Organizational Trust and Retirement Plan Investment Choice

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Abstract

Employer-sponsors of defined contribution retirement plans can decide how to label the funds on their plan investment menus. They can decide to use organizations' names, such as asset managers, in the fund labels, or to use generic "white" labels. We show experimentally that participants' trust in named organizations changes their allocations to investment funds. Organizational trust matters even when the organization's name conveys nothing about the fund's relative quality. We further show that trust causes participants to expect higher returns and lower losses from investments in funds labelled with the names of more trusted organizations, and that participants' expectations influence their allocations. Organizational trust operates more strongly when participants have lower financial literacy. Our findings show that employer-sponsors' seemingly harmless choice of fund labels can affect participants' investment decisions in unintended ways.

Keywords: Pensions; Choice experiment
JEL codes: G51; G21; G41

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1 Introduction

More than 120 million people in the U.S. choose investments from retirement plan menus designed by their plan sponsors. Plan sponsors must design menus with their fiduciary duties to participants in mind, and recent lawsuits show the possible high cost to sponsors who fail in these duties (Chambers, 2021). Some sponsors have pared down their investment menus, fearing the risk of litigation (Gropper, 2023). Even plan sponsors that meet fiduciary (ERISA) standards[1], however, can find that seemingly harmless menu features, such as fund names, influence participants in unintended ways (Huberman, 2001; Cooper et al., 2005; Green and Jame, 2013).

Names on funds in retirement plan investment menus are changing. Many U.S. retirement plans are introducing generically-named funds into investment menus. These options, commonly referred to as "white-label" funds, are usually assembled from several funds by plan sponsors, with the aim of improving diversification and enabling easier modifications of the components. The white label shows that the fund has been tailored for the plan, and is not the product of a specific asset manager. White label funds can be labelled by their asset class or investment style, or also carry the name of the employer-sponsor. With the discretion to choose names comes the potential for plan sponsors, intentionally or unintentionally, to steer participants' investment choices. This potential is concerning given that participants can be influenced by financially irrelevant factors like investment menu composition or cosmetic changes to fund names (Agnew, 2006; Benartzi and Thaler, 2001; Brown et al., 2007; Huberman and Jiang, 2006; Liang and Weisbenner, 2002) while neglecting relevant factors like fees (Choi et al., 2010).

In this study, we investigate the influence of fund names on retirement plan participant investment choices. We conduct an incentivized experiment using generic white label funds as a benchmark, and evaluate the impact of two types of fund labels: conventional asset manager labels and employer named white labels. The hypothetical funds in this experiment are index funds, where the fees are assumed to be waived, and non-portfolio services are not on offer.[2] Rational subjects in the experiment should be indifferent between funds in any asset class that differ only by label.

Our experiment is more than a general test of irrelevant labels. We hypothesize that the effects we measure are caused by ínvestors' trust in the organization on the fund label. Prior work has shown that organizational trust (i.e., "confidence that a firm is dependable and can be relied on") shapes expectations of the firm's future behavior (Grégoire and Fisher, 2008, p. 41). These positive expectations come from the perception that an organization demonstrates ability, benevolence (i.e., concern for stakeholders) and integrity (i.e., standards of moral behavior) (Mayer et al., 1995; Lewicki et al., 1998; Gillespie and Dietz, 2009). When funds carry the names of asset managers or employers, plan participants' trust in the organization on the label will influence their behavior. To test this hypothesis, we vary fund labels to show either a high-trust or low-trust asset manager or employer name.

[1] Employee Retirement Income Security Act of 1974 ("ERISA")

[2] Note that Choi et al. (2010) run a related experiment where participants choose between four SP500 index funds that differ only by label and fees. In their experiment, the lowest fee index fund dominates.

We test the organizational trust hypothesis in two studies. Study One compares highly- and poorly-trusted asset manager labels. We pre-tested the asset manager names to ensure that they differed by organizational trust and not by related factors such as consumers' familiarity with, or knowledge of, the asset manager. Then, in Study Two, we compare highly- and poorly-trusted employer names collected from subjects in the experiment. Study Two tests whether general organizational trust, rather than trust related to financial organizations, impacts allocations.

We collect data from more than 940 currently-employed retirement plan participants who are members of the Understanding America Study (UAS) panel (University of Southern California). UAS ran the lab-in-the-field experiments in late 2018.[3] The experiments gather subjects' incentivized investment allocations and risk and return estimates for different funds. The investment task asked subjects to choose allocations for their retirement plan balances from menus that include five asset classes: U.S. money market, U.S. bonds, U.S. large cap stocks, U.S. small cap stocks and global stocks. Depending on a randomly assigned condition, the menu offers two funds within each asset class: a generic white-label fund and an asset manager- or employer-named alternative. For Study One, subjects assigned to Conditions 1 and 2 see menus that include either: i) generic white-label and high-trust-manager-label funds, or, ii) generic white-label and low-trust-manager-label funds. For Study Two, subjects in Condition 3 see menus that include generic white-label and own-employer-named white-label funds. Here we divide the sample into low- and high-employer-trust groups based on subjects' self-reported ratings of their trust in their employer. The control (Condition 4) provides a benchmark where subjects see a menu that has only one generic white-label fund in each asset class. In all conditions, subjects also give their predictions of one-year investment returns by allocating balls to bins in a distribution builder (Goldstein et al., 2008).

Our results show that trust in organizations influences plan participants' allocations simply through labelling. Using distribution-builder methods for measuring expectations, we show that this response is driven in part by trust-related differences in subjects' expectations of investment returns and losses. We further document that these effects are moderated by subjects' financial literacy; the effect of organizational trust is weaker for more financially literate subjects than for subjects with low financial literacy.

In Study One, we find that organizational trust matters both directly and indirectly to participants' investment choices. On average, subjects who were offered the high-trust-manager fund report significantly higher expected returns and lower probability of loss to a one-year investment than those offered the low-trust-manager fund. By and large, this tendency is more marked among subjects with low financial literacy than among subjects with high financial literacy. Panel model estimations show that these return and loss expectations significantly influence allocations to the manager-labeled options. This finding is evidence for an indirect effect of organization trust on asset allocation via expected returns and losses. To identify any direct effect, we propose a two-step allocation model where participants first decide on broad asset class allocations and then decide on the division between fund-manager labeled and generic options within each asset class. We estimate this

[3] The codebook and details of the experiment are available at `https://uasdata.usc.edu/index.php`.

model using 2SLS, implementing a machine learning-generated instrument to account for endogeneity. The results reveal that differences in organizational trust change retirement plan allocations both indirectly via expected returns and risk, and directly.

In Study Two, we conduct a similar analysis and again confirm the direct effect of organizational trust. We compare the influence of highly-trusted employer-named funds with poorly-trusted employer-named funds. While we do not identify significant indirect effects via expected returns or probability of loss, this may be due to the small sample size of Study Two, and our inability to experimentally manipulate trust in one's employer, and should be investigated further. Our results have practical implications. Before choosing labels for new funds in plan menus, plans sponsors should consider whether participants' trust in those organizations, both fund managers and employers, could distort participants' asset allocations.

Related Literature: Our study adds to evidence that fund labels change investment decisions. Investors tend to choose what they know, such as company stock, due to familiarity bias, implied endorsement, or loyalty (Agnew, 2006, Benartzi and Thaler, 2001, Cohen, 2009, Huberman, 2001). Flows into mutual funds rise after cosmetic changes from "cold style" names to popular, or "hot style," names, independent of any actual change in asset holdings to reflect the new style (Cooper et al., 2005). Even fluent names - short names that people can process easily - induce greater breadth of ownership for the companies that adopt them, and larger fund flows to mutual funds that choose them (Green and Jame, 2013), as do names ranking higher in the alphabetic order (Jacobs and Hillert, 2016; Doellman et al., 2019). In the context of mutual funds, prior work on financial decision-making has shown a positive impact of good "brand" names on mutual fund purchase decisions, even when the name belongs to a fund's management company and not the fund itself, and over and above conventional rational drivers for investment choices (Wang and Tsai, 2014, Sialm and Tham, 2016, Karoui and Ghoul, 2022). Our findings measure the impact on investments of a more or less trustworthy organization's name, controlling for familiarity (Mayer et al., 1995, Lewicki et al., 1998, Gillespie and Dietz, 2009, Grégoire and Fisher, 2008; Sirdeshmukh et al., 2002).[4] We also clarify the effect of an employer name in a new way, by testing employer names that appear on white-label index funds, not on company stock.

