 1, ..., N-1)$ or to opt out $(y = N)$. Equation (1) from above, due to Matějka and McKay (2015), implies that:

$$\begin{aligned} \Pr(y < N) &= \frac{\sum_{j=1}^{N-1} e^{(v_j+\alpha_j)/\lambda}}{\sum_{j=1}^{N} e^{(v_j+\alpha_j)/\lambda}} \\ \Pr(y = N) &= \frac{e^{(v_N+\alpha_N)/\lambda}}{\sum_{j=1}^{N} e^{(v_j+\alpha_j)/\lambda}} \end{aligned} \tag{5}$$

We assume that participants have homothetic preferences, such that:

$$\begin{aligned} v_i &= m * \overline{v_i} \quad \forall i < N \\ v_N &= \omega * \overline{v_N}, \end{aligned} \tag{6}$$

where $\overline{v_i}$ is the fundamental value of option i when the endowment is \$1, $\overline{v_N}$ is the fundamental value of opting out when the outside option is \$1, and m and ω are respectively the endowment and the outside option.

We rewrite (5) by replacing v_i with $\ln v_i$ and dividing both the numerator and denominator by $e^{(\ln\omega+\ln\overline{v_N}+\alpha_N)/\lambda}$:

$$\begin{aligned} \Pr(y < N) &= \frac{e^{\left(\mu+\frac{\ln m}{\lambda}-\frac{\ln\omega}{\lambda}\right)}}{1+e^{\left(\mu+\frac{\ln m}{\lambda}-\frac{\ln\omega}{\lambda}\right)}} \\ \Pr(y = N) &= \frac{1}{1+e^{\left(\mu+\frac{\ln m}{\lambda}-\frac{\ln\omega}{\lambda}\right)}} \end{aligned} \tag{7}$$

where

$$\mu = \ln\left\{\sum_{j=1}^{N-1} e^{(\ln\overline{v_j}-\ln\overline{v_N}+\alpha_j-\alpha_N)/\lambda}\right\}.$$

In the estimation, μ is a fixed effect in a conditional logit. μ is specific to a given slope of the budget line.

We allow the half of the sample with lower decision-making skill to have a different lambda from the other half of the sample with higher decision-making skill. Accordingly, the μ for a given slope of the budget line is allowed to vary with decision-making skill.