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SELECTION INTO FINANCIAL EDUCATION AND EFFECTS ON PORTFOLIO CHOICE

IRINA GEMMO
PIERRE-CARL MICHAUD
OLIVIA S. MITCHELL

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Selection into Financial Education and Effects on Portfolio Choice^{*}

Irina Gemmo[†], Pierre-Carl Michaud[‡] and Olivia S. Mitchell[§]

Abstract/Résumé

To examine how financial education affects financial outcomes, one must evaluate whether and how sample selection may bias inferences regarding program impacts. Our incentivized experiment reveals how such selection influences estimated financial education effects. The more financially literate and those expecting higher gains pay more to purchase education, while those who consider themselves very financially literate pay less. Using portfolio allocation tasks, we show that the financial education increases portfolio efficiency and welfare by almost 20 and 3 percentage points, respectively. In our setting, selection does not greatly influence estimated program effects, comparing those participating and those who do not.

Pour examiner comment l'éducation financière affecte les résultats financiers, il faut évaluer si et comment la sélection de l'échantillon peut biaiser les conclusions concernant l'impact du programme. Notre expérience incitative révèle comment une telle sélection influence les effets estimés de l'éducation financière. Les personnes les plus instruites sur le plan financier et celles qui s'attendent à des gains plus importants paient davantage pour acquérir une éducation, tandis que celles qui se considèrent comme très instruites sur le plan financier paient moins. En utilisant des tâches d'allocation de portefeuille, nous montrons que l'éducation financière augmente l'efficacité du portefeuille et le bien-être de près de 20 et 3 points de pourcentage, respectivement. Dans notre contexte, la sélection n'influence pas beaucoup les effets estimés du programme, en comparant les participants et les non-participants.

Keywords/Mots-clés: Financial Education, Financial Literacy, Portfolio Choice, Selection / Éducation financière, littératie financière, choix du portefeuille, sélection

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[†] HEC Montréal, Canada: irina.gemmo@hec.ca

[‡] HEC Montréal, Canada, NBER and CIRANO: pierre-carl.michaud@hec.ca

[§] Corresponding author. Wharton School of the University of Pennsylvania, and NBER: mitchelo@wharton.upenn.edu

1 Introduction

Financial literacy levels in developed countries are surprisingly low: many in the U.S., Europe, and Japan lack an understanding of interest rate compounding, inflation, and risk diversification (Lusardi and Mitchell, 2011); mutual fund expenses (Choi et al., 2010); and retirement planning (Lusardi and Mitchell, 2007). As a result, they earn lower returns and manage, as well as accumulate wealth, far less effectively (Lusardi and Mitchell, 2014; Lusardi et al., 2017). Moreover, getting financial advice is far from a perfect substitute for financial sophistication (Hackethal and Inderst, 2013). Accordingly, enhancing financial knowledge may be critical for better financial decision making through the lifetime.

Nevertheless, evidence is mixed regarding the effectiveness of financial education programs.¹ A key concern is that, when participation is voluntary, sample selection may bias measured program effects when comparing participants and non-participants. In general, selection into treatment has been understudied in this literature, though real-world programs inevitably involve voluntary participation with the potential for selection. The average effect on those treated could then depend on who shows up for the program, making it important to better understand the mechanisms producing such selection. To the best of our knowledge, there are no studies looking at the effects of financial education on portfolio choice which investigate the selection mechanism.

In this paper, we elicit individuals' willingness to pay to participate in financial education, and we quantify the effect of the program on investment behavior. We conduct a large-scale incentivized experiment on a representative sample of Canadian households. In the experiment, we first ask subjects to allocate an endowment across three different hypothetical assets that differ in expected re-

¹See for instance Agarwal et al. (2011) and Kaiser et al. (2022) for reviews of financial education program effectiveness.

turn and volatility. After observing participants' investment decisions, we inform respondents that they will face the same allocation exercise again later in the survey, and that their final payouts will depend on their actual investment choices. Next, we offer some participants the opportunity to acquire financial knowledge that can help them with the allocation task. This program provides educational content on portfolio diversification and risk-adjusted portfolio returns. We elicit participants' willingness to pay using the well-known BDM mechanism (Becker et al., 1964), and we motivate subjects to report their willingness to pay for financial knowledge by tying their decisions to the actual payouts they receive upon survey completion.

We measure the causal effect of the education by comparing the group that received it with a control group offered the intervention but which did not receive it. Hence, we can investigate the average-effect-on-the-treated impact of the financial education. In particular, the BDM mechanism provides an opportunity to exploit the missing at random assumption, conditional on peoples' willingness-to-pay for the program. In terms of outcomes, we develop preference-free performance measures originating from the standard efficiency frontier framework, and we also compare results with commonly-used heuristic strategies for portfolio allocation, such as 1/K (dividing assets equally across funds), and return-chasing allocations (where respondents systematically pick the asset with the highest expected return irrespective of volatility; Thaler et al., 2001).

Additionally, the experimental design enables us to study the drivers of willingness to pay for financial education. In our setting, program participation is proportional to willingness-to-pay. We test whether those willing to pay more are also those who expect to benefit the most from the education, a prediction that arises naturally from a rational model of financial literacy acquisition (Lusardi et al., 2020).

We find that the education intervention increases heterogeneity in portfolio allocations. In particular, it leads participants to customize their portfolios and move away from allocations using simple heuristics. For example, the education leads half of the respondents who previously spread their endowments equally across all three funds, to pick a different allocation. We also find that those receiving the education are 20 percentage points more likely to either improve expected returns or reduce their portfolio variance, without doing worse in the other dimension, thereby moving closer to the efficiency frontier. In addition, irrespective of their levels of risk aversion, respondents in the treated group are three percentage points more likely to unambiguously improve their asset allocations. Participants with higher cognitive ability and numeracy benefit more from the education than do participants scoring lower. Despite the apparent high value of the financial education, we find that almost one quarter of participants do not wish to receive it, even when provided free of charge. Elicited willingness to pay for the education is driven mainly by participants' expectations about their ability to transform the financial information from the intervention into better performance. In addition, a higher level of revealed financial sophistication boosts peoples' willingness to receive the education, while having more self-reported financial knowledge decreases their willingness to pay for it. Despite this apparent selection into the program, we show that it does not greatly influence estimated program effects in our setting. This suggests a low correlation between the characteristics predicting selection and portfolio performance.

2 Related Literature

This paper contributes to the literature exploring individuals' willingness to acquire financial knowledge or financial advice. [Jappelli and Padula \(2013\)](#) present

a two-period model where savers can acquire financial knowledge to boost the return on their savings. They predict that those with a higher propensity to save are also more willing to invest in financial knowledge; accordingly they hypothesize a complementarity between savings and financial knowledge. Exploiting this complementarity to explain wealth inequality, [Lusardi et al. \(2017\)](#) calibrate a multi-period stochastic life cycle model in which savers choose between investing in financial knowledge or private consumption. In those models, financial knowledge is akin to human capital. Savers choose their investment in financial knowledge by comparing the marginal cost of investing in financial knowledge (measured in money and time) to the marginal benefit associated with greater knowledge. One key benefit is to obtain higher (risk-adjusted) returns. The authors show that this mechanism can generate substantial wealth inequality. In our approach below, we measure empirically how greater financial literacy shapes investment performance.

This framework is well-suited to help us think about the effect of financial education on financial outcomes. For instance, [Lusardi et al. \(2020\)](#) use this approach to generate pseudo-experimental data where some individuals receive financial education and others do not. When allowed to choose to participate in financial education, they do so on the basis of their perceived expected gains from the program. The authors show that, in this model, the least financially savvy but who have higher saving needs elect the program. Accordingly, simply comparing participants and non-participants would deliver biased estimates of program effects, leading the econometrician to over-estimate the average effect of the program on outcomes. This type of rational selection is at the root of models exploring selection bias and its impact on inequality ([Heckman and Honoré, 1990](#)).

This rational selection can be muted or amplified by two factors. Before de-

Deciding to participate, some individuals may incorrectly perceive how the program will affect their outcomes. If those who would benefit most from the education underestimate the program effects (and vice-versa), selection bias may be lessened. For example, optimistic eligible participants may not enroll although they could benefit from participating in the program. Alternatively, the selection effect could be amplified if the cost of investing in knowledge, and in particular the maintenance cost of the accumulated knowledge (which can depreciate over time), is correlated with other characteristics such as cognitive skills or numeracy. Then those with low cognitive or numeracy skills may shy away from the financial education, because their marginal cost of acquiring knowledge is high. Ultimately, the extent to which selection biases inferences is an empirical question. Nevertheless, there is little evidence in the literature on what drives participation in financial education programs and how this alters inferences about the effectiveness of such programs. Our paper tackles this issue head-on, by designing and fielding an experiment to explore selection and demonstrate how it impacts inference.

The empirical literature on the effectiveness of financial education is rich (Lusardi and Mitchell, 2014; Kaiser et al., 2022). While early studies used non-experimental research designs,² more recent studies use randomized control trials (RCT) which randomize the allocation to treatment. Kaiser et al. (2022)'s meta-analysis of those RCTs concludes that there are sizeable effects across a range of financial decision making domains. Given that compliance with assignment to treatment may not be perfect, that study focuses on intent-to-treat effects, namely the effect of being assigned to treatment on outcomes, rather than more traditional average effects on the treated or average treatment effects. As a result, existing RCTs do not reveal how those who show up at the door differ from

²See Bernheim et al. (2001) for example.

the potential pool of eligible participants.³

A few studies provide a hint that selection into treatment might be non-random in the investment performance domain, but they focus on financial advice rather than education. Advice differs from education, because the treatment provides a recommendation; nevertheless, one might expect that similar mechanisms may operate. Furthermore, some of the interventions in these studies contain a mix of advice and education. For instance, [Bhattacharya et al. \(2012\)](#) conducted a field experiment where a treatment was offered consisting of a mix of advice and financial education. Those most likely to need advice, based on their sub-optimal past allocations, proved to be least likely to elect the advice. This type of selection does not conform with the rational selection model unless those same investors are pessimistic about the marginal benefit from receiving the treatment or face a high cost of receiving the treatment. In another experiment, [Hung and Yoong \(2013\)](#) showed that older, wealthier, and less financially literate respondents were more likely to seek advice. Without more information, one cannot pinpoint why selection worked differently across the two studies. As detailed below, in our work, we collect data on perceived and objectively measured financial literacy as well as a number of other traits such as cognitive skills and numeracy. Furthermore, participants perform an investment task prior to being offered treatment, allowing us to look at the effect of selection on changes in portfolio allocations.

Interestingly, those who received the advice in the [Bhattacharya et al. \(2012\)](#) experiment often did not follow the recommendations provided, and therefore did not substantially change their allocations. Conversely, [Hung and Yoong \(2013\)](#) estimated that those who voluntarily sought advice also did better in a portfolio allocation task. Nevertheless, these results are not directly comparable. To

³See [Deaton and Cartwright \(2018\)](#) for a similar critique of policy decisions informed solely on the basis of evidence from RCTs.

estimate the effect of advice on portfolio allocations, [Hung and Yoong \(2013\)](#) compared participants to non-participants and therefore could not control for selection. Instead, they offered an intent-to-treat estimate of the effect of offering advice on portfolio allocations. [Bhattacharya et al. \(2012\)](#), by contrast, undertook a before-and-after performance among those who participated. In our setting described in more detail next, we exploit elicited willingness-to-pay to receive education, to identify the effect of selection on inferences regarding program effectiveness. We also elicit expectations about the education’s effectiveness, to trace the mechanisms by which selection effects can materialize.

3 Experiment

Our experiment was fielded in the fall of 2021 using the online panel of *Asking Canadians*, a Canadian survey organization. Of the respondent pool aged 25 to 80, 2,005 subjects were randomly selected. Participants were paid in loyalty program rewards.⁴ Our survey instrument consists of two modules. In the first, we collected extensive information about respondents’ background and preferences, while the second module was devoted to the investment experiment.

3.1 Survey Module

The first module gathered information on participants’ demographics and financials (balance sheet and income). We also elicited preferences in two domains using procedures developed in the literature: risk aversion ([Holt and Laury, 2002](#)) and ambiguity aversion ([Dimmock et al., 2016](#)). In order to capture subjects’ cognitive ability and numeracy, we employ the cognitive reflection test introduced by

⁴Retailers included but were not limited to Aeroplan (Air Canada), the department store Hudson’s Bay, Petro-Canada, and VIA Rail. In total, we paid an equivalent of about \$ 66k in incentives to participants.