Labeling a new retirement plan investment fund with the name of a fund family or assigning an employer name to a white-label fund, can be instances of "umbrella marketing", where firms signal the quality of a new product by using the reputation of an existing one (Wernerfelt, 1988; Erdem and Sun, 2002; Sialm and Tham, 2016). Mullainathan et al. (2008) present a theory of strategic signalling, used by firms to exploit customers who rely on the associative reasoning that underpins umbrella marketing. Customers may transfer positive attributes of products across analogous, co-categorized situations even when the information they transfer is not informative, such as associat-

[4] An extensive literature in marketing has shown that brand is consequential (Zeithaml, 1988; Richardson et al., 1994, Ahluwalia et al., 2000; Ahluwalia et al., 2001; Raju et al., 2009). In finance, high brand visibility can correlate with more precise information flows about firms (Frieder and Subrahmanyam, 2005). Companies with recognizable brands, that therefore promise better quality information, will attract investors. By contrast, investors sometimes follow naive investment strategies where they equate good investments with well-run companies, chasing such "glamour stocks", and failing to account fully for price (Lakonishok et al., 1994).

ing an asset manager's poor performance in an actively managed growth fund with their capacity to operate an index fund. This co-categorization allows customers to be influenced by sellers who exploit analogous frames. Our study demonstrates the transfer of organizational trust into investment decisions where it is uninformative, and shows a potential for stakeholders to motivate associative thinking in participants by using labels.

Our findings also reveal more about the relation between forms of trust and risk perception (Siegrist, 2021). For example, Guiso et al. (2009) find that trusting cultures accept more financial risk. Theoretical and experimental studies in finance predict that investors will take on more risk when relying on trusted advisers (Gennaioli et al., 2015) and that people whose personal values mean that they tend to trust others (rather than themselves) will take more risky investments (Klein and Shtudiner, 2016). We show the connection between expectations of loss and organizational trust, specifically that participants assign lower probabilities of loss to investments with more trusted manager labels. Trust can also be construed as a way to reduce complexity in unfamiliar contexts or technologies, implying that more knowledgeable people will rely less on trust in experts (Siegrist, 2021). This is a mechanism that we confirm. More expert (financially literate) subjects in our experiments are, on average, less influenced by labels that vary by organizational trustworthiness.

Lastly, our data and analysis provide a new source of evidence on the connection between return expectations and portfolio choice. Stock market participation and stock shares in portfolios have been shown to depend on subjective beliefs about returns and risk (Adam et al., 2021, Shin, 2021, Giglio et al., 2021, Merkoulova and Veld, 2022). We confirm earlier findings that allocations are increasing in expected returns and decreasing in expected losses, and that the size of impacts on allocations is small.

2 White label investment funds in retirement plans

While white label funds are not new, they are increasingly popular options in defined contribution retirement plans. A Hewitt study estimated in 2014 that approximately 25% of plans offer a white label option (Hewitt EnnisKnup, 2014). Healy (2020) estimates based on PIMCO's 2020 Defined Contribution Consulting Study that 30% of assets in plans with more than $1 billion dollars are invested in white label funds. The total estimated amount ranges between $750 billion and $1 trillion. White label funds appear to be more common in larger plans according to a report analyzing Fidelity Management Trust Company (FMTC) data (Fidelity Investments 2021). In 2020, FMTC reported that 1% of their 23,000 plans, across all asset sizes, offered white label funds. In contrast, a much larger 18% of plans with over $1 billion in assets included this type of fund. Thus while the number of plans offering these funds may be small, the actual number of participants choosing from menus with white label options is larger. The reasons often cited by plan sponsors for adopting these generically named funds include menu simplification, lower fund costs, and the potential to offer plan participants more sophisticated and diversified funds that can leverage the expertise of multiple fund managers (Bare et al., 2017). On the other hand, some requirements, like customized participant communications and increased fiduciary responsibility, present obstacles to further white label adoption by plan sponsors because they increase costs.

Until recently, researchers interested in white label funds were limited to studying hard-to-access proprietary administrative data or conducting their own surveys.[5] However participant-level data on white label offerings have become available through the 2020 release of the Public Retirement Research Lab (PRRL) Database (https://www.prrl.org/).[6] The PRRL 2020 database includes 212 plans from which we sample 207 plans that fall into the collection's three main plan types: 401(a); 401(k); and 457(b). In total, plan assets account for $112 billion dollars and 2.3 million accounts. Using account and plan-level data from this sample, we show how frequently plan menus contain white label options, the types of plans that include them, and the common ways in which menus combine white label options with manager-named options.

We break down plan menus into four types: 1) all manager labeled, 2) mixed menu, 3) only stable-value white label, and 4) all white labeled. All-manager-labeled menus have no white label options. Mixed menus include white label and manager-labeled options. Only-stable-value white label menus are a special case where all the options are manager-labeled except for one white label fund in the stable-value class. All-white-labeled menus include only white label options but may also include a self-directed brokerage option. A plan offering a white label option, according to our definition, can either be a plan with all-white-labeled menus or mixed menus.

Figure 1 shows the percentage of the 207 plans we sampled from the PRRL database with white label fund options, by plan size measured by participants enrolled in the plan. A significant 66% of participant accounts are in plans offering white label funds. These proportions vary with plan type: 91% of participant accounts in 401(a) plans; 51% of participant accounts in 401(k) plans; and 54% of participant accounts in 457(b) plans, are in plans offering white label funds. Larger plans are more likely to offer white label options, probably because implementation costs can be too high for smaller plans. Consistent with this, Figure 1 shows that the percentage of plans offering white label funds increases with the number of participants enrolled in the plan.

Mixed menu plans are not uncommon. Mixed menus include both manager label and white label funds. While the 401(k) plans in the database offer only all-white-label menus, mixed menus represent approximately 40% of 401(a) and 457(b) plans in the data. Figure 2 shows the proportions of each menu type when weighted by participant accounts.

All-white-label and mixed menus tend to be simpler. Table 1 shows that all-white-label menus and mixed menus have a lower average number of investment options (10.0 options and 14.7 options)

[5] While researchers interested in plan menus often turn to public data from annual filings of Form 5500, this form does not require information related to white label assets (Healy, 2020).

[6] The Employer Benefit Research Institute (EBRI) and the National Association of Government Defined Contribution Administrators (NAGDCA) created the Public Retirement Research Lab (PRRL) Database (https://www.prrl.org/). Plan sponsors voluntarily join the Public Retirement Research Lab and their record keepers transmit de-identified, participant-level data on their plans' behalf. Public sector employees can be offered several defined contribution plans to join and one person may represent multiple accounts in the PRRL database. Because of this, we conduct a plan-level analysis of 'participant accounts' not unique participants.

Figure 1: **Percentage of plans offering white label funds**

This graph shows the percentage of plans with white label fund options by plan size measured by participants enrolled in the plan.

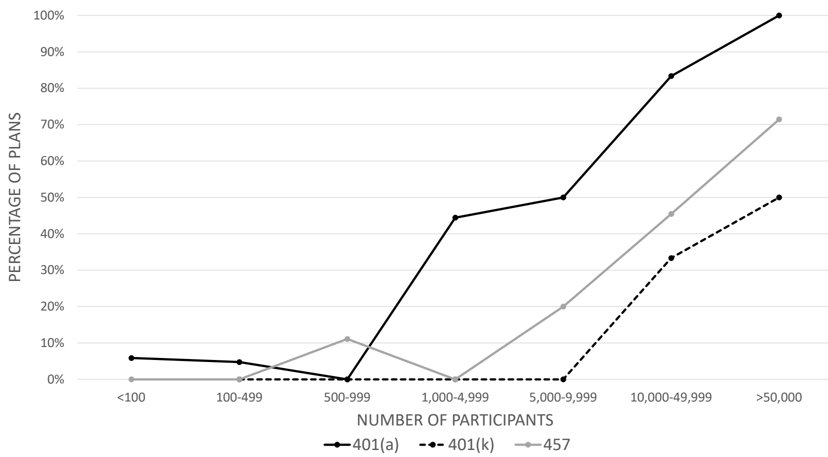
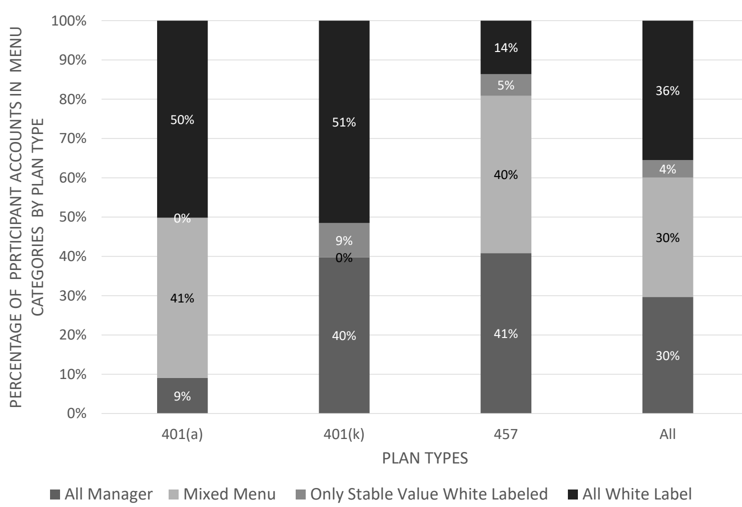


Figure 2: **Percentage of participant accounts in menu categories by plan type**

This graph shows the percentage of participants accounts in each type of plan by menu category. Calculations are based on 207 plans from the PRRL database.



than all-manager menus (26.1 options). Whereas the average number of options for all-manager menus (26.1 options) is close to the average for menus with one white-label stable-value option. We see a similar pattern with average numbers of fund families represented in the menus. However, the white label and mixed menus still offer a similar broad selection of asset classes relative to manager-labelled menus.

Table 1: **Plan menu characteristics**

This table reports the number of investment options, asset classes and fund families averaged over plans in each menu category. Calculations are based on 207 plans from the PRRL (2020) database.

Plan menu classification:	All Manager	Mixed Menu	Only Stable Value White Label	All White Label
	Average no. per plan			
Investment options	26.1	14.7	25.0	10.0
Asset classes	4.8	5.4	4.8	4.2
Fund Families	11.2	5.8	13.7	1.0

To sum up, the PRRL data shows that around 66% of plans offer their participants mixed or all-white-label investment menus, that mixed and all-white-label menus have four or five asset classes on average, and that they are simpler, offering around half as many investment options as menus that do not feature white label funds.

3 Experiment: Pre-testing, task design and sample

Motivated by research into organizational trust, we collected responses to an online survey put to members of the University of Southern California's Understanding America Study (UAS) panel.[7] The online survey set two tasks, each designed to test the effects of fund labels on investment choice. We labelled investment options in the experiment with names that evoked different levels of organizational trust in subjects, so that we could test whether the general trust that subjects held in the organization transferred to their retirement plan decisions.

White label funds are the benchmark and control in our experimental design and key to our identification strategy. For instance, in the first task, we randomly assigned subjects to four conditions that varied investment option labels: i) high-trust financial-manager-named funds paired with generic (anonymous) 'white label' funds; ii) low-trust financial-manager-named funds paired with generic white label funds; iii) the subject's employer-named white label funds paired with generic white label funds; or iv) generic white label funds only. The second task also followed this pattern by collecting subjects' expectations of the probability and range of investment returns to high- or low-trust financial-manager-named funds, employer-named white label funds and generic white label

[7] Before we launched the full survey, we conducted two focus group sessions, facilitated by Distillery, Inc., to check if our tasks were understandable to typical subjects. The focus groups helped us to choose clear labels for funds and to design a video that explained how to use the distribution builder.

funds. The comparison between generic white labels, employer-named white labels and financial-manager-named labels is not only of academic interest; it depicts a choice between labels that plan sponsors and financial managers must make in practice.

3.1 Pre-test of investment manager names and distribution builder

Before fielding our two main studies, we ran a pretest to identify two investment managers that were significantly different in terms of organizational trust and not different on other related variables. To do this, we asked 128 subjects to indicate their familiarity with (1 = very unfamiliar, 7 =very familiar), knowledge of (2-item scale: "I consider myself knowledgeable," "I consider myself informed," 1 = strongly disagree, 7 = strongly agree; α= .96; Raju et al., 2009), and trust in (3-item, 7-point scale: very undependable/very dependable, very incompetent/very competent, of low integrity/of high integrity; α= .96; Grégoire and Fisher, 2008) each of six investment managers. From this output, we identified one high-trust investment manager (M = 3.81) and one low-trust investment manager (M = 3.49) to use in subsequent experiments. These two managers differed by organizational trustworthiness, as measured by integrity, competence and dependability that indicate 'ability to deliver' ($F(1,123) = 6.17$, $p = .01$) while they were not significantly different from each other by familiarity or knowledge (all Fs < 2.05, ps $> .16$). The pre-test results increase our confidence that we can attribute any observed effects to differences in organizational trust between the two investment managers and not to familiarity. To protect anonymity, we do not disclose here the names of the investment companies we tested. Instead we refer to them as the high-trust manager and the low-trust manager.[8]

3.2 Task 1: Investment fund choices

For the first task, we asked subjects to imagine that their employer had started a new retirement plan, and explained that they would need to decide how to invest their retirement savings. We showed subjects (see Figure 3) a description of the types of funds that they could invest in. The description page also explained the naming convention for the funds.

In Study One (Conditions 1 and 2) subjects read:

> The funds that you can choose from may be managed by one or more portfolio managers.
>
> If you see the name of a professional investment company preceding the fund name, the fund is managed by that company.
>
> If you see "White Label" preceding the fund name, this means the fund has been put together for your employer's retirement plan and given a generic name. The fund may include one or more mutual funds which hold the same type of investment.

[8] The pretest also showed whether subjects could understand the distribution builder used in task two - the graphical interface that measured subjects' return and risk expectations for different asset classes. Most pre-test subjects appreciated the instructional video that explained how to execute this task, and completed the task competently.

For Study Two (Condition 3), these instructions were slightly modified. We removed the second sentence about the professional investment company and replaced it with this sentence:

> If you see the initials of your employer preceding the fund name, this means the fund has been put together for your employer's retirement plan. The fund may include one or more mutual funds which hold the same type of investment.

The sentence above matches the white-label description almost exactly but does not include "and given a generic name" in the description. Figure 3 shows the fund description pages for Conditions 1 and 2 (Panel a) and Condition 3 (Panel b). Subjects assigned to the all-white-label control condition saw the page shown in Panel (b) with the sentence referring to the employer omitted.

Figure 3: **Screen shots of fund descriptions**

Panel (a) shows the investment fund description screen for conditions 1 and 2. Panel (b) shows the investment fund description screen for Condition 3.

Important Note: All fees related to all fund investments have been waived.

On the next page, you will be asked to allocate your retirement funds to different types of mutual funds. Mutual funds are investments that pool money together from investors to purchase a collection of stocks, bonds, and/or other investment products. A portfolio manager typically oversees the investments.

You can choose among several mutual funds invested in different asset types. They are described below.

Mutual Fund Asset Type Descriptions

- **Money Market Funds**: These funds aim to earn interest for investors while protecting the value of the original investment. They hold different combinations of short-term (less than one year), high quality, liquid government and corporate U.S. dollar investments.
- **U.S. Bond Funds**: These funds mainly hold fixed income investments, including bonds issued by the U.S. Government, corporate bonds and other forms of debt backed by mortgages or other assets.
- **Large Cap U.S. Funds**: These funds invest in U.S. stocks issued by relatively large companies. Stocks from the largest 70 percent of firms, when firm size is measured by the number of shares times the market price of shares, are usually classified as large-cap stocks.
- **Small Cap U.S. Funds**: These funds invest in U.S. stocks issued by relatively small companies. Stocks from the smallest 10 percent of firms, when firm size is measured by the number of shares times the market price of shares, are usually classified as small-cap stocks.
- **Global Funds**: These funds invest in stocks of established companies operating around the world. Funds can also restrict investments to companies operating in specific global regions. A fund investing in companies located only outside of the United States is an example. Investments are diversified among many countries and industries.

Mutual Fund Names

The funds that you can choose from may be managed by one or more portfolio managers.