Frederick (2005) and the Berlin numeracy test introduced by Cokely et al. (2012). To record subjects’ financial literacy, we calculate a financial literacy score based on the Big Three questions designed by Lusardi and Mitchell (2007).⁵

The experimental module consists of three parts: an initial portfolio allocation task, a willingness-to-pay elicitation for financial education, and a follow-up portfolio allocation task. The willingness-to-pay elicitation is used to determine who receives financial education. Next, we provide details on each of these tasks and the assignment mechanism to the program. A summary of the experimental timeline appears in Appendix Figure B1.

3.2 Experimental Module

3.2.1 Part 1: Baseline Portfolio Decision (“Allocation Task 1”)

Respondents first received a hypothetical endowment of \$ 30 to allocate across three funds, along with information about the expected 5-year returns (μ) and volatility (σ) of each fund.⁶ Further, we provided explanations about each fund’s average return and volatility. To express volatility, we illustrated the probabilities of different realizations of 5-year returns for each fund.

3.2.2 Part 2: Willingness-to-Pay Elicitation

After respondents allocated their first endowment, they received a second endowment of the same amount (\$ 30). We then randomly assigned respondents to each of two arms: one group to whom no financial education was offered (a control arm); and a second group offered the financial education program (education

⁵The exact formulation of the questions appears in the survey instrument posted with other information on the experiment at <https://pcmichaud.github.io/Questionnaire-Gemmo-Michaud-Mitchell.pdf>.

⁶We choose a simple $\mu - \sigma$ characterization of each fund since these are fund characteristics that many respondents are likely to have heard of. Higher order moments, or correlations, are likely to be harder to grasp.

arm), namely educational content on portfolio diversification and risk-adjusted returns. The information given to the second set of respondents before their willingness to pay elicitation is important. For the education arm, respondents were told that they could use this endowment to purchase an educational program that might help them make better financial decisions and help them improve in a second allocation task, in which they would invest the remaining amount of their second endowment. To elicit individuals' willingness-to-pay for financial education, we use a Becker-DeGroot-Marschak (BDM) mechanism (Becker et al., 1964). Subjects had to state the maximum amount of their endowment they were willing to pay for the education, in an interval from zero to five dollars. A random number generator then determined the actual purchase price within this interval; if the price was below the respondent's elicited willingness-to-pay, she received the program (at the price generated by the random number generator), otherwise she did not.⁷

Using this BDM mechanism, we randomly generated a treatment and a control group within the educational arm described above. For most of our analyses, we restrict our sample to what we call the analysis sample, or the people that received the program offer. The group that received the financial education consists of around 43% ($N = 686$), and the remaining 57% ($N = 906$) comprised the control group.⁸

⁷One can show that respondents have no incentive to report anything but their true willingness-to-pay with this mechanism (Becker et al., 1964).

⁸Our rationale for including in the experimental design a control arm not offered the program is that those who wished to purchase financial knowledge but were not selected might have had different motivations when facing the second financial decision versus the first; for instance, they might have been disappointed or felt deceived. The same could have been the case for respondents who did not wish to purchase financial knowledge but were selected. For this reason, the control group never offered the program permits us to isolate learning effects from the first portfolio allocation task and test for disappointment effects. In Online Appendix Table A10, we show that the program effects based on the full sample including the control arm do not differ from those reported here using the analysis sample. Similar results hold if we drop those offered the treatment but not assigned to treatment, using only the control arm as a control group (results available upon request).

3.2.3 Part 3: Follow-up Portfolio Decision (“Allocation Task 2”)

After receiving the education program, we again asked all respondents (independent of whether they received the program) to allocate their endowments across the same three funds presented in Allocation Task 1. At this step, subjects’ endowments corresponded to what they received in Allocation Task 2 (\$30), minus the price paid for the program (if received). Hence, the endowment going into Allocation Task 2 was random, conditional on the respondent’s willingness-to-pay. Again, respondents allocated their entire (remaining) endowments across the three funds using the same $\mu - \sigma$ representation used in Allocation Task 1.

3.3 The Educational Program

The financial education targeted two important concepts related to portfolio choice: diversification and risk-adjusted returns. The intervention consisted of several screens displayed to participants, where the first defined the process of portfolio allocation, and subsequent screens discussed the value of diversification and risk-adjusted returns. To that end, we first illustrated a hypothetical investment opportunity consisting of three different funds that had the same expected return and standard deviation (referred to as variability). The education illustrated verbally and graphically that a portfolio’s standard deviation decreases when an endowment is spread equally across the three funds, relative to investing everything in a single fund, while the expected return is unchanged. We then related this decrease in variability to the term diversification.

In the next step, the education focused on the concept of risk-adjusted returns. To that end, we presented a second hypothetical investment opportunity consisting of three funds with different expected returns and standard deviations. The instructions suggested that subjects first build a portfolio by spreading the endowment equally across the three funds, and then they discussed how sub-

jects could increase the portfolio’s expected return while keeping the standard deviation unchanged. To achieve this, we suggested that subjects calculate risk-adjusted returns of each fund by dividing its expected return by its standard deviation, and then allocating more money to funds with higher risk-adjusted returns.

4 Portfolio Choice: Task 1

A total of 2,005 participants completed our survey; we dropped 12 respondents who did not disclose their gender as we use that as a control variable in all analyses. Online Appendix Table A1 reports demographics, financial information, measures of financial knowledge, and preferences for the 1,993 respondents. Respondents were age 53 on average, almost half (44.5%) were female, 65.4% were married, and 61.2% had children. Half the sample (51.6%) had at least a Bachelor’s degree (or more). Respondents earned an average of \$84,113 in annual household income (18.9% refused to disclose this information) and they had an average of \$248,562 in financial wealth.⁹

Nearly 27% of respondents held domestic stocks and 19.1% held individual stocks in plans or accounts such as Canadian Registered Retirement Savings Plans (RRSP) and Tax-Free Savings Accounts (TFSA); the latter are tax-preferred investment vehicles. A minority of respondents had traded stocks or other financial instruments (36.3%), implying that stock market experience was likely low for many respondents. Only 8.3% of respondents reported having high knowledge of the stock market, and 2.5% very high knowledge.

Fewer than 12.9% (5%) of respondents in our sample assessed their overall financial knowledge as high (very high), and fewer than 30% of respondents stud-

⁹This includes assets held in Registered Retirement Savings Plans, Tax-Free Savings Accounts, individual stocks, defined contribution plans, mutual funds, and other accounts.

ied economics or finance in high school. In addition to self-reported measures of sophistication, we use three scores to measure individuals' objective financial knowledge levels. The Financial Literacy Score refers to the total number of correct answers to the Big Three financial literacy questions (Lusardi and Mitchell, 2007, 2011). The Cognitive Ability Score is the sum of correct answers to the cognitive reflection questions by Frederick (2005) that measure cognitive ability; and the Numeracy Score is the sum of correct answers to the three-question Berlin numeracy test by Cokely et al. (2012). Overall, this sample of respondents scored relatively well on financial literacy: two-thirds (66.1%) of respondents answered all three questions correctly. The average score on cognitive skills was lower (0.97 out of 3, on average), and the average numeracy score was also low, 0.55 out of 3.

We measure risk attitudes with a Holt and Laury (2002) multiple price list; using the point at which respondents switched to the risky lottery, we obtain a measure of their risk aversion. Fewer than 6% switched at the last choice (9). If we include those who never switched, a substantial fraction, 20.4%, exhibited high risk aversion; the median switch point was close to 5. These numbers are in line with those reported in Boyer et al. (2022) who elicited risk aversion for Canadians using an incentivized experiment. Finally, we measure ambiguity aversion as in Dimmock et al. (2016), defined as the difference between the matching probability reported by the respondent and 0.5, expressed in percent. Overall, a reasonable fraction of our respondents was ambiguity averse (54%).¹⁰

In Allocation Task 1, all respondents were asked to allocate their endowments across the three investment options. Let i denote a respondent, and k an investment option. Each investment option is characterized by an expected return μ_k and a standard deviation of returns σ_k . Let $w_{1,i,k}$ be the weight put by respon-

¹⁰For the U.S., Dimmock et al. (2016) showed that 52% of respondents were ambiguity averse.

dent i in Task 1 on investment option k . Given the absence of correlation across investment options (by construction), the expected return and variance of the portfolio selected are given by:

$$\mu_{1,i} = \sum_k w_{1,i,k} \mu_k, \quad \sigma_{1,i}^2 = \sum_k w_{1,i,k}^2 \sigma_k^2 - \mu_{1,i}^2 \quad (1)$$

Next, we measure investment performance and potentially sub-optimal choices. The opportunity to identify sub-optimal choices in portfolio allocations is complicated by the fact that we do not precisely know each respondent's preferences, so we have no respondent-specific benchmark. Someone who picked a high expected return/high risk vs. a low expected return/low risk allocation cannot be classified as making a sub-optimal choice, since even in this simple world, the answer depends on respondents' risk aversion (there is no risk-free asset in this problem).

Instead of relying on the elicited measure of risk aversion, we therefore characterize sub-optimal behavior independent of risk aversion. We exploit the efficient frontier as the set of weights which provides the highest expected return for a given level of risk (or vice-versa) (Markowitz, 1952). A respondent picking a portfolio below the frontier would be making a sub-optimal choice, irrespective of risk aversion, since she could increase her return for a given level of risk leading to greater welfare (assuming her utility is increasing in wealth). Alternatively, she could decrease her portfolio risk holding expected return constant, leading to higher utility for any concave utility function or level of risk aversion.

To characterize respondents' allocations in terms of investment performance, we measure the Sharpe ratio of a given portfolio in Task 1, $S_{1,i} = \mu_{1,i}/\sigma_{1,i}$. Taking σ_i as given, we denote $\{w_{1,k}^*\}_{k=1,2,3}$ as the weights that maximize the portfolio's expected return. These are the weights that would bring the respondent to the ef-

efficient frontier for a given level of risk (measured by standard deviation). Let $S_{\mu,i}^*$ be the Sharpe ratio for those weights. Then, the relative mean return loss is defined as $RML_{1,i} = 1 - \frac{S_{1,i}}{S_{\mu,i}^*}$, which measures the relative vertical distance between a portfolio allocation and the point on the efficient frontier in the mean-variance space. We can also compute the point on the efficient frontier that minimizes the standard deviation for a given expected return (the horizontal distance in mean-variance space). This yields the relative difference in risk between the efficient frontier and what the respondent selected. Let $S_{\sigma,i}^*$ be the Sharpe ratio that minimizes the standard deviation for a given level of expected return. Then the relative return loss with respect to the standard deviation is $RSL_{1,i} = 1 - \frac{S_{1,i}}{S_{\sigma,i}^*}$.¹¹

Table 1 reports summary statistics on respondents' investment performance in Allocation Task 1. The average expected return is 31.7%, ranging from 18.9% to 44.4%. We also find considerable variation in $\sigma_{1,i}$, with a mean of 26.1% and a wide range, of 7.4% to 50.2%. The relative mean loss $RML_{1,i}$ averages 3.9%, again with a wide range, from 0 to 33.1%. The relative standard deviation loss, $RSL_{1,i}$, is larger, 7.63% on average, again with a large range. We also compute the fraction of respondents who put equal weights on each of the three funds, which we label 1/K allocation behavior, a naive heuristic that people often use (Thaler et al., 2001). We find that close to one-quarter of respondents (24.4%) used such a rule. We also report the frequency of respondents who invested their entire endowments in the fund with the highest return. This behavior, which we label return chasing, characterized one in 10 respondents (10.8%). Overall, we identify considerable heterogeneity in portfolio allocations and much scope for

¹¹We derive the relative mean return loss and relative standard deviation loss from the relative Sharpe ratio loss concepts introduced by Calvet et al. (2007). The authors define the relative Sharpe ratio loss as $RSRL_i = 1 - \frac{S_i}{S_B}$, where S_B is the Sharpe ratio of a common benchmark index. Since we have no benchmark index in our experiment, we instead use as a benchmark for each participant the portfolio with the highest possible mean given her chosen standard deviation (for the RML), or the portfolio with the lowest possible standard deviation given her chosen mean (for the RSL).

improvement in peoples’ portfolio allocations.