If you see the name of a professional investment company preceding the fund name, the fund is managed by that company.

If you see "White Label" preceding the fund name, this means the fund has been put together for your employer's retirement plan and given a generic name. The fund may include one or more mutual funds which hold the same type of investment.

(a) Study One–High/low trust manager versus white label fund description page

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- **Large Cap U.S. Funds**: These funds invest in U.S. stocks issued by relatively large companies. Stocks from the largest 70 percent of firms, when firm size is measured by the number of shares times the market price of shares, are usually classified as large-cap stocks.
- **Small Cap U.S. Funds**: These funds invest in U.S. stocks issued by relatively small companies. Stocks from the smallest 10 percent of firms, when firm size is measured by the number of shares times the market price of shares, are usually classified as small-cap stocks.
- **Global Funds**: These funds invest in stocks of established companies operating around the world. Funds can also restrict investments to companies operating in specific global regions. A fund investing in companies located only outside of the United States is an example. Investments are diversified among many countries and industries.

Mutual Fund Names

If you see the initials of your employer preceding the fund name, this means the fund has been put together for your employer's retirement plan. The fund may include one or more mutual funds which hold the same type of investment.

If you see "White Label" preceding the fund name, this means the fund has been put together for your employer's retirement plan and given a generic name. The fund may include one or more mutual funds which hold the same type of investment.

(b) Study Two–Employer name versus white label fund description page

After viewing the fund descriptions, subjects received the following instructions:

> Now, we would like for you to imagine that your employer has started a new retirement plan. You must decide how to allocate the money that you have in your retirement account.
>
> On the next page, you will see a retirement account allocation form. Please read through the form carefully, think about how you would allocate your retirement account, and then decide how to allocate your retirement account balance among the investment options listed.

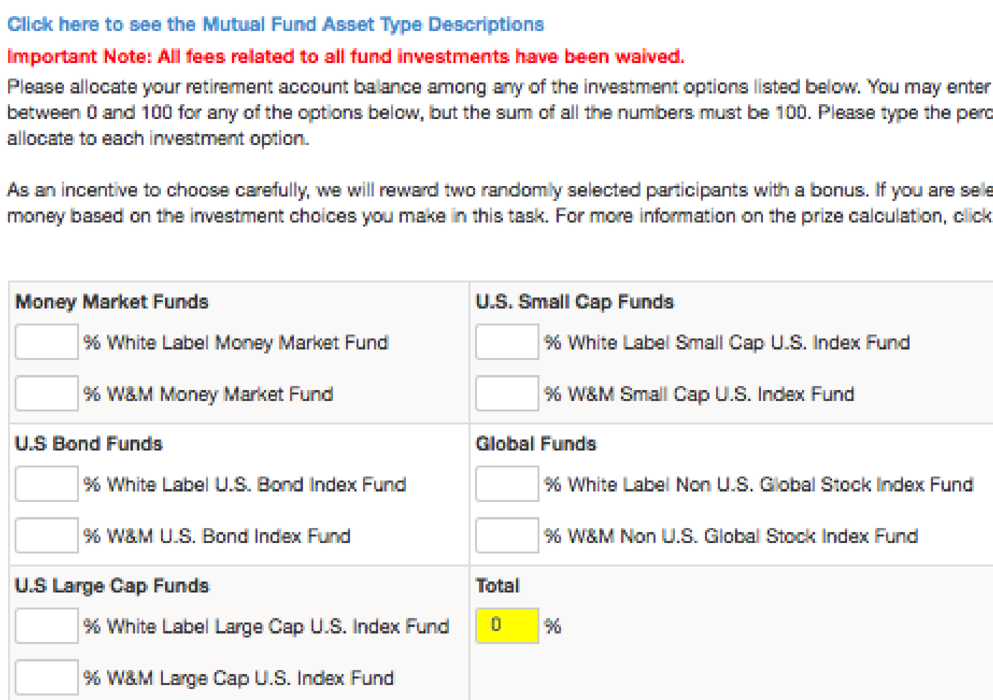
Depending on which condition they were assigned to, subjects then saw one of four possible allocation screens, that closely resembled retirement plan fund selection forms. We also asked subjects to assume that investment fees for all the funds are waived. We showed subjects in Conditions 1-3 a menu of ten funds. The menu included two Money Market funds, two U.S. Bond Index funds, two U.S. Large Cap Index funds, two U.S. Small Cap Index funds, and two non-U.S. Global Index funds. The menu for subjects in Condition 1 had a high-trust-manager label option for each type of fund, and a white label option for each type of fund. For example, for the money market fund, the menu included a high-trust-manager label money market fund and a white label money market fund. The menu for subjects in Condition 2 had a low-trust-manager label option for each type of fund, and a white label option for each type of fund. The menu for subjects in Condition 3 had an employer-named white-label option and a white label option for each type of fund. Note that in Condition 3, subjects were asked at the beginning of the survey to provide the initials or a nickname for their employer. The survey was designed so the inputs from those answers were piped into the fund's names as they proceeded through the experiment. Thus, each employer fund was personalized to the participant. (See Figure 4 for an example of the allocation page for Condition 3.) The menu for subjects in Condition 4 included only five options: a white-label option for each type of fund. Condition 4 is our control condition.

The allocation screen asked subjects to enter whole numbers between 0 and 100, representing percentages of their retirement account balance, among the menu options. To incentivize this task, we told subjects that two people would be randomly selected to earn a bonus based on their allocations and invited them to click a link to a more detailed description of the bonus calculation.[9] In this way, the allocation task collected subjects' stated preferences for manager- or employer-labeled versus white-label funds when both are offered together. This comparison allows us to understand the influence of fund labeling within subjects, as well as between subjects in different conditions.

[9] The link told subjects "You will be rewarded a bonus based on your allocations in this task. We will assume you invest $25 according to the allocation that you enter for five years. Your bonus will equal your initial portfolio value of $25 plus or minus any gains or losses you make on your chosen portfolio. The 5 year returns for the specific funds you chose will be generated using commonly accepted methods." We bootstrapped 10 years (February 2008 - December 2018) of monthly total returns to representative funds in each asset class to compute 60 month returns to the allocation chosen by two randomly selected subjects, and used an average of returns to the representative funds to generate 'white label' returns. The final rewards were $35.67 and $35.15.

Figure 4: **Allocation task screen shot**

This figure shows an example of the allocation task screen for Condition 3 where subjects chose how to divide their retirement account balance between white label funds and white label funds with their employer's name. For this example we use the initials 'W&M' to represent the employer. Subjects to the survey gave a nickname or initials that stood for their employer's name. For subjects in Condition 3, their employer's nickname or initials were piped into the fund names for this task.



3.3 Task 2: Predictions of Investment Returns

For the second task, subjects used a graphical interface to show their predictions of one-year returns to a $100,000 investment in each of the funds (money market, bond, etc.) labeled according to the condition. Specifically, subjects in Condition 1 built distributions for high-trust manager-labeled funds, subjects in Condition 2 built distributions for low-trust manager-labeled funds, subjects in Condition 3 built distributions for employer-named white label funds, and subjects in Condition 4 built distributions for white label funds. For conditions 1 to 3, subjects were not required to complete the distribution builders for the 'generic' white label options because the exercise would have been too taxing and time-intensive for them to repeat. Our control, Condition 4, provides the information needed for the 'generic' white label options. Subjects' assignments of balls to bins allow us to calculate the theoretically important values of expected returns and measures of risk perception, such as an expected probability of loss.[10]

We chose not to ask subjects directly for these statistics, instead using the distribution builder, because studies of lay people show that responses to graphical interfaces are more accurate representations of expected outcomes direct responses (Goldstein and Rothschild, 2014)[11] We model our distribution builder on the ball and bin graph design in Delavande and Rohwedder (2008). However, we asked subjects to distribute 100 balls, instead of 20, following Goldstein and Rothschild (2014). They argue that by using 100 balls, subjects can express percentages as frequencies (X out of 100). This approach also aligns with studies that find that when questions about probabilities are framed in terms of natural frequencies they are better understood (Gigerenzer, 2011; Goldstein et al., 2008). In addition, our analysis is simplified because we can directly interpret distribution builder outcomes as percentages. Figure 5 shows an image of our distribution builder.