Table 1: Performance on Allocation Task 1

	N	mean	sd	min	median	max
Mean ₁		31.679	6.498	18.9	30.264	44.4
Standard Deviation ₁		26.056	11.480	7.410	21.605	50.2
Sharpe Ratio ₁		1.374	0.412	0.682	1.401	2.704
RML ₁		3.883	5.861	0	1.375	33.086
RSL ₁		7.628	11.473	0	3.365	59.852
1/K ₁		0.244	0.430	0	0	1
Return Chasing ₁		0.108	0.310	0	0	1
<i>N</i>	1993					

Note: This table presents summary statistics for respondents’ performance in Allocation Task 1 based on the full sample. For continuous variables, we show the mean and standard deviation. For binary variables, we report a fraction. $1/K_1$ is equal to one if a respondent spread her endowment equally over all three funds, and zero otherwise. Return chasing₁ is equal to one if a respondent invested her entire endowment in the fund with the highest expected return, and zero otherwise. RML is the relative mean loss, while RSL is the relative standard deviation loss.

To account for some of the heterogeneity observed in Task 1, we run a set of regressions for different outcome variables using a vector of respondent characteristics as controls. Online Appendix Table A2 reports the results. We find that higher-income respondents were more likely to select lower return and slightly lower risk portfolios, and the wealthier had higher Sharpe ratios. There is a negative association between education and the mean return as well as the standard deviation, but the effects are not statistically significant.

Turning to measures of knowledge and cognition, respondents with higher cognition scores selected less risky allocations (with lower expected returns), and those allocations had higher Sharpe ratios. We also find that people who scored higher on the numeracy questions obtained better Sharpe ratios. Those with experience trading stocks were more likely to pick riskier portfolios (with higher expected returns). The more risk averse tended to select less risky portfolios (not reported in Table A2).

Pointing to sub-optimal allocation metrics, the better-educated were more likely to have larger relative return losses, both in terms of expected returns and risk. This result is consistent with [Calvet et al. \(2007\)](#) who found that the more highly-educated tend to suffer larger return losses. One interpretation is that, by exposing themselves to more risk, better-educated respondents were also more likely to make mistakes. Yet this cannot explain our results here, as we show that the more educated tended to select less risky portfolios. Interestingly, return losses are seen across the sample, and they were not concentrated in particular groups. In terms of heuristics, those scoring higher on the financial literacy index were less likely to use the 1/K rule when picking their portfolios. Interestingly, those who thought they were very financially knowledgeable were more likely to be return chasers and invest their endowments entirely in the investment fund with the highest expected return. Those experienced in trading stocks were also more likely to be return chasers.

5 Willingness to Pay for Financial Education

Next, we randomize the offer of financial education across respondents: around 80% received the program offer (N=1,592), while the remaining 20% (N=401) did not. In what follows, we restrict our attention to the analysis sample receiving the educational offer.¹² Respondents were told that they could receive an educational program which might increase their performance in a second allocation task, financed with a new endowment of \$30. They were allowed to pay up to \$5 for this education, and they could opt out of the program by not reporting any willingness-to-pay. Given a respondent's willingness-to-pay response, a price over the same interval was randomly drawn. If the respondent's willingness to pay

¹²Participants not offered the program never stated a willingness to pay for the program, so we cannot examine their willingness to pay nor use it to analyse program effects.

exceeded her price, the price was deducted from her endowment available for Allocation Task 2. Hence, there was a real opportunity cost of receiving financial education.

We find that 24.5% of respondents offered the program elected not to receive it, even if they had to pay nothing for it. For those who did agree to pay, their average willingness to pay was \$2.91 (median of \$3), and fewer than 4.9% of respondents were willing to pay zero.¹³ Moreover, respondents were not particularly confident they would be able to apply the information gained in this exercise. Only 46.2% of respondents offered the program indicated that they expected to be able to apply the information received, while 19.3% reported that they did not know if they could. Almost half (46.7%) of respondents believed that their return in Allocation Task 2 would be higher than in Task 1 if they received the program, while 26.9% reported that they did know whether they would do better.

To understand what factors influenced respondents' willingness to pay for the financial education program, we next assess who rejected the education even if available at no cost (extensive margin), as well as the factors shaping how much participants were willing to pay for the intervention (intensive margin). The marginal effects on the extensive margin (from a Logit regression) appear in Column 1 of Table 2; estimated coefficients on the intensive margin appear in Column 2. Column 3 combines both margins with a dependent variable equal to 0 if the participant rejected the program, and as the willingness to pay if the participant provided one.

Participants had to trade off their willingness to pay against their expected benefit from the educational program. Accordingly, it is reasonable to find that

¹³These statistics are reported in Online Appendix Table A3. Also, Online Appendix Figure B2 reports the distribution of respondents' stated willingness to pay (conditional on being offered and not rejecting the program). Overall, the average willingness to pay was \$2.196 (setting WTP = 0 for participants rejecting the program), with heaping at integer values from 0 – 5. Overall, there was a sizeable dispersion in elicited willingness-to-pay values.

Table 2: Regression Estimates of Factors Associated with Willingness to Pay for Financial Education

	(1)		(2)		(3)	
	Reject		Willingness to		Willingness	
	program		pay (≥ 0)		to pay	
Ability to apply information: yes	-0.067	(0.025)	0.399	(0.111)	0.508	(0.110)
Ability to apply information: dk	0.045	(0.026)	0.091	(0.149)	-0.083	(0.133)
Exp. higher return in task 2: yes	-0.129	(0.026)	0.338	(0.119)	0.588	(0.117)
Exp. higher return in task 2: dk	0.017	(0.025)	0.056	(0.142)	-0.072	(0.129)
Female	-0.029	(0.020)	0.073	(0.094)	0.138	(0.091)
College or some university	0.042	(0.030)	-0.112	(0.142)	-0.187	(0.135)
Bachelor degree or more	0.059	(0.030)	-0.221	(0.141)	-0.307	(0.135)
ln(Household income)	0.020	(0.006)	-0.017	(0.021)	-0.060	(0.022)
Household income missing	0.128	(0.022)	-0.154	(0.140)	-0.573	(0.117)
Financial wealth	-0.005	(0.003)	0.012	(0.010)	0.019	(0.010)
Financial Literacy Score	-0.045	(0.013)	-0.029	(0.073)	0.150	(0.063)
Cognitive Ability Score	0.017	(0.011)	0.046	(0.051)	0.012	(0.050)
Numeracy Score	-0.055	(0.015)	-0.066	(0.058)	0.061	(0.059)
Financial knowledge: high	0.010	(0.037)	-0.499	(0.154)	-0.446	(0.153)
Financial knowledge: very high	0.038	(0.051)	-0.519	(0.247)	-0.482	(0.236)
St. market knowledge: high	-0.000	(0.046)	-0.109	(0.194)	-0.107	(0.192)
St. market knowledge: very high	0.054	(0.071)	-0.141	(0.354)	-0.250	(0.336)
Has traded stocks	-0.047	(0.024)	0.008	(0.100)	0.141	(0.100)
Has studied economics	0.016	(0.022)	0.149	(0.099)	0.090	(0.096)
Mean ₁	-0.069	(0.045)	-0.001	(0.180)	0.114	(0.180)
Standard Deviation ₁	0.035	(0.022)	-0.002	(0.090)	-0.055	(0.089)
Sharpe Ratio ₁	-0.067	(0.150)	-0.151	(0.619)	0.066	(0.611)
RML ₁	-0.037	(0.021)	0.040	(0.084)	-0.024	(0.086)
RSL ₁	0.005	(0.005)	0.004	(0.020)	-0.004	(0.020)
1/K ₁	0.083	(0.030)	-0.165	(0.144)	-0.392	(0.136)
Return Chasing ₁	0.102	(0.081)	-0.105	(0.350)	-0.434	(0.343)
_cons			3.112	(4.379)	-1.096	(4.373)
Mean	0.245		2.909		2.196	
N	1592		1202		1592	
chi2	426.906					
r2			0.080		0.200	

Standard errors in parentheses

Note: This table is based on the analysis sample. Reject program is an indicator variable equal to one if a respondent indicated that she did not want to receive the financial education. Willingness to pay takes the value of 0 if she indicated that she did not want the education; otherwise it takes the value the respondent was willing to pay for it. Willingness to pay (≥ 0) indicates the respondent's stated willingness to pay for the education if she elected to receive it. Column 1 reports marginal effects from a Logit regression. Columns 2-3 report OLS coefficient estimates. All columns also control for the respondent's region of residence, ownership of individual stocks, ownership of domestic stocks, marital status, children, number of HH members, age, and preferences such as risk aversion, ambiguity aversion, and patience.

participants rationally based their demand for financial education on their expectation about whether they would be able to apply the program information conveyed, and whether they expected that the knowledge would boost their return in Allocation Task 2. Participants who expected to be able to apply the financial education were 6.7 percentage points less likely to refuse the program, and they were willing to pay more for it than those participants who did not think that they could apply it. Analogously, participants who expected to obtain a higher return in Task 2 if they received the education were 12.9 percentage points less likely to refuse the treatment and were also willing to pay more for it, than their counterparts.¹⁴ Interestingly, participants with high levels of revealed sophistication - measured by their financial literacy and numeracy scores - were less likely to reject the educational program,¹⁵ while self-reported financial knowledge was negatively related to participant willingness to pay for the intervention. Interestingly, higher household income and greater formal education were associated with a lower willingness to receive the program, while participants experienced in trading stocks were 4.7 percentage points less likely to reject the education.

Participants who spread their endowments equally across all funds in the first allocation task were 8.3 percentage points more likely to reject the program, and they were also less willing to pay for the intervention, compared to others. Beyond this, we find no evidence that participants' performance in Allocation Task 1 affected their willingness to receive the financial education that might improve

¹⁴Note that, technically, participants with a stated willingness to pay of zero still had a chance to receive the program when the random price generated was zero. For participants who did not expect any benefit from the program, it could therefore be rational to reject the program, rather than stating a zero willingness to pay. A higher probability of rejecting the program, even if offered at no cost, likely reflects respondents' opportunity cost of time associated with receiving the program. [Kim et al. \(2016\)](#) show, in a theoretical setting, that acquiring financial knowledge can be sub-optimal for certain individuals, given opportunity costs of time.

¹⁵Note that these results hold even though we control for participants' expectations about their ability to apply the program information conveyed.

their performance in Allocation Task 2.¹⁶ The market revelation mechanism introduced by [Becker et al. \(1964\)](#) allows us to elicit participants' willingness to pay for the education on the condition that respondents understood the mechanism sufficiently well for it to work.¹⁷ To this end, during the experiment, participants were provided with information on the mechanism and provided examples. Furthermore we included a control question to test whether participants understood the process, and over half responded correctly.¹⁸

As noted above, one important driver of respondents' willingness to pay was their perception of the anticipated benefits from the intervention. That is, respondents were willing to pay more for the intervention if they expected to be able to apply the new information to Allocation Task 2, and if they expected the return from the second task to be higher than that earned on Task 1. While we do not observe how individuals formed their expectations, we can explore the association between respondent expectations about the benefits of the education with their measured socio-demographic characteristics, cognitive ability, and performance in Allocation Task 1. Results in Online Appendix Table [A4](#) show that women were less confident than men in their ability to apply the new information, and they frequently responded that they did not know if they had that ability. Financial literacy was positively related to the perceived ability to apply the program information and to earn a higher return in Allocation Task 2,

¹⁶Since some of the performance measures in the first allocation task are correlated, we also ran our analysis on each individual performance measure separately, without including the others. The results do not differ qualitatively from the results presented in Table [2](#).

¹⁷Note that even if participants did not understand the mechanism, they may still have stated their true willingness to pay based on intuition, but we cannot test if this was the case.

¹⁸This control question first provided participants a hypothetical stated willingness to pay for the program as well as a hypothetical price. Next they were asked to state whether or not they would receive the program in this case, and if so, what price they would have to pay. As a robustness check, we split the analysis sample into one group of participants who responded correctly to the control question (54.15%), and another which did not (45.85%). We repeat our analyses on the determinants of willingness to pay on these two sub-samples, and though we lose power when we split the group, our results still hold qualitatively for both sub-samples. Results appear in Online Appendix Table [A7](#).

conditional on receiving it.