Three other points deserve mention with regard to our distribution builder design. First, notice that we labelled the bin boundary points in dollars rather than percentage returns. We use dollars because previous research shows that subjects with poor numeracy skills may have difficulty with percentages (Bautista et al., 2011). Second, we made one of the dividing points equal to the value of the starting portfolio of $100,000. This allows us to easily calculate the probability that the participant thinks the investment will lose money. Third, we chose the ranges of the bins so that knowledgeable subjects could pick (objectively) plausible returns distributions, without excluding other valid choices. At the same time, we made the bins in the middle of the distribution builder narrower than the outer bins. This gave us richer information on the range of values that are most objectively probable, and thus more precise estimates of subjects' expected returns and expected variations in returns.

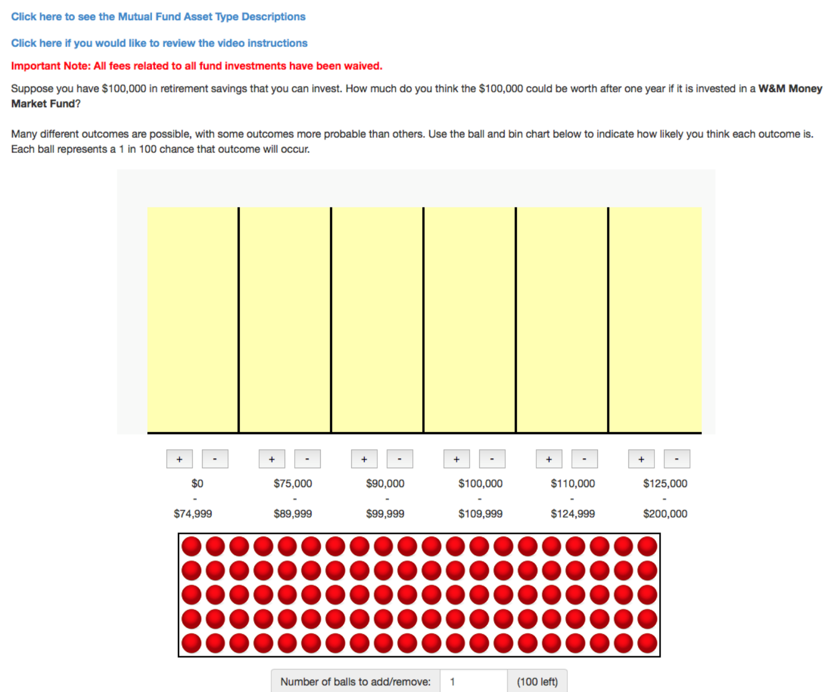
Returning to the survey, subjects viewed the pretested instructional video prior to completing the distribution builder task. An example is shown in Figure 4. After watching the video, we asked sub-

[10] We include proxies for lower partial moments in measures of risk perception because experiments and surveys show that probability of loss relative to initial price represents risk perception and propensity to invest better than symmetric measures like variance (Unser, 2000; Duxbury and Summers, 2004; Holzmeister et al., 2020).

[11] The accuracy of these elicitation methods is supported by numerous other studies (Page and Goldstein, 2016; Delavande and Rohwedder, 2008; Goldstein et al., 2008).

Figure 5: **Distribution builder task screen shot**

This figure shows an example of the prediction (distribution builder) task screen for Condition 3 where subjects assigned balls to bins to show their expectation of returns to a $100,000, one-year investment. The task collected expected returns for each asset class so that each subject completed five balls-and-bins tasks. Subjects in conditions 1 and 2 made predictions for the funds with manager labels, subjects in Condition 3 made predictions for employer-named white label funds and subjects in Condition 4 (control) made predictions for generic white label funds. For this example we use the initials 'W&M' to represent the employer. Subjects to the survey gave a nickname or initials that stood for their employer's name. For subjects in Condition 3, their employer's nickname or initials and was piped into the fund names for this task.



jects:

> Suppose you have $100,000 in retirement savings that you can invest. How much do you think the $100,000 could be worth after one year if it is invested in a [Insert Manager name] [Insert Fund Type] Fund?
>
> Many different outcomes are possible, with some outcomes more probable than others. Use the ball and bin chart below to indicate how likely you think each outcome is. Each ball represents a 1 in 100 chance that outcome will occur.

After the distribution builder task, we collected subjects' opinions of the mutual funds they had assessed in the tasks (i.e., high- or low-trust manager labeled, employer labeled, white labeled) for several characteristics (Bad-Good, Unfavorable-Favorable, Negative-Positive, Low quality-High quality) on seven point scales. We also collected subjects' ratings of their familiarity, knowledge and organizational trust (dependability, competence, integrity, safety and predictability) of the manager, employer or white label. These additional indicators complement the pre-tests for this study that identified which investment companies are generally rated as high or low trust.

The survey then moves to questions on the degree to which the subject trusts several different institutions and groups. Using a seven point scale where 1 is "I do not trust at all" and 7 is "I trust completely," we ask about trust in the stock market, banks, insurance companies, stock brokers, investment advisers, their employer, their employer's retirement plan, and people in general. The last bank of questions asks about willingness to take financial risks, household financial decision making responsibility, past engagement with investments and self-assessed understanding of investments.

3.4 Survey implementation and sample

We fielded the experiment from October through November of 2018. For the main survey, UAS invited a sample of 2,171 panel members who are currently employed, and who had previously participated in survey modules on financial literacy and asset ownership. Of those invited by UAS, 74.62% completed the survey: the remaining invited panel members either did not start or did not complete the survey. In addition, 585 responses did not meet further eligibility or consent conditions, and another 82 had responses for two questions incorrectly recorded, leaving 952 complete and eligible responses. [12]

On joining the survey, subjects were screened to ensure that they were currently enrolled in an employer-sponsored retirement plan that offered investment choices, or that at some point in their life they had been.[13] If they passed this screen they were asked to confirm that they were over 18 years of age and that they consented to complete the survey.

We assigned subjects randomly to one of four conditions, as shown in Table 2.[14] Appendix Table A.1 reports descriptive statistics of the subjects' demographics showing that the conditions are evenly balanced.

[12]To view the survey for Condition 3 (employer named white-label option v. white label option), please go to this link: `https://uas.usc.edu/survey/playground/uas148/test/index.php` There are three subjects whose answers to demographic questions were missing or who were not employed at the time this survey was complete, so the final sample for analysis was 949 subjects.

[13]Retired plan participants were pre-screened by UAS: only panel members who were said that they were currently employed were invited to take the survey.

[14]At this point, the survey collected a employer nickname or initials from subjects assigned to the employer-name white label condition to be used to label the funds in the tasks.

Table 2: **Condition Group Sample Sizes**

Condition	Study	Description	N
1	1	High-Trust Manager versus White Label	233
2	1	Low-Trust Manager versus White Label	231
3	2	Employer White Label versus White Label	260
4	Control	White Label Only	228

4 Results

Table 3 shows the average over subjects of the percentages of their balances that they allocated to money market, bond and stock index funds (task one). The top panel in Table 3 shows average allocations in conditions 1-4 and the bottom panel breaks out allocations in Condition 3 by employer-trust group. The third column in each condition panel shows results from tests of equal means in the two preceding columns. The average allocations show patterns that allude to the impact of organizational trust on investment choices.

First, the average percentage allocated to each broad asset class is very similar across the four experimental conditions. Comparing values in "Total" columns across the rows shows that average total allocations to money market funds range from 26% (Condition 3) to 30% (Condition 4), allocations to bond funds average 14% for all conditions, and average allocations to stock funds range from 56% to 60%. Each of the large cap, small cap and global stock funds, and the employer-trust break out in the bottom panel, follow the same pattern. This similarity in average total allocations across conditions suggests that the investment menu labels we test here do not change subjects' allocation preferences for broad asset classes.

Second, and by contrast, average percentages allocated by subjects' *within* asset classes are significantly different across conditions. Average allocations to the high-trust-manager labeled funds were significantly higher than average allocations to the white label funds in Condition 1, while the opposite applied to the low-trust-manager labeled funds in Condition 2. Taking U.S. Large Cap Equity allocations as an example, subjects in Condition 1 allocated twice as much (18%) on average to the index fund with the high-trust-manager label than the white-label equivalent (9%). On the contrary, in Condition 2, subjects placed one-third more, on average, in the white-label fund (15%) than in the low-trust manager labeled option (11%). Subjects favored employer-labeled over generic-white-labeled funds in Condition 3. Further, the bottom panel in Table 3, that breaks out average allocations by subjects' trust in their employer, shows that the differences arise from the allocations of subjects with high or medium-high trust in their employer.

Table 3: **Mean Allocations to Funds**

This table shows averages over subjects' percentage allocations to index funds (task 1) by asset class and fund. The top panel shows allocations for conditions 1-4 and the bottom panel breaks out allocations in condition 3 by employer trust group. The third column in each condition panel shows results from tests of equal means in the two preceding columns, where "***" denotes $p \leq .01$, "**" denotes $p \leq .05$, "*" denotes $p \leq .1$, and "–" denotes non-significance $p > .1$. For example, the "**" in row 1 of column 3 indicates the that null of equal means for allocations to the high-trust-manager label money market fund (mean = 17%) and allocations to the white label money market fund (mean = 10%) is rejected at the 1% level or less.

	Condition 1 (N=232)				**Condition 2 (N=230)**				**Condition 3 (N=260)**				**Condition 4 (N=227)**
	High Trust	White-Label		Total	Low Trust	White-Label		Total	Emp. (All)	White-Label		Total	Total
Money Market	17%	10%	***	27%	12%	15%	–	28%	17%	9%	***	26%	30%
U.S. Bonds	10%	5%	***	14%	6%	8%	*	14%	9%	5%	***	14%	14%
All Stocks	38%	21%	***	58%	24%	35%	***	58%	36%	24%	***	60%	56%
U.S. Large Cap	18%	9%	***	26%	11%	15%	***	26%	17%	11%	***	29%	24%
U.S. Small Cap	10%	6%	***	16%	8%	10%	*	18%	10%	7%	***	17%	17%
Global Stocks	9%	6%	***	16%	5%	9%	***	14%	9%	6%	***	14%	15%
Total Allocations	64%	36%	***		42%	58%	***		63%	37%	***		

Condition 3

	Employer Trust High (N=112)				**Employer Trust Medium (N=86)**				**Employer Trust Low (N=62)**			
	Emp.	White-Label		Total	Emp.	White-Label		Total	Emp.	White-Label		Total
Money Market	20%	6%	***	26%	16%	9%	*	25%	14%	12%	–	26%
U.S. Bonds	9%	4%	***	13%	10%	5%	**	15%	9%	7%	–	15%
All Stocks	40%	21%	***	61%	36%	24%	***	60%	31%	28%	–	59%
U.S. Large Cap	18%	10%	***	27%	18%	13%	*	31%	15%	13%	–	27%
U.S. Small Cap	11%	6%	***	18%	10%	6%	**	17%	8%	9%	–	17%
Global Stocks	10%	5%	***	16%	7%	5%	*	12%	9%	7%	–	15%
Total Allocations	69%	31%	***		62%	38%	***		53%	47%	–	

Results in Table 3 raise the question of how many subjects allocated their balances to funds with only one type of label. Percentages in Table 4 show that around one-half of subjects chose either white-label or organization-label funds exclusively. Consistent with results in Table 3, the proportion of subjects choosing only funds labeled with a trusted organization's name is higher than the proportion choosing a less-trusted organization labeled fund. For instance, 38% of subjects in Condition 1 allocated their balance exclusively to funds with the high-trust manager label, in contrast with 18% of subjects in Condition 2 who chose only the low-trust manager label. In summary, these patterns from task 1 offer preliminary evidence that plan participants are affected by trusted organization labels on otherwise identical funds.

Table 4: **Percentage of subjects who chose one or both types of funds**

This table shows the percentage of subjects in each condition who allocated their balance exclusively to funds with one type of label (task 1), and the percentage who chose from funds with both labels.

	High Trust Manager (N=233)	**Low Trust Manager (N=231)**	**Employer White Label (N=260)**	**Employer Trust High (N=112)**	**Employer Trust Medium (N=86)**	**Employer Trust Low (N=62)**
Org. Label only	38%	18%	40%	50%	38%	26%
White label only	12%	33%	17%	13%	17%	23%
Mixed	49%	49%	43%	38%	44%	52%

Task 2 shows how expected returns and risk perceptions are affected by organizational versus white labels. We use responses to the distribution builder task to calculate approximate one-year expected returns and the expected probability that the investment will lose money. We define the expected rate of return as:

$$R_{i,j} = \sum_{n=1}^{6} P_{i,j,n} \frac{(B_{n,u} + B_{n,l})/2 - 100,000}{100,000} \tag{1}$$

where $R_{i,j}$ is subject i's 1-year expected rate of return to asset class j ($j = 1, \ldots, 5$), calculated as the sum over all bins n ($n = 1, \ldots, 6$) of the probability-weighted rate of return to a $100,000 investment, where the outcome value is the bin-interval mid-point. $P_{i,j,n}$ is the number of balls (out of 100) that subject i assigns to bin n for asset class j and $B_{n,u}$ and $B_{n,l}$ are bin upper and lower bounds.

We measure risk by each subject's probability of loss. We focus on this proxy for lower partial moments in measures of risk perception because of evidence from previous experiments and surveys (Unser, 2000; Duxbury and Summers, 2004; Holzmeister et al., 2020). These studies show that probability of loss relative to initial price is more related to risk perception and propensity to invest than symmetric measures like variance .

Probability of loss is the sum of the number of balls subject i assigns to the loss (first three) bins for each asset class j:

$$L_{i,j} = \sum_{n=1}^{3} P_{i,j,n} \tag{2}$$

Table 5, top panel shows the expected returns for each condition, with the employer condition broken out by trust group. The bottom panel shows the related results for probability of loss. For each asset class, the expected return is higher and the expected probability of loss is lower for the high-trust organization, compared to the low-trust organization. Notable also is that subject expectations are not well calibrated to historical returns distributions for index funds in the asset classes. Average expected returns to money market funds are notably high, as are the related probabilities of loss.[15] These expectations are even more remarkable when compared with the low expectations of returns to investments in U.S. small cap and global stock funds. The results in Table 5 suggest that financial literacy, as well as organizational trust, is likely to explain some of the patterns in the experimental data. In the next section we model subjects' choices in two studies.

[15]The bin sizes limit the precision of expected returns and probabilities of loss. Intervals near zero returns are the same width for money market, bond and stock funds and this is part of the reason for very high expected return values for the money market fund.

Table 5: **Expected one-year returns and probability of loss by condition and asset class.**

This table shows means of expected returns (top panel) and probabilities of loss (bottom panel) inferred from the distribution builder (task 2). In task 2, subjects assigned 100 balls, each representing 1 percentage point of probability, to six bins representing intervals of possible outcomes for a one year investment of $100,000. Subjects completed this task for each of the five classes of index fund. Funds were labeled according to the experimental condition, i.e., high-trust manager label (condition 1); low-trust manager label (condition 2); own-employer white label (condition 3); and generic white label (condition 4). Expected returns are calculated by equation 1 and probability of loss by equation 2.

	Expected return E(R)						
	High Trust Manager (N=233)	**Low Trust Manager (N=231)**	**Employer White Label (N=260)**	**Employer Trust High (N=112)**	**Employer Trust Medium (N=86)**	**Employer Trust Low (N=62)**	**White Label (N=228)**
Asset class							
Money Market	5.6%	2.9%	7.1%	7.3%	7.8%	6.0%	7.5%
U.S. Bonds	4.6%	2.2%	4.9%	4.9%	4.8%	4.8%	4.5%
U.S. Large Cap	8.2%	4.3%	6.5%	7.5%	6.0%	5.4%	7.6%
U.S. Small Cap	3.5%	0.8%	3.9%	4.8%	3.3%	3.1%	4.3%
Global Stocks	4.4%	1.5%	3.9%	4.3%	4.2%	2.9%	6.0%

	Probability of Loss P(Loss)						
	High Trust Manager (N=233)	**Low Trust Manager (N=231)**	**Employer White Label (N=260)**	**Employer Trust High (N=112)**	**Employer Trust Medium (N=86)**	**Employer Trust Low (N=62)**	**White Label (N=228)**
Asset class							
Money Market	21%	29%	23%	20%	22%	29%	24%
U.S. Bonds	24%	32%	22%	18%	23%	27%	25%
U.S. Large Cap	29%	35%	31%	27%	33%	36%	32%
U.S. Small Cap	34%	40%	35%	33%	35%	37%	35%
Global Stocks	36%	43%	38%	37%	38%	42%	36%

We divide the main results into two studies. The first study investigates the impact of organizational trust using variation in financial manager names on fund labels, comparing Condition 1 and Condition 2. The second study investigates whether the impact of organizational trust can be generalized to settings that are not associated with financial managers by conducting similar analysis for employer-named white label funds in Condition 3. In both studies, we use generic white-label alternatives within conditions for comparison. We use responses collected under Condition 4 for preliminary comparisons between conditions at the asset class level, and then later to compute an instrument for 2SLS estimations.