Interestingly, high self-reported financial knowledge was positively and significantly associated with the perceived ability to apply the education. Participants with past stock trading experience were 7.4 percentage points more confident that they could transform the information acquired into a higher return in Allocation Task 2 (relative to the returns earned in Allocation Task 1). Respondents who studied economics and finance in high school were, respectively, 7.5 and 6 percentage points more likely to believe that they could apply the information and that it would lead to a higher return. Finally, peoples' performance in Allocation Task 1 was associated with their beliefs about whether the program would help them achieve a higher return in Allocation Task 2. Respondents with a higher mean, Sharpe ratio, or relative mean loss in Task 1 were less likely to respond "don't know" to the question about whether they believed that their return in Task 2 would be higher if they received the program. Respondents with a higher standard deviation in Task 1 were more likely to respond "don't know" to this question.¹⁹

To elicit respondents' willingness to pay for the intervention, we associate the likelihood of receiving the educational program to their elicited willingness to pay. Clearly the financial education was not allocated randomly across participants: the respondents who ended up in the treated group had a higher average willingness-to-pay. Let d_i equal one if the respondent is selected to receive the program, and let w_i be her willingness to pay. Then the probability of being assigned to the program is $\Pr(d_i = 1|w_i) = w_i/w_{\max}$ where w_{\max} is the maximum price that could be paid for the education (\$ 5). Let $y_{i,0}$ be a potential outcome in Task 2 if the respondent did not get the program and $y_{i,1}$ if she received it.

¹⁹Since some of the performance measures in the Allocation Task 1 were correlated, we also re-ran our analyses on each individual performance measure separately, excluding the others. These results do not differ qualitatively from those appearing in Appendix Table A4.

We only observe $y_i = d_i y_{i,1} + (1 - d_i) y_{i,0}$ which generates the classical problem of causal inference. We cannot rely on random assignment, since the missing at random assumption ($:= y_{i,0}, y_{i,1} \perp d_i$) is unlikely to hold. Those willing to pay more for financial education are likely to be respondents who expect to gain more from it ($y_{i,1} > y_{i,0}$) if rational selection is operating. Therefore, a simple comparison of outcomes between the treated and untreated groups would not deliver an estimate of the average program effect. Define $\Delta_i = y_{i,1} - y_{i,0}$. Then it is clear that comparing the treated to the untreated does not generate an unbiased estimate of the average treatment effect, i.e., $E(\Delta_i) \neq E(y_i | d_i = 1) - E(y_i | d_i = 0)$. But, conditional on willingness to pay, the program was assigned randomly: each respondent with the same willingness to pay had the same probability of being selected in the program. Specifically, a missing at random assumption given by $y_{i,0}, y_{i,1} \perp d_i | w_i$ can be exploited. We can thus estimate the effect of our financial education intervention using this missing at random assumption in a regression framework.

To check that willingness-to-pay is a sufficient statistic for selection into the program, we test whether assignment was independent of respondent characteristics X_i , which can include Task 1 outcomes, conditional on willingness to pay $d_i \perp X_i | w_i$. We conduct a conditional independence test with the null hypothesis $E(d_i | w_i, Z_i) = E(d_i | w_i)$, and report results in Online Appendix Table A5. The results suggest that the program allocation was not random when we do not control for willingness to pay (i.e., several characteristics are predictive of program assignment). Nevertheless, once we include willingness to pay as an explanatory variable, the overall test statistic for the joint hypothesis that all estimated coefficients on characteristics X_i are zero confirms that the willingness to pay is a sufficient statistic for assignment to the program (p-value = 0.522).

6 Portfolio Choice: Task 2

After being offered or receiving the educational program, participants then had to perform a second portfolio allocation task. We generate several indicators of investment performance improvements based on a comparison of subjects' performance in the first and the second allocation tasks. First, we define Δ Sharpe Ratio = Sharpe Ratio₂/Sharpe Ratio₁ - 1 to measure the improvement in the portfolio's Sharpe Ratio. For participants in Task 1 who spread their endowments equally across all assets (1/K allocations), and for those who invested everything in the fund with the highest mean return (return chasers), we define an indicator variable equal to 1 if the respondent changed her allocation in Task 2.²⁰ Further, we compute the absolute difference between the relative mean losses in the two allocation tasks, as well as the absolute difference between the relative standard deviation losses. That is, $\Delta RML = RML_2 - RML_1$ and $\Delta RSL = RSL_2 - RSL_1$.

To construct measures of portfolio improvements that are independent of preferences, we use the concepts of relative mean loss and relative standard deviation loss. Getting closer to the efficient frontier along either dimension (return or volatility) without worsening the other could be classified as an improvement. Consider an indicator equal to 1 if either RML or RSL improves. Formally, we define an efficiency improvement as:

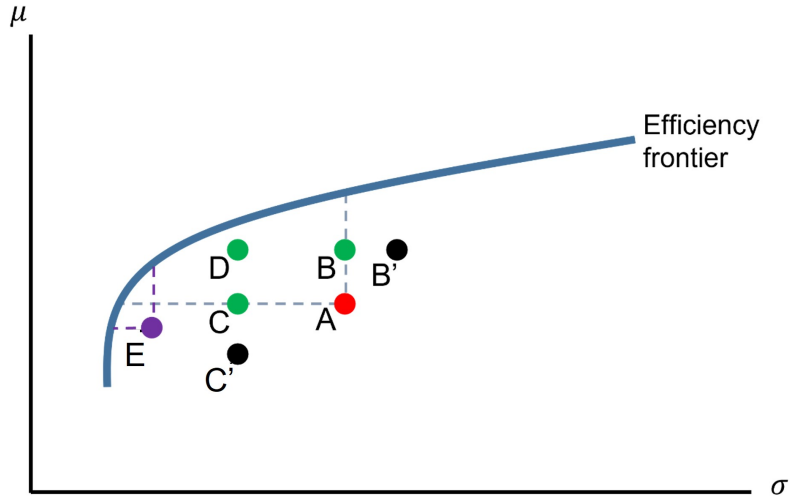
$$\begin{aligned} \Delta E_i = & \mathbb{I}(\Delta RML_i < 0)\mathbb{I}(\Delta RSL_i < 0) \\ & + \mathbb{I}(\Delta RML_i = 0)\mathbb{I}(\Delta RSL_i < 0) + \mathbb{I}(\Delta RML_i < 0)\mathbb{I}(\Delta RSL_i = 0), \end{aligned} \quad (2)$$

where $\mathbb{I}(\cdot)$ equals one if the argument is true, and zero if not. While this mea-

²⁰The endowment for the second allocation task is heterogeneous for participants who purchased the program, since it is net of the educational price paid. As that number may not be easily divided by three, we allowed for a small imbalance across funds to account for this (0.01 percent).

sures an improvement in efficiency, it does not measure a unambiguous welfare improvement. The reason is that it is not independent of preferences (risk aversion).

Figure 1: Efficiency and Welfare in Portfolio Allocations



Note: Suppose a participant chose allocation A in Task 1; other allocations are considered in Task 2. Allocations C' and B' are further away from the efficiency frontier in at least one dimension; hence, they do not represent an efficiency improvement. Among the remaining allocations, E is an improvement in terms of efficiency but not in terms of welfare. A participant with flat indifference curves (low risk aversion) may prefer A to E. However, allocations C, B, and D are preferred for any level of risk aversion (provided the participant exhibits some risk aversion). Those are captured by the improvement measure W_i defined in Equation 3 in the text.

In Figure 1, allocation E is an efficiency improvement from A, yet it does not represent an unambiguous welfare improvement. A respondent with a high tolerance for risk (with relatively flat indifference curves in this space) might prefer A to E. Assuming positive risk aversion, and therefore positively sloped indifference curves, B, C, and D represent both efficiency and welfare improvements. Accordingly, we construct a more refined measure aimed at capturing these improvements, by defining a welfare metric using the expected return and

the standard deviation of the portfolio directly:

$$\begin{aligned} \Delta W_i = & \mathbb{I}(\Delta\mu_i > 0)\mathbb{I}(\Delta\sigma_i < 0) \\ & + \mathbb{I}(\Delta\mu_i > 0)\mathbb{I}(\Delta\sigma_i = 0) + \mathbb{I}(\Delta\mu_i = 0)\mathbb{I}(\Delta\sigma_i < 0). \end{aligned} \quad (3)$$

Hence, ΔW equals 1 if there is an improvement along one dimension, without the other one deteriorating; it is zero otherwise. It is easy to show that ΔW_i picks out a subset of portfolio allocations captured by ΔE_i .

Table 3: Performance on Allocation Task 2

	N	mean	sd	min	median	max
Mean ₂	1592	31.458	6.036	18.9	30.264	44.4
Standard Deviation ₂	1592	25.327	10.577	7.410	22.337	50.2
Sharpe Ratio ₂	1592	1.384	0.390	0.682	1.346	2.721
RML ₂	1592	3.468	5.142	0	1.375	33.086
RSL ₂	1592	7.072	10.292	0	3.365	59.852
1/K ₂	1592	0.173	0.379	0	0	1
Return chasing ₂	1592	0.077	0.266	0	0	1
Δ Sharpe Ratio	1592	0.039	0.276	-0.726	0	2.644
Δ RML	1592	-0.410	5.966	-33.086	0	31.711
Δ RSL	1592	-0.517	11.876	-59.852	0	57.051
Δ 1/K	395	0.489	0.501	0	0	1
Δ Return chasing	165	0.473	0.501	0	0	1
Δ E	1592	0.342	0.474	0	0	1
Δ W	1592	0.035	0.184	0	0	1

Note: This table is based on the analysis sample. The performance improvement measures are defined as follows: Δ Sharpe Ratio = Sharpe Ratio₂/Sharpe Ratio₁ - 1; Δ RML = RML₂ - RML₁; Δ RSL = RSL₂ - RSL₁; Δ 1/K = 1-1/K₂ if 1/K₁=1; Δ Return chasing = 1-Return chasing₂ if Return chasing₁=1; Δ E = 1 if (Δ RML < 0 & Δ RSL \leq 0) or (Δ RSL < 0 & Δ RML \leq 0); Δ W = 1 if (Mean₂-Mean₁ > 0 & Standard Deviation₂-Standard Deviation₁ \leq 0) or (Mean₂-Mean₁ \geq 0 & Standard Deviation₂-Standard Deviation₁ < 0)

Table 3 presents summary statistics of these portfolio performance measures in Allocation Task 2. Both the average expected return and the average standard deviation of participants' portfolios are now slightly lower (mean₂=31.458 and

$sd_2=25.327$) compared to Task 1 ($mean_1=31.594$ and $sd_1=25.912$).²¹ Combining these measures suggests that participants' investment performance improved between allocation tasks, if we compare the average Sharpe ratio increase (Sharpe Ratio₁=1.378 and Sharpe Ratio₂=1.384), though the improvement is small. Of the 395 participants who previously spread their endowment equally across all three funds in Allocation Task 1, 50.9% changed their allocations in the second task. Of the 165 participants who put their entire endowments in the fund with the highest expected return in Task 1, 47.3% adjusted this behavior in Task 2. Both our portfolio efficiency measures in Allocation Task 2, the vertical distance to the efficiency frontier (RML) and the horizontal distance to the efficiency frontier (RSL), are smaller, on average, relative to the average values achieved in Task 1. Finally, Table 3 shows that 34.2 % of the participants improved their portfolio efficiency by decreasing their RML without increasing their RSL, by decreasing their RSL without increasing their RML, or by decreasing both (ΔE_i). A small group, 3.5% of participants, achieved a welfare improvement (ΔW_i).

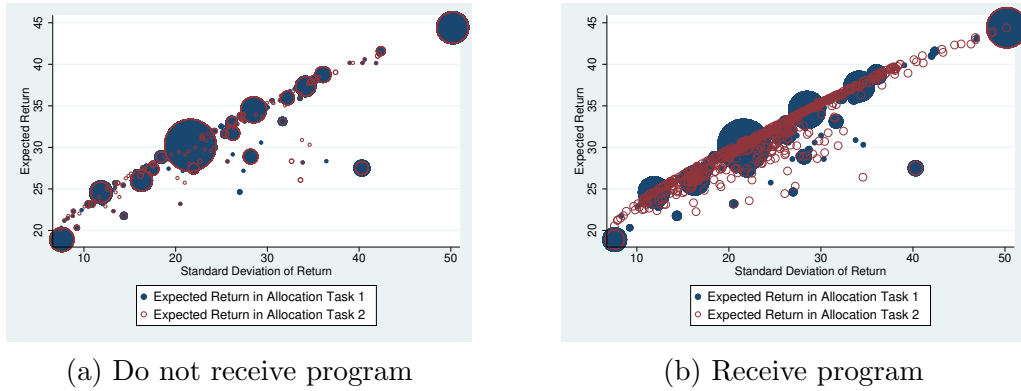
To illustrate how portfolio allocations changed, Figure 2 compares combinations of expected returns and standard deviations of returns in both tasks achieved by respondents offered the financial education. The size of the markers is proportional to the number of participants choosing the respective allocations. Panel (a) reports portfolio allocations for participants offered but who did not end up receiving the education, while panel (b) reports the same distribution for those who received it. For those not receiving the education, allocations did not change much.²² Among the treated group, there was much more change in the

²¹The values reported here for performance in Task 1 differ from those presented in Table 1, since Table 1 reports summary statistics for Task 1 on the full sample. For a meaningful comparison between the performance in Tasks 1 and 2, we report summary statistics for both tasks just for the analysis sample offered the treatment. The summary statistics for performance on Tasks 1 and 2 in the full sample are similar.

²²The same holds for those not offered the treatment and who therefore did not receive it.

Task 2 allocations. A Logit regression of an indicator variable equal to 1 if a participant offered the education did not change her allocation between Tasks 1 and 2 confirms that the observed increase in heterogeneity was mainly driven by whether participants received the education (see Online Appendix Table A6).

Figure 2: Portfolio Allocations in Tasks 1 and 2 by Financial Education Receipt



Note: This figure illustrates all combinations of expected return and standard deviation of return achieved by respondents in Allocation Tasks 1 and 2, among those offered the financial education (the analysis sample). Panel (a) reports allocations of those offered the program but who ended up not receiving it (due to the randomization) and in Panel (b), of those who received the program. The size of the markers is proportional to the number of participants who picked a particular allocation.

To estimate the educational program’s causal effect, we exploit the treatment assignment design and the implicit missing at random assumption, $d_i \perp X_i | w_i$. We regress the difference in outcomes from Task 2 versus 1 on the willingness to pay (w_i), which is effectively the (scaled) probability of being treated. We also control for other factors to reduce noise. Specifically, we estimate:

$$y_i = \alpha d_i + \eta w_i + X_i \beta + \varepsilon_i, \quad (4)$$

where y_i is the change in outcomes in Tasks 2 versus 1, X_i is a set of controls,

and ε_i is an error term. The estimated effect of the treatment is given by α .²³

Table 4 reports the average treatment effect on our measures of portfolio improvement.²⁴ Columns 1-3 report OLS coefficient estimates, and Columns 4-7 report marginal effects from Logit regressions.²⁵ To investigate how sample selection potentially biases inferences, we evaluate three specifications. First, we estimate a specification without controls. This delivers unbiased estimates if there is no selection, even on observables. We then estimate a second specification with a set of controls for observables (demographics, knowledge, preferences, and cognition). We do not control for the willingness to pay in this specification. Finally, we estimate a third specification where we add the willingness to pay as a control.

Focusing first on the full specification (row c), we find no statistically significant effects of the treatment on improved Sharpe ratios, RMLs, or RSLs. We document that the financial education produced a 19.6 percentage point increase in the propensity to achieve an efficiency improvement (i.e., a lower RML with constant RSL, a lower RSL with constant RML, or both a lower RML and RSL). That is, the financial education substantially improved peoples' portfolio efficiency, measured by their proximity to the efficiency frontier. We also find

²³We also explored including non-linear controls for w_i with no change in the results (available upon request.)

²⁴Table 4 reports the average treatment effect of the educational program for our analysis sample. Online Appendix Table A10 provides the results of the same analyses on the full sample (including those not offered the educational program). The combined analysis produces very similar effects of the educational treatment on improvements in portfolio allocations.

²⁵Note that for estimating the average treatment effect on the treated, it should not matter whether participants correctly understood the BDM process, since we control for willingness to pay in order to eliminate selection effects and selection is based on stated willingness to pay, irrespective of whether this reflected a participant's true willingness to pay. Nevertheless, we also undertake a separate robustness check based on the response to the BDM control question; results appear in Online Appendix Tables A8 and A9. The treatment effect on efficiency improvements is similar for both subgroups, though splitting the sample by answers to the BDM control questions as well as those who allocated their endowments equally across all assets in Task 1, versus those who invested everything into the highest expected return asset, produces sub-samples too small to estimate regression models of $\Delta 1/K$ and Δ Return chasing.

a treatment effect of around 3 percentage points in the preference-independent welfare improvement metric. That is, financial education increased the likelihood that participants improved their welfare, independent of their preferences, by 3 percentage points. Moreover, individuals who initially spread their endowments equally across all assets, as well as those who invested everything in the fund with the highest expected return, were, respectively, 49.6 and 27.1 percentage points more likely to alter this behavior when they received the financial education, compared to those who did not.

Without controls (row a), the financial education reduced RML, moved respondents away from $1/K$ and return chasing allocations, and improved efficiency as well as welfare. Controlling for observables (row b) does not alter these conclusions by much, compared to the specification without controls. When we control for the willingness to pay (panel c), most treatment effects are smaller, despite the fact that the willingness to pay coefficient is not statistically significant. The only exception is the effect on RML which becomes larger but statistically insignificant.

Overall, these results provide some evidence that the selection bias leads to an overestimation of the effectiveness of the treatment, yet the effects are minor and the differences are not statistically significant. Willingness to pay itself is not statistically significant in each specification, implying that there was little selection into treatment that biased inferences. Participants willing to pay more were those who thought they would be able to apply information acquired in the treatment and also those who expected higher returns in Task 2. In other words, while peoples' expectations were potentially correlated with actual treatment effects, this did not materialize in Allocation Task 2. We explore this further in the next section.

Table 4: Effects of Financial Education on Portfolio Allocation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ Sharpe Ratio	Δ RML	Δ RSL	Δ 1/K	Δ Return chasing	Δ E	Δ W
<i>a. No controls</i>							
Received program	0.017 (0.014)	-0.592 (0.302)	-0.422 (0.601)	0.552 (0.032)	0.377 (0.047)	0.256 (0.019)	0.033 (0.010)
<i>b. Adding controls for observables</i>							
Received program	0.013 (0.014)	-0.621 (0.313)	-0.495 (0.625)	0.539 (0.035)	0.384 (0.059)	0.245 (0.020)	0.033 (0.011)
<i>c. Adding control for WTP</i>							
Received program	-0.007 (0.021)	-0.842 (0.456)	-1.101 (0.910)	0.496 (0.059)	0.271 (0.115)	0.196 (0.032)	0.029 (0.014)
Willingness to pay	-0.001 (0.007)	0.102 (0.150)	0.291 (0.298)	0.007 (0.022)	0.036 (0.035)	0.018 (0.011)	-0.003 (0.005)
Mean	0.039	-0.410	-0.517	0.489	0.473	0.342	0.035
N	1592	1592	1592	395	163	1592	1592

Standard errors in parentheses

Note: This table is based on the analysis sample. Columns 1-3 report OLS coefficient estimates, while Columns 4-6 report marginal effects from Logit regressions. Three specifications are estimated. In row (a), we report the results without other controls. In row (b), we add controls for gender, region, marital status, children, number of HH members, age, economic characteristics such as income, wealth, ownership of individual stocks, ownership of domestic stocks, and perceived and revealed knowledge variables, and preferences, such as risk aversion, ambiguity aversion, and patience. In row c), we add the elicited willingness to pay as a control. Δ Sharpe Ratio, ΔRML and ΔRSL are changes in Sharpe ratio, relative mean return loss, and relative standard deviation loss, Δ 1/K denotes a move away from an equal allocation across funds from Task 1 to Task 2, Δ Return Chasing denotes a move away from an allocation where everything is invested in the fund with the highest return, ΔE denotes an improvement in efficiency defined in Equation (2), and ΔW denotes an improvement in welfare defined in Equation (3). All dependent variables are formally defined in the table notes of Table 3. The number of observations in specifications 4 and 5 is lower since the sample only includes respondents who either had 1/K or return chasing allocations in Task 1, respectively.

The financial education was anticipated to enhance peoples' knowledge of concepts useful for portfolio allocation. After the experiment, we asked all respondents three True-False questions about return chasing, the importance of risk-adjusted returns, and whether it is always best to spread one's money equally

Table 5: Effect of the Financial Education on Knowledge

	(1)		(2)		(3)		(4)	
	Knowledge Score		Q: Return chasing		Q: Risk-adjusted returns		Q: 1/K	
Received program	0.161	(0.054)	0.146	(0.032)	0.008	(0.030)	0.011	(0.031)
Willingness to pay	-0.011	(0.018)	-0.016	(0.011)	0.011	(0.010)	-0.002	(0.010)
Mean	2.334		0.727		0.826		0.781	
N	1592		1592		1592		1592	

Standard errors in parentheses

Note: This table is based on the analysis sample. The dummy variables Q:Return chasing, Q:Risk-adjusted returns, and Q: 1/K equal 1 if the participant responded correctly to the respective True-False question about return chasing, the importance of risk-adjusted returns, or whether it is always best to spread one’s money equally across available funds. Knowledge Score is the sum of correct answers to these questions. Column 1 reports OLS coefficient estimates, while Columns 2-4 report marginal effects from Logit regressions. In all regressions, we also control for rejecting the treatment and for an extensive set of characteristics, including gender, region, marital status, children, number of HH members, age, economic characteristics such as income, wealth, ownership of individual stocks, ownership of domestic stocks, and perceived and revealed knowledge variables, performance in Task 1, and preferences such as risk aversion, ambiguity aversion, and patience.

across available funds.²⁶ We code responses where each variable was equal to 1 if the participant responded correctly to the question (and 0 otherwise). We also compute a knowledge score defined as the sum of correct answers to all three questions. The average total score was 2.33 (out of 3), and over 70 percent (respectively, 72.7%, 82.6%, and 78.1%) of the participants responded correctly to all three questions. We report in Table 5 estimates of the effect of the financial education on knowledge, conditional on willingness to pay.²⁷ We document that

²⁶The statement on risk-adjusted return is *Comparing risk-adjusted returns across funds can help you increase your expected return for a given variability, by putting more money in certain funds than in others.* The statement for return chasing is *Imagine that Fund Q yields the highest expected return of investment opportunities available to you. Then you will always earn the highest return when you invest everything into Fund Q.* while the statement for 1/K as an optimal strategy is *Spreading your money across all available funds equally is the best investment strategy for everyone.*

²⁷Table 5 reports the average treatment effect of the educational program for our analysis sample. Online Appendix Table A11 provides the results of the same analyses on the full sample (including the group not offered the educational program). Both samples show very similar effects of the education on financial knowledge.

the program increased the knowledge score by 0.16, or 7 percent. This effect is mainly driven by peoples' improved understanding of return chasing, with a 14.6 percent increase in the proportion of correct answers to the return chasing question. Accordingly, participants did gain knowledge about expected returns, in particular, which helped them achieve better portfolio allocations in Task 2 compared to untreated participants.

7 Examining Heterogeneity

Table 6 reports the estimated effect of financial education with respect to efficiency improvements in the portfolio allocation tasks for a series of group pairs, testing for differences in treatment effects across groups. We form these groups to compare efficiency improvements resulting from the treatment between participants with more vs. less formal education; with above vs. below average financial literacy, cognitive ability, and numeracy; and with high vs. low self-reported financial/stock-market knowledge. The efficiency improvement resulting from the treatment is significantly larger for participants scoring higher on cognitive ability and numeracy, versus their lower-scoring counterparts. Hence, there is complementarity between cognition, numeracy, and improved outcomes following financial education, consistent with the hypothesis suggested by [Jappelli and Padula \(2013\)](#). There are no significant effect differences in efficiency when we compare respondents according to their highest degree of education, objective financial literacy scores, subjective self-reported financial knowledge, or self-reported stock market knowledge. This implies that people with high prior knowledge do not benefit more from the education than do their less knowledgeable counterparts, perhaps because they may have already known some of the information conveyed in the educational intervention.