4.1 Study One: Comparing High- and Low-Trust-Manager Labels

Recall that in Condition 1, survey subjects chose their investment portfolios from a menu consisting of white-label funds and high-trust-manager label funds. In Condition 2, subjects chose from a menu consisting of white label funds and low-trust-manager label funds. Since the labels apply to no-fee index funds, investors should be indifferent between manager-label and white-label funds, regardless of the trustworthiness of the organization on the label. However if subjects *are* influenced by labels, possibly because they mistakenly associate a financial managers' ability to deliver in other settings with investment outcomes in this setting, we are likely to find that subjects perceive differences in expected returns and risk to labeled funds, and that subjects have a higher propensity to allocate their savings to funds carrying the high-trust name.

4.1.1 Distributions of expected returns and losses

Responses to the "balls and bins" task allow us to make within-subject comparisons of expected losses and returns by asset type (i.e., individual subjects' differences in expected loss and return for money market, bond, and equity funds) and between-subject comparisons of loss and return by asset type and manager label (i.e., differences between high- and low-trust-manager money market, high- and low-trust-manager bond fund etc.). As a result, we can test for the effect of organizational trust on expectations and we can also break out these effects by individual subject characteristics. At the heart of these questions is the issue of whether organizational trust and return and risk perceptions are linked, and likewise, whether individual knowledge, as gauged by financial literacy, leads to more or less reliance on manager labels.

Fitted probability densities of expected returns and losses give a more complete illustration of the average differences between conditions shown in Table 5. Figure 6 compares densities for high and low trust conditions for money market, bond and large cap stock indices. (We omit the U.S. Small Cap and Global Stock densities to save space and since they are similar to the U.S. Large Cap graph.) Expected return densities (Panel a) for the high-trust condition (solid line) have more mass around zero, and low, positive returns, and thinner tails, than the densities for the low-trust condition (dashed line). Further, the high-trust stock return density has more mass to the right of zero and in the right tail. Turning to losses, Panel (b) graphs a markedly larger mass over higher losses for the low-trust condition for all three asset classes, confirming that subjects in this condition thought that larger losses were more likely for all three asset classes than subjects in the high trust condition.

Subjects with higher financial literacy are likely to have more accurate expectations of investment outcomes by asset class than those with less knowledge and experience. For example, financially literate subjects probably know that nominal losses to money market investments are unlikely and that high returns are extremely unlikely. We hypothesize that fitted densities will vary between high- and low-financial literacy subjects. We defined high financial literacy using an indicator variable that equals 1 if the subject answered 11 of 14 financial literacy questions correctly, 0 otherwise. (See Table 7 for variable definitions.) The financial literacy questions test simple interest, time value of money, inflation, knowledge of financial securities (e.g., stock and bonds) and diversification.[16]

Figure 7 contrasts expected returns and losses for high and low financially literate subjects. The graphs confirm that more financially literate subjects assign higher probabilities to zero or low-positive money market fund returns than less financially literate subjects. They also give higher weight to low positive returns to the large cap stock index fund. Consistent with these views on expected returns, we find that the financially literate subjects expect that low losses are more likely than very large losses in all three asset classes.[17]

Table 6 reports p-values for Kolmogorov-Smirnov tests of the hypothesis that the samples used to estimate the kernel densities shown in Figures 6 and 7 are drawn from the same distribution. The null hypothesis is rejected in each case, giving more evidence that one-year risk and returns expectations differ significantly by fund label and by the financial literacy of subjects.

Table 6: **Kolmogorov-Smirnov two-sample test results**

The table reports p-values for Kolmogorov-Smirnov tests that samples are drawn from the same distribution. P-values < 0.1 indicate that the null that the distributions are the same is rejected at the 10% level.

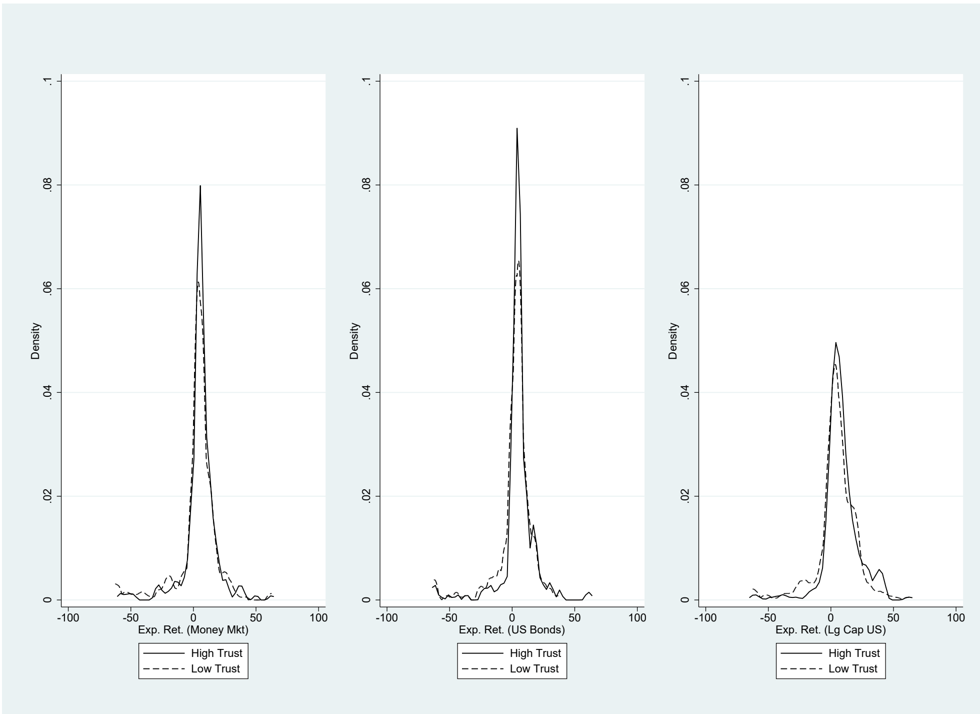
	High Trust v. Low Trust Manager Condition				
	Money Market	US Bonds	US Large Cap	US Small Cap	Global Stock
	Combined KS p-value				
Expected Return densities	0.091	0.009	0.033	0.010	0.010
Probability of Loss densities	0.000	0.008	0.000	0.000	0.000
	High v. Low Financial Literacy				
	Money Market	US Bonds	US Large Cap	US Small Cap	Global Stock
	Combined KS p-value				
Expected Return densities	0.051	0.009	0.015	0.030	0.017
Probability of Loss densities	0.000	0.001	0.001	0.000	0.000

[16] Responses are taken from UAS 121 `https://uasdata.usc.edu/index.php`.