Table 6: Heterogeneity in the Efficiency Effects of Financial Education

	N	ΔE	Diff.
Education			
less than college	768	0.193	
college	824	0.242	-0.049
Financial literacy score			
low	530	0.190	
high	1,062	0.232	-0.042
Cognitive ability score			
low	728	0.078	
high	864	0.323	-0.245
Numeracy score			
low	1,025	0.151	
high	567	0.309	-0.158
Subj. financial knowledge			
low	1,312	0.216	
high	218	0.180	0.036
Stock market knowledge			
low	1,427	0.207	
high	165	0.320	-0.113
Ability to apply information			
low	857	0.168	
high	735	0.260	-0.092

Note: This table reports coefficients of linear probability models that regress the efficiency improvement indicator ΔE (in equation 2) on a full set of controls (as in Table 4) and willingness to pay in the analysis sample. We split the sample along several dimensions. Along with point estimates, we also report the p-values for the difference between the treatment effects estimated for each group. The financial literacy score split is done at the mean of all participants (< 2.647), and 0 otherwise. A similar split is done at the means of the cognitive score (< 1.071) and numeracy score (< 0.618). A participant is defined as having high subjective financial knowledge if her self-assessment was high/very high. A similar split was done for stock market knowledge. The split for Ability to apply information is equal to 1 if the participant responded "yes" or "probably" to the question "Do you think you will be able to apply the financial information provided to your investment decision in Allocation Task 2, later in this survey?" and 0 otherwise.

If participants aligned their willingness to pay for financial education with their expected benefit from such treatment, they would need an accurate understanding of their own abilities. For this reason, we next evaluate whether treated participants correctly evaluated their own ability to apply the information conveyed in the educational intervention. The last two rows of Table 6 examine the financial education treatment effects on efficiency improvements, comparing

participants who stated that they could apply the information gained, and those who did not believe they could do so (the latter group includes those responding "don't know" or "refuse to answer").²⁸ Although the financial education effect on efficiency for those who believed that they could apply the information was higher than for their counterparts, the difference is not statistically significant.

In sum, we conclude that many people lack accurate beliefs about their own ability to process financial information, which helps explain why their willingness to pay for financial education is poorly aligned with their benefit from it. This has important implications for selection: although we do see some selection based on subjective expected benefits from financial education, actual outcomes do not differ since peoples' expectations are only weakly associated with actual outcomes.

8 Conclusions

To understand how selection may impact inferences about the effect of financial education on investment performance, we constructed an online survey experiment in which participants made two portfolio allocations and, in between, were offered the opportunity to purchase a financial education treatment. We elicited participants' willingness to pay for the education via the [Becker et al. \(1964\)](#) mechanism, which introduced useful randomization. Purchasing the treatment intervention had real monetary implications, as the price for the intervention was deducted from subjects' endowment available for the incentivized second allocation task. Hence, participants had to trade off the potential increase in investment performance and related monetary benefit they could gain from taking financial

²⁸Note that the question "*Do you think you will be able to apply the financial information provided to your investment decision in Allocation Task 2, later in this survey?*" was asked before participants received the treatment.

education, against the price they were willing to pay for it. This experiment illuminates the determinants of peoples' willingness to pay for financial education in the investment domain (the subjective value that participants placed on financial knowledge), as well as the performance change resulting from the treatment (the objective gain resulting from receiving financial knowledge).

Our findings highlight the importance of understanding selection mechanisms into financial education programs. We document that almost a quarter of participants did not wish to receive the educational treatment, even when it was provided free of charge. Peoples' stated willingness to pay for the treatment was mainly driven by their expectations about whether they would be able to transform the new financial information into a higher return. In addition, objectively more sophisticated (more financially literate) participants were more willing to receive the financial education, while those feeling themselves very confident regarding finances were less willing to pay for the education. Overall, selection into financial education was positive on a number of objective traits associated with the ability to benefit from the treatment, and negative on self-assessed confidence or self-assessed financial literacy. Optimism about own ability drove some away from program participation. This supports [Gaudecker \(2015\)](#)'s suggestion that over-confident respondents (who rate their skills highly but perform poorly) tend to be those who most need the financial education, yet they do not participate. Additionally, we generalize [Bhattacharya et al. \(2012\)](#)'s conclusion that those who with the worst past financial performance are also least likely to receive advice. While we do not find strong evidence that performance in Allocation Task 1 drove selection, we do confirm that perceived financial knowledge, conditional on objective financial knowledge, is negatively associated with willingness to participate in financial education. Accordingly, expectations and perceptions are quite predictive of peoples' willingness to undertake financial education.

In terms of investment performance, the financial education program increased heterogeneity in portfolio allocations, indicating that it encouraged some people to tailor their portfolios differently from their initial allocations. For example, the educational treatment substantially lowered participants' propensity to spread their endowments equally across all funds (by around 50 percentage points). It also reduced their likelihood of investing everything in the fund with the highest expected return (by 27 percentage points), and it boosted their understanding of why this allocation strategy was sub-optimal. Moreover, we document that financial education did not significantly change peoples' Sharpe ratios, relative mean losses, or relative sigma losses. To further analyze whether financial education in our experimental setting improved participants' financial decisions, we then developed two novel measures of investment performance: a portfolio efficiency metric, and a measure of preference-independent welfare improvement. We confirm that the financial education increased respondents' likelihood of achieving efficiency and welfare improvements, by almost 20 and 3 percentage points, respectively. We also find strong evidence that the educational effects were larger for those with higher numeracy and cognitive skills, suggesting that these skills are inputs into the production of financial literacy.

In our experiment, selection bias did not have important effects on investment performance following the education. If anything, not controlling for selection led to slightly inflated effects of the program on investment performance. This suggests that, despite selection into treatment on a number of unobservable traits, there was a low correlation between actual and perceived expected gains from the education. Our experimental evidence indicates that those who misperceived their abilities or the education's effectiveness were less likely to participate. Reaching these individuals should be of interest if one seeks to boost financial literacy and investment performance.

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A Online Appendix Tables

Table A1: Respondent Characteristics

	Mean	SD	Median
<i>Demographics</i>			
Female	0.445	0.497	0
Age	52.950	14.128	54
Married or common-law	0.654	0.476	1
Has children	0.612	0.487	1
Number of household members	2.125	1.168	2
<i>Education</i>			
College or some university	0.347	0.476	0
Bachelor degree or more	0.516	0.500	1
<i>Financials</i>			
ln(Household income) (log of \$ '000)	4.035	1.975	4.605
Household income missing	0.189	0.392	0
Financial wealth (\$ 00'000)	2.486	4.890	0.5
Ownership of individual stocks	0.191	0.393	0
Ownership of domestic stocks	0.268	0.443	0
<i>Sophistication</i>			
Financial Literacy Score	2.513	0.776	3
Cognitive Ability Score	0.966	1.056	1
Numeracy Score	0.554	0.859	0
Financial knowledge: high (self-reported)	0.129	0.336	0
Financial knowledge: very high (self-reported)	0.050	0.218	0
Stock market knowledge: high (self-reported)	0.083	0.276	0
Stock market knowledge: very high (self-reported)	0.025	0.156	0
Has traded stocks	0.363	0.481	0
Has studied economics or finance in high school	0.298	0.457	0
<i>Preferences</i>			
Risk averse: 2	0.013	0.113	0
Risk averse: 3	0.047	0.212	0
Risk averse: 4	0.180	0.384	0
Risk averse: 5	0.218	0.413	0
Risk averse: 6	0.140	0.347	0
Risk averse: 7	0.090	0.287	0
Risk averse: 8	0.052	0.222	0
Risk averse: 9	0.204	0.403	0
Impatient: 2	0.607	0.489	1
Impatient: 3	0.135	0.342	0
Impatient: 4	0.037	0.189	0
Ambiguity averse	7.903	20.080	3

Note: This table presents summary statistics on control variables for the full sample. For continuous variables, we show mean and standard deviation; for binary variables we show the share. Household income missing =1 if a respondent refused to provide information on household income, 0 otherwise. We report the log of annual household income and impute missing values of this variable with the sample's mean income. Financial wealth is the sum of wealth held in RRSPs, TFSAs, defined contribution plans, and other accounts. Financial Literacy Score is the sum of correct answers to Big Three questions measuring financial literacy (Lusardi and Mitchell, 2007, 2011), Cognitive Ability Score is the sum of correct answers to the three question cognitive reflection test (Frederick, 2005), and Numeracy Score is the sum of correct answers to the 3 question Berlin numeracy test (Cokely et al., 2012). Indicators of risk aversion report where in the multiple price list respondents switched to the riskier lottery. A higher switching point suggests higher risk aversion. N = 1993.

Table A2: Factors Associated with Performance on Allocation Task 1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Mean ₁	Standard Deviation ₁	Sharpe Ratio ₁	RML ₁	RSL ₁	1/K ₁	Return Chasing ₁
Female	0.002 (0.311)	0.332 (0.552)	0.014 (0.020)	0.359 (0.284)	0.286 (0.558)	-0.022 (0.020)	0.026 (0.015)
College or some university	-0.218 (0.462)	0.023 (0.821)	0.002 (0.029)	0.530 (0.423)	0.979 (0.830)	-0.059 (0.028)	-0.005 (0.022)
Bachelor degree or more	-0.781 (0.463)	-0.575 (0.822)	0.039 (0.029)	1.097 (0.423)	1.631 (0.830)	-0.034 (0.028)	0.004 (0.022)
ln(Household income)	-0.178 (0.075)	-0.224 (0.133)	0.008 (0.005)	0.139 (0.068)	0.227 (0.134)	-0.005 (0.005)	-0.006 (0.003)
Financial wealth	-0.064 (0.034)	-0.111 (0.061)	0.005 (0.002)	0.006 (0.031)	0.014 (0.061)	-0.003 (0.003)	-0.000 (0.002)
Financial Literacy Score	0.006 (0.217)	0.163 (0.385)	0.001 (0.014)	0.229 (0.198)	0.484 (0.389)	-0.065 (0.012)	-0.001 (0.010)
Cognitive Ability Score	-0.570 (0.171)	-0.909 (0.303)	0.042 (0.011)	0.136 (0.156)	0.102 (0.307)	-0.006 (0.011)	-0.001 (0.008)
Numeracy Score	-0.324 (0.201)	-0.606 (0.357)	0.027 (0.013)	-0.046 (0.184)	-0.074 (0.361)	-0.021 (0.014)	-0.000 (0.010)
Financial knowledge: high	0.684 (0.523)	1.334 (0.928)	-0.003 (0.033)	0.010 (0.478)	-0.564 (0.938)	-0.053 (0.037)	0.053 (0.023)
Financial knowledge: very high	0.525 (0.837)	1.041 (1.487)	-0.047 (0.053)	0.098 (0.766)	0.210 (1.503)	-0.023 (0.056)	0.004 (0.041)
St. market knowledge: high	-0.033 (0.648)	0.313 (1.150)	-0.012 (0.041)	0.544 (0.592)	0.993 (1.162)	0.002 (0.047)	0.004 (0.029)
St. market knowledge: very high	0.462 (1.130)	-0.171 (2.007)	0.022 (0.072)	-1.533 (1.033)	-3.101 (2.027)	0.020 (0.078)	0.009 (0.052)
Has traded stocks	0.712 (0.346)	1.243 (0.615)	-0.010 (0.022)	-0.161 (0.317)	-0.559 (0.621)	-0.052 (0.023)	0.045 (0.016)
Has studied economics	0.011 (0.328)	0.237 (0.582)	-0.024 (0.021)	0.365 (0.300)	0.843 (0.588)	-0.003 (0.022)	-0.011 (0.016)
Mean	31.679	26.056	1.374	3.883	7.628	0.244	0.108
r2	0.055	0.045	0.054	0.029	0.024		
chi2						177.675	54.232

Standard errors in parentheses

Note: This table is based on the full sample. The dependent variables are defined in the table notes of Table 1. Columns 1-5 report OLS coefficient estimates. Columns 6-7 report marginal effects from Logit regressions. All regressions control for region, ownership of individual stocks, ownership of domestic stocks, marital status, children, number of HH members, age, and preferences such as risk and ambiguity aversion as well as patience; we also include a control for having missing income information. N = 1993.

Table A3: Descriptive Statistics on Willingness to Pay for the Educational Program and Expectations about Results

	N	mean	sd	median
Received program	1592	0.431	0.495	0
Reject program	1592	0.245	0.430	0
Willingness to pay	1592	2.196	1.816	2.5
Willingness to pay (≥ 0)	1202	2.909	1.514	3
Ability to apply information: yes	1592	0.462	0.499	0
Ability to apply information: dk	1592	0.193	0.395	0
Exp. higher return in task 2: yes	1592	0.467	0.499	0
Exp. higher return in task 2: dk	1592	0.269	0.444	0

Note: This table is based on the analysis sample. Received program is a dummy variable equal to one if the respondent received the educational treatment. Reject program is a dummy variable equal to one if the respondent indicated that she did not want to receive the program in any case. Willingness to pay takes the value of 0 if the respondent indicated that she did not want to receive the program at all; otherwise it takes the value the respondent stated as her willingness to pay for the program. Willingness to pay (≥ 0) indicates the respondent's stated willingness to pay for the program if she elected to receive it. Ability to apply information: yes and ability to apply information: dk are dummy variables equal to one if the participant responded with "yes" or "don't know" to the question "Do you think you will be able to apply the financial information provided to your investment decision in Allocation Task 2, later in this survey?". The dummy variables exp. higher return in task 2: yes and exp. higher return in task: dk equal one if the participant responded with "yes" or "don't know" to the question "Do you expect your total return from Allocation Task 2 to be higher than the total return from Allocation Task 1, if you acquire additional financial information?".

Table A4: Regression Estimates of Factors Associated with Respondent Expectations about the Financial Education Program

	(1)	(2)	(3)	(4)
	Apply information: yes	Apply information: dk	Exp. higher return: yes	Exp. higher return: dk
Female	-0.078 (0.025)	0.049 (0.020)	-0.027 (0.025)	0.024 (0.022)
College or some university	0.051 (0.038)	-0.027 (0.028)	0.036 (0.038)	-0.026 (0.032)
Bachelor degree or higher	0.051 (0.038)	-0.043 (0.029)	0.038 (0.038)	-0.059 (0.032)
ln(Household income)	0.010 (0.006)	0.007 (0.006)	0.006 (0.006)	0.022 (0.007)
Household income missing	-0.181 (0.032)	0.128 (0.022)	-0.136 (0.032)	0.130 (0.025)
Financial wealth	0.001 (0.003)	-0.001 (0.003)	-0.001 (0.003)	-0.002 (0.003)
Financial Literacy Score	0.071 (0.018)	-0.036 (0.013)	0.065 (0.018)	-0.058 (0.014)
Cognitive Ability Score	0.007 (0.013)	0.007 (0.012)	0.023 (0.014)	0.001 (0.013)
Numeracy Score	0.046 (0.016)	-0.024 (0.015)	0.041 (0.016)	-0.008 (0.015)
Financial knowledge: high	0.176 (0.043)	-0.020 (0.039)	0.067 (0.043)	-0.070 (0.043)
Financial knowledge: very high	0.015 (0.065)	-0.061 (0.063)	-0.040 (0.066)	-0.106 (0.067)
St. market knowledge: high	-0.104 (0.054)	0.005 (0.049)	-0.103 (0.054)	0.040 (0.054)
St. market knowledge: very high	-0.094 (0.092)	0.011 (0.089)	-0.110 (0.094)	0.146 (0.087)
Has traded stocks	0.030 (0.027)	-0.039 (0.024)	0.074 (0.027)	-0.070 (0.026)
Has studied economics	0.075 (0.026)	-0.076 (0.023)	0.060 (0.026)	-0.047 (0.025)
Mean ₁	0.022 (0.049)	-0.005 (0.042)	0.082 (0.050)	-0.131 (0.048)
Standard Deviation ₁	-0.005 (0.025)	-0.008 (0.021)	-0.038 (0.025)	0.058 (0.023)
Sharpe Ratio ₁	0.183 (0.168)	-0.231 (0.147)	0.195 (0.170)	-0.336 (0.164)
RML ₁	-0.009 (0.023)	0.008 (0.020)	0.014 (0.024)	-0.043 (0.021)
RSL ₁	0.011 (0.005)	-0.005 (0.005)	0.011 (0.005)	-0.005 (0.005)
1/K ₁	-0.029 (0.038)	-0.032 (0.031)	-0.073 (0.038)	0.024 (0.033)
Return Chasing ₁	-0.102 (0.094)	0.148 (0.085)	-0.145 (0.094)	0.179 (0.091)
Mean	0.462	0.193	0.467	0.269
chi2	272.890	164.537	256.316	219.204

Standard errors in parentheses

Note: This table reports marginal effects from Logit regressions for the analysis sample. The dependent variables are defined in the table notes of Table A3. All regressions also control for region, ownership of individual stocks, ownership of domestic stocks, marital status, children, number of HH members, age, and preferences such as risk aversion, ambiguity aversion, and patience.

Table A5: Factors Associated with Educational Program Assignment Conditional on Willingness to Pay: Is WTP Sufficient to Confirm the Missing at Random Assumption?

	(1)		(2)	
	Received program		Received program	
Willingness to pay			0.154	(0.002)
Female	0.010	(0.026)	-0.006	(0.018)
College or some university	-0.057	(0.039)	-0.030	(0.026)
Bachelor degree or higher	-0.080	(0.039)	-0.031	(0.026)
ln(Household income)	-0.014	(0.006)	-0.006	(0.004)
Household income missing	-0.105	(0.034)	0.049	(0.025)
Financial wealth	0.003	(0.003)	-0.001	(0.002)
Financial Literacy Score	0.063	(0.019)	0.019	(0.014)
Cognitive Ability Score	0.015	(0.014)	0.005	(0.009)
Numeracy Score	0.009	(0.017)	-0.007	(0.011)
Financial knowledge: high	-0.083	(0.044)	-0.020	(0.029)
Financial knowledge: very high	-0.095	(0.069)	0.009	(0.046)
St. market knowledge: high	-0.119	(0.056)	-0.079	(0.037)
St. market knowledge: very high	-0.056	(0.096)	0.005	(0.066)
Has traded stocks	0.072	(0.028)	0.033	(0.019)
Has studied economics	0.030	(0.027)	-0.008	(0.019)
Mean ₁	0.098	(0.052)	0.053	(0.034)
Standard Deviation ₁	-0.052	(0.026)	-0.031	(0.017)
Sharpe Ratio ₁	-0.008	(0.173)	-0.061	(0.118)
RML ₁	0.033	(0.025)	0.021	(0.016)
RSL ₁	0.000	(0.006)	-0.001	(0.004)
1/K ₁	-0.118	(0.039)	-0.038	(0.026)
Return Chasing ₁	-0.085	(0.097)	0.027	(0.067)
Mean	0.431		0.431	
chi2	150.397		1154.095	

Standard errors in parentheses

Note: This table reports marginal effects from Logit regressions for the analysis sample. Received program is a dummy variable equal to one if the respondent received the educational treatment. Both models control for region, ownership of individual stocks, ownership of domestic stocks, marital status, children, number of HH members, age, and preferences such as risk aversion, ambiguity aversion, and patience. Financial education was assigned using the [Becker et al. \(1964\)](#)-mechanism. That is, a participant received the program if her willingness to pay for it was higher than or equal to a random price. The overall test statistic for the joint hypothesis that all coefficients (except the coefficient for willingness to pay) in column 2 are zero provides a test of randomness with respect to treatment assignment. The respective p-value is 0.5219. N = 1592.

Table A6: Regression Estimates of Factors Associated with Maintaining the Same Investment Choice between Allocation Tasks 1 and 2

	(1)	
	Allocation Unchanged	
Received program	-0.484	(0.032)
Willingness to pay	-0.011	(0.008)
Female	0.014	(0.021)
College or some university	-0.024	(0.032)
Bachelor degree or higher	-0.029	(0.032)
ln(Household income)	-0.002	(0.005)
Household income missing	0.017	(0.026)
Financial wealth	0.004	(0.002)
Financial Literacy Score	-0.030	(0.014)
Cognitive Ability Score	0.033	(0.011)
Numeracy Score	-0.001	(0.014)
Financial knowledge: high	-0.008	(0.035)
Financial knowledge: very high	-0.041	(0.054)
St. market knowledge: high	0.052	(0.043)
St. market knowledge: very high	0.095	(0.078)
Has traded stocks	-0.058	(0.024)
Has studied economics	0.016	(0.022)
Risk aversion: 2	-0.003	(0.105)
Risk aversion: 3	-0.123	(0.063)
Risk aversion: 4	-0.121	(0.048)
Risk aversion: 5	-0.091	(0.046)
Risk aversion: 6	-0.096	(0.049)
Risk aversion: 7	-0.098	(0.054)
Risk aversion: 8	-0.091	(0.060)
Risk aversion: 9	-0.026	(0.047)
Amiguity Averse	0.001	(0.000)
Mean	0.323	
chi2	600.450	

Standard errors in parentheses

Note: This table reports marginal effects from a Logit regression of an indicator variable equal to 1 if the participant did not change her portfolio between Allocation Tasks 1 and 2, given she was offered the educational program (for the analysis sample). We also control for region, ownership of individual stocks, ownership of domestic stocks, marital status, children, number of HH members, age, and preferences such as risk aversion, ambiguity aversion, and patience. N = 1592.

Table A7: Regression Estimates of Factors Associated with Willingness to Pay for Financial Education, by Response to BDM Control Question

	(1)	(2)	(3)	(4)	(5)	(6)
	Reject program for BDM=1	Willingness to pay (≥ 0) for BDM=1	Willingness to pay for BDM=1	Reject program for BDM=0	Willingness to pay (≥ 0) for BDM=0	Willingness to pay for BDM=0
Ability to apply information: yes	-0.073 (0.028)	0.361 (0.139)	0.528 (0.146)	-0.024 (0.042)	0.537 (0.191)	0.475 (0.169)
Ability to apply information: dk	0.019 (0.030)	0.373 (0.188)	0.251 (0.191)	0.095 (0.043)	-0.354 (0.255)	-0.357 (0.186)
Expected higher return in task 2: yes	-0.074 (0.029)	0.083 (0.148)	0.271 (0.155)	-0.149 (0.044)	0.604 (0.204)	0.780 (0.180)
Expected higher return in task 2: dk	0.013 (0.029)	-0.219 (0.180)	-0.258 (0.186)	0.021 (0.040)	0.458 (0.237)	0.170 (0.179)
Female	-0.039 (0.023)	0.167 (0.114)	0.247 (0.121)	-0.009 (0.034)	-0.054 (0.174)	0.003 (0.138)
College or some university	0.000 (0.035)	-0.145 (0.181)	-0.121 (0.191)	0.081 (0.047)	-0.016 (0.238)	-0.204 (0.191)
Bachelor degree or higher	0.028 (0.035)	-0.270 (0.180)	-0.288 (0.190)	0.107 (0.048)	-0.147 (0.239)	-0.315 (0.193)
ln(Household income)	0.005 (0.006)	-0.034 (0.026)	-0.044 (0.028)	0.035 (0.010)	-0.007 (0.037)	-0.081 (0.035)
Household income missing	0.062 (0.026)	0.008 (0.174)	-0.325 (0.171)	0.167 (0.036)	-0.377 (0.242)	-0.661 (0.163)
Financial wealth	-0.010 (0.005)	0.001 (0.011)	0.014 (0.013)	-0.001 (0.004)	0.036 (0.018)	0.027 (0.015)
Financial Literacy Score	-0.020 (0.016)	-0.058 (0.099)	0.058 (0.099)	-0.048 (0.020)	-0.043 (0.117)	0.102 (0.085)
Cognitive Ability Score	0.011 (0.012)	0.059 (0.061)	0.033 (0.063)	0.031 (0.019)	0.047 (0.097)	-0.052 (0.079)
Numeracy Score	-0.041 (0.016)	-0.097 (0.065)	-0.003 (0.071)	-0.054 (0.027)	0.012 (0.118)	0.155 (0.103)
Financial knowledge: high	0.035 (0.037)	-0.466 (0.179)	-0.549 (0.189)	-0.007 (0.065)	-0.654 (0.294)	-0.481 (0.259)
Financial knowledge: very high	0.077 (0.050)	-0.850 (0.293)	-0.968 (0.305)	0.076 (0.094)	0.033 (0.468)	-0.256 (0.380)
St. market knowledge: high	0.019 (0.047)	0.231 (0.232)	0.175 (0.245)	-0.106 (0.082)	-0.550 (0.365)	-0.203 (0.309)
St. market knowledge: very high	-0.011 (0.085)	0.192 (0.418)	0.243 (0.449)	0.041 (0.121)	-0.072 (0.691)	-0.299 (0.515)
Has traded stocks	0.002 (0.026)	-0.009 (0.120)	0.003 (0.129)	-0.099 (0.039)	0.023 (0.181)	0.269 (0.155)
Has studied economics	0.000 (0.024)	0.171 (0.115)	0.161 (0.122)	0.035 (0.038)	0.122 (0.194)	0.015 (0.154)
Mean ₁	-0.171 (0.052)	0.003 (0.206)	0.285 (0.218)	0.009 (0.081)	-0.123 (0.366)	-0.090 (0.314)
Standard Deviation ₁	0.088 (0.025)	-0.013 (0.103)	-0.157 (0.108)	-0.005 (0.041)	0.076 (0.186)	0.051 (0.158)
Sharpe Ratio ₁	-0.215 (0.161)	-0.173 (0.696)	0.160 (0.736)	0.088 (0.276)	-0.208 (1.278)	-0.473 (1.071)
RML ₁	-0.082 (0.023)	-0.024 (0.096)	0.114 (0.101)	-0.005 (0.039)	-0.058 (0.183)	-0.011 (0.153)
RSL ₁	0.006 (0.005)	0.008 (0.023)	-0.005 (0.024)	0.004 (0.009)	-0.004 (0.044)	-0.020 (0.036)
1/K ₁	0.018 (0.033)	-0.130 (0.178)	-0.209 (0.185)	0.119 (0.052)	-0.032 (0.258)	-0.402 (0.209)
Return Chasing ₁	0.013 (0.079)	0.237 (0.400)	0.113 (0.419)	0.191 (0.153)	-0.545 (0.719)	-0.790 (0.600)
.cons		3.028 (5.008)	-4.026 (5.322)		5.731 (8.730)	3.867 (7.521)
Mean	0.126	3.023	2.644	0.386	2.717	1.668
N	862	754	862	730	448	730
chi2	149.149			244.222		
r2		0.087	0.135		0.167	0.244

Standard errors in parentheses

Note: This table compares regression results of Willingness to Pay for financial education, comparing participants who responded correctly to the BDM control (BDM = 1) question and those who did not (BDM = 0), in the analysis sample. This control question first provides participants a hypothetical stated willingness to pay for the program, as well as a hypothetical price. Next they are asked to state whether or not they would receive the program in this case, and if so, what price they would have to pay. The independent variables are defined in the table notes of Table 2. Columns 1 and 4 report marginal effects from Logit regressions. Columns 2,3,5, and 6 report OLS coefficient estimates. All regressions also control for region, ownership of individual stocks, ownership of domestic stocks, marital status, children, number of HH members, age, and preferences such as risk aversion, ambiguity aversion, and patience.

Table A8: Regression Estimates of Factors Associated with Change in Investment Performance between Allocation Tasks by Response to BDM Control Question

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Sharpe Ratio for BDM=1	Δ Sharpe Ratio for BDM=0	Δ RML for BDM=1	Δ RML for BDM=0	Δ RSL for BDM=1	Δ RSL for BDM=0
Received program	-0.000 (0.025)	-0.027 (0.039)	-1.235 (0.572)	-0.232 (0.797)	-1.867 (1.130)	0.051 (1.609)
Willingness to pay	-0.003 (0.009)	0.005 (0.012)	0.206 (0.200)	-0.085 (0.240)	0.487 (0.395)	-0.058 (0.484)
Reject program	-0.077 (0.036)	-0.052 (0.034)	0.127 (0.820)	0.132 (0.685)	0.174 (1.621)	0.665 (1.383)
Female	0.004 (0.020)	0.016 (0.024)	-0.005 (0.463)	-0.064 (0.479)	0.055 (0.915)	-0.320 (0.966)
College or some university	0.001 (0.032)	0.035 (0.033)	0.383 (0.732)	-0.788 (0.666)	1.015 (1.446)	-1.843 (1.345)
Bachelor degree or higher	0.027 (0.032)	0.024 (0.033)	0.141 (0.726)	-1.116 (0.670)	1.012 (1.435)	-2.684 (1.353)
ln(Household income)	0.003 (0.005)	0.009 (0.006)	-0.058 (0.107)	-0.200 (0.122)	-0.145 (0.210)	-0.332 (0.247)
Household income missing	-0.047 (0.029)	-0.022 (0.028)	0.782 (0.658)	-0.185 (0.571)	1.523 (1.300)	-0.712 (1.152)
Financial wealth	-0.005 (0.002)	-0.002 (0.003)	-0.012 (0.048)	0.036 (0.053)	-0.009 (0.095)	0.026 (0.108)
Financial Literacy Score	-0.004 (0.016)	0.005 (0.015)	-0.086 (0.379)	0.358 (0.296)	-0.318 (0.749)	0.750 (0.598)
Cognitive Ability Score	0.001 (0.010)	-0.006 (0.014)	-0.423 (0.241)	-0.255 (0.276)	-0.779 (0.477)	-0.595 (0.558)
Numeracy Score	-0.012 (0.012)	0.008 (0.018)	0.058 (0.272)	-0.027 (0.358)	0.139 (0.537)	0.155 (0.722)
Financial knowledge: high	0.005 (0.031)	-0.019 (0.044)	-0.425 (0.719)	-0.441 (0.901)	-0.401 (1.420)	-0.891 (1.819)
Financial knowledge: very high	0.033 (0.051)	-0.042 (0.065)	-0.535 (1.165)	-0.171 (1.323)	-1.505 (2.302)	-1.217 (2.672)
St. market knowledge: high	0.009 (0.041)	0.014 (0.053)	0.451 (0.945)	0.239 (1.082)	0.917 (1.866)	1.072 (2.185)
St. market knowledge: very high	0.064 (0.074)	-0.015 (0.088)	1.904 (1.715)	-0.127 (1.781)	3.186 (3.388)	0.084 (3.597)
Has traded stocks	-0.022 (0.021)	0.042 (0.027)	0.263 (0.494)	0.409 (0.541)	0.821 (0.975)	0.844 (1.093)
Has studied economics	0.001 (0.020)	-0.039 (0.026)	-0.442 (0.464)	-0.643 (0.536)	-1.078 (0.917)	-1.389 (1.083)
_cons	0.018 (0.085)	-0.081 (0.089)	-0.819 (1.959)	0.900 (1.811)	-1.813 (3.869)	0.895 (3.658)
Mean	0.035	0.045	-0.455	-0.358	-0.461	-0.584
N	862	730	862	730	862	730
r2	0.030	0.061	0.046	0.035	0.040	0.035

Standard errors in parentheses

Note: This table compares regression results of performance measures Δ Sharpe Ratio, Δ RML, and Δ RSL, comparing participants who did/did not respond correctly to the BDM control question (for a definition of the BDM control question, see Online Appendix Table A7), in the analysis sample. The independent variables are defined in the table notes of Table 3. All regressions also control for region, ownership of individual stocks, ownership of domestic stocks, marital status, children, number of HH members, age, and preferences such as risk aversion, ambiguity aversion, and patience. N = 1592.

Table A9: Regression Estimates of Factors Associated with Change in Performance between Allocation Tasks by Response to BDM Control Question

	(1)		(2)	
	ΔE for BDM=1		ΔE for BDM=0	
Received program	0.214	(0.039)	0.172	(0.056)
Willingness to pay	0.031	(0.014)	0.009	(0.017)
Reject program	0.020	(0.068)	-0.051	(0.053)
Female	-0.047	(0.034)	-0.013	(0.036)
College or some university	-0.030	(0.053)	0.090	(0.050)
Bachelor degree or higher	0.008	(0.053)	0.047	(0.051)
ln(Household income)	-0.004	(0.008)	0.005	(0.009)
Household income missing	-0.029	(0.050)	0.032	(0.044)
Financial wealth	0.002	(0.003)	-0.000	(0.004)
Financial Literacy Score	0.059	(0.029)	-0.006	(0.023)
Cognitive Ability Score	0.009	(0.018)	0.022	(0.020)
Numeracy Score	0.012	(0.019)	-0.037	(0.027)
Financial knowledge: high	-0.021	(0.053)	0.036	(0.066)
Financial knowledge: very high	-0.079	(0.089)	0.182	(0.096)
St. market knowledge: high	0.021	(0.068)	-0.044	(0.083)
St. market knowledge: very high	0.016	(0.126)	-0.160	(0.153)
Has traded stocks	0.010	(0.035)	0.007	(0.040)
Has studied economics	-0.027	(0.034)	0.035	(0.040)
Mean	0.361		0.319	
N	862		730	
chi2	130.359		84.500	

Standard errors in parentheses

Note: This table compares marginal effects from Logit regressions of the efficiency improvement ΔE (defined in the table notes of Table 3) between participants who did/did not respond correctly to the BDM control question, in the analysis sample. For a definition of the BDM control question, see Online Appendix Table A7. All regressions also control for region, ownership of individual stocks, ownership of domestic stocks, marital status, children, number of HH members, age, and preferences such as risk aversion, ambiguity aversion, and patience. $N = 1592$.

Table A10: Effects of Financial Education on Portfolio Allocation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Δ Sharpe Ratio	Δ RML	Δ RSL	Δ 1/K	Δ Return chasing	Δ E	Δ W
Received program	-0.005 (0.022)	-0.846 (0.444)	-1.129 (0.904)	0.509 (0.063)	0.340 (0.116)	0.193 (0.032)	0.025 (0.012)
Willingness to pay	-0.003 (0.007)	0.112 (0.145)	0.316 (0.296)	0.015 (0.022)	0.020 (0.035)	0.017 (0.011)	-0.002 (0.004)
Mean	0.042	-0.335	-0.478	0.461	0.433	0.322	0.030
N	1993	1993	1993	486	212	1993	1846

Standard errors in parentheses

Note: This table is based on the full sample. The independent variables are defined in the table notes of Table 3. We set to 0 the Willingness to pay for participants not offered the financial education. Columns 1-3 report OLS coefficient estimates, while Columns 4-6 report marginal effects from Logit regressions. All regressions also control for gender, region, marital status, children, number of HH members, age, economic characteristics such as income, wealth, ownership of individual stocks, ownership of domestic stocks, perceived and revealed knowledge variables, and preferences such as risk aversion, ambiguity aversion, and patience. The number of observations in specifications 4 and 5 is lower since the sample includes only respondents who had either 1/K or return chasing allocations in Task 1, respectively.

Table A11: Effects of Financial Education on Knowledge

	(1)	(2)	(3)	(4)
	Knowledge Score	Q: Return chasing	Q: Risk-adjusted returns	Q: 1/K
Received program	0.157 (0.054)	0.148 (0.033)	0.005 (0.029)	0.011 (0.030)
Willingness to pay	-0.011 (0.018)	-0.016 (0.011)	0.010 (0.009)	-0.002 (0.010)
Mean	2.337	0.717	0.834	0.786

Standard errors in parentheses

Note: This table is based on the full sample. The independent variables are defined in the table notes of Table 5. We set to 0 the Willingness to Pay of those participants not offered the financial education. Column 1 reports OLS coefficient estimates, while Columns 2-4 report marginal effects from Logit regressions. All regressions also control for rejecting the educational program and for gender, region, marital status, children, number of HH members, age, economic characteristics such as income, wealth, ownership of individual stocks, ownership of domestic stocks, perceived and revealed knowledge variables, performance in Task 1, and preferences such as risk aversion, ambiguity aversion, and patience. N = 1993.

B Online Appendix Figures

Figure B1: Experimental Timeline

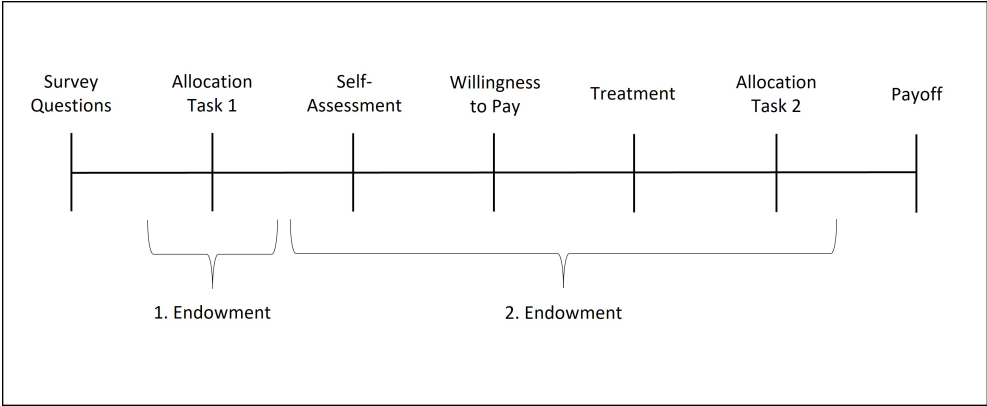


Figure B2: Distribution of Willingness to Pay (\$)