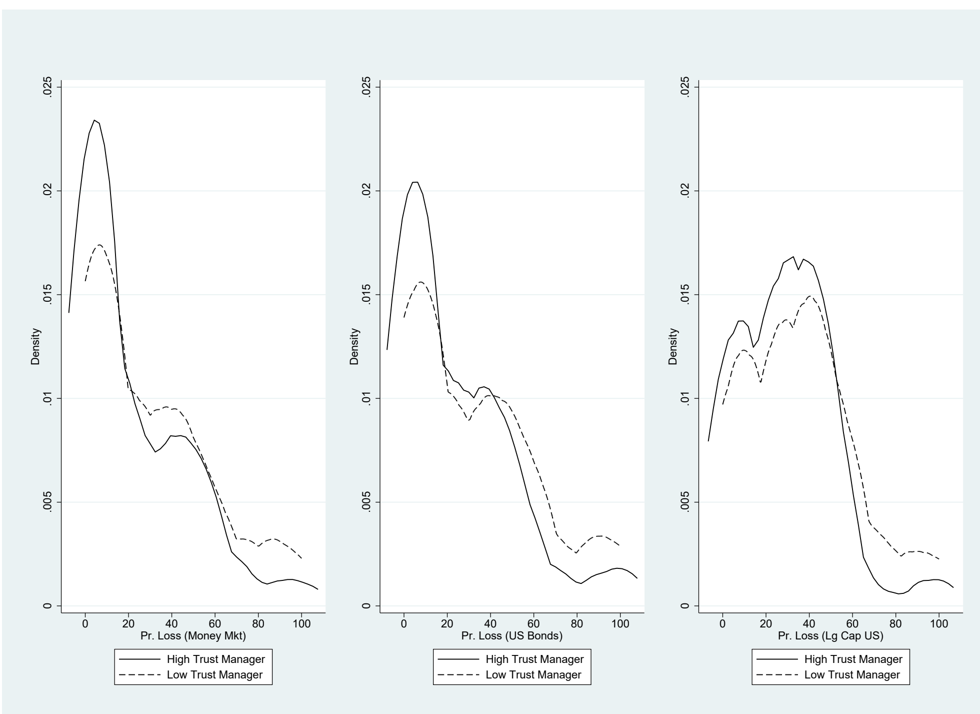
[17] Following recent work (e.g. Liang (2024), we separately analyze behavior for subjects who provide incorrect answers to financial literacy questions versus subjects who say "I don't know" in Appendix C.

Figure 6: **Fitted densities: Expected returns and probabilities of loss by high-trust manager and low-trust manager**

Panel (a) Shows kernel densities for expected one-year returns to a $100,000 investment in manager-labeled money market, US Bond index and US Large Cap index funds. The solid line is the fitted density for the expected returns of subjects in Condition 1 who were treated with the high-trust-manager label. The dashed line is the fitted density for the subjects in Condition 2 who were treated with the low-trust-manager label. Panel (b) shows the kernel densities for the one-year probability of loss to a $100,000 investment of the same groups of subjects.



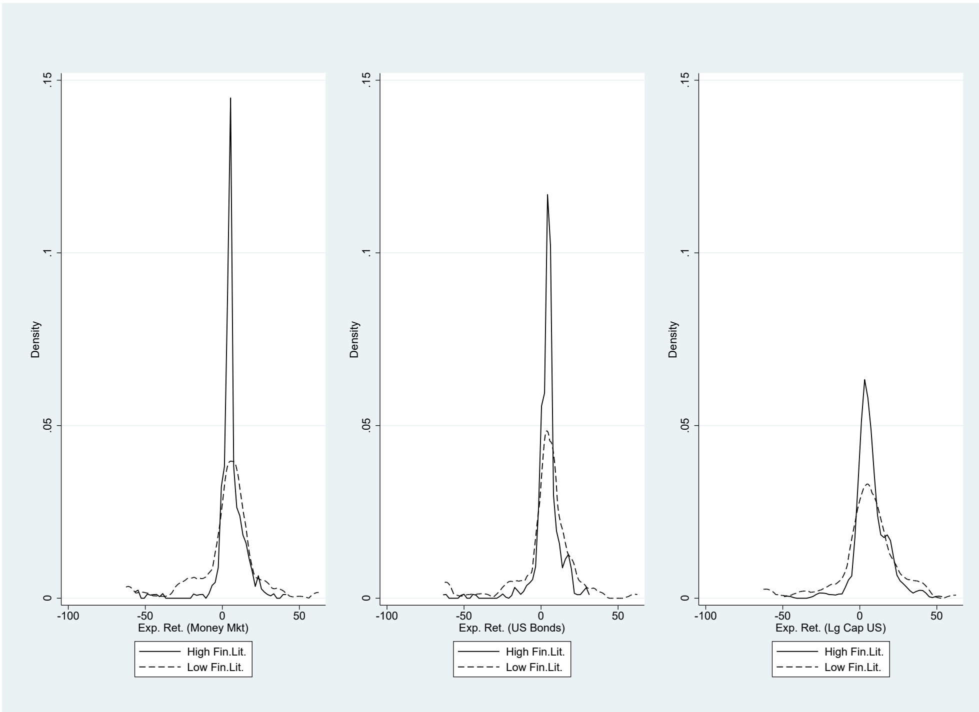
(a) Fitted density of expected returns by high/low trust manager condition



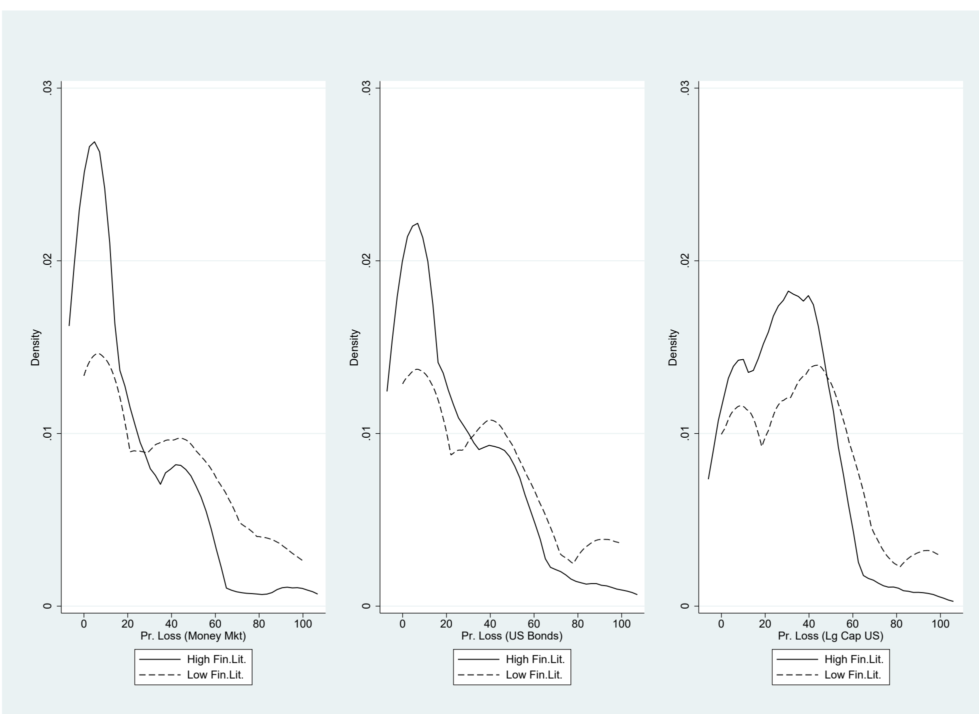
(b) Fitted density of probability of loss by high/low trust manager condition

Figure 7: **Fitted densities: Expected returns and probabilities of loss by high and low financial literacy**

Panel (a) Shows kernel densities for expected returns to manager-labeled money market, US Bond index and US Large Cap index funds. The solid line is the fitted density for the expected returns of high financial literacy subjects in conditions 1 and 2. The dashed line is the fitted density for the low financial literacy subjects in conditions 1 and 2. Panel (b) shows the kernel densities for the probability of loss of the same groups of subjects.



(a) Fitted density of expected returns by high/low financial literacy



(b) Fitted density of probability of loss by high/low financial literacy

4.1.2 Effects of organizational trust and financial literacy on expected returns and losses

Having shown that manager trust condition and subject financial literacy are associated with differences in distributions of expectations, we now turn to estimate the marginal effect of these factors on expectations. We compute marginal effects from OLS regressions:

$$M_{i,j} = \alpha_{1,j} + \Gamma X_i + \beta_{1,j} C_i + \beta_{2,j} FL_i + \beta_{3,j} C_i * FL_i + \varepsilon_{i,j} \tag{3}$$

where the dependent variable is either a measure of expected return or probability of loss ($M_{i,j} : R_{i,j}; L_{i,j}$) for participant i and asset class j, C_i is an indicator for the high-trust manager condition (versus the low-trust manager condition), FL_i is an indicator for high financial literacy (versus low financial literacy) and X_i is a vector of control variables comprising gender, marital status, age, education, household income, race, stock ownership, trust in the finance sector and attention to the survey. Table 7 reports variable definitions. We use estimates of equation 3 to compute differences in predictive margins for the effects of organizational trust and financial literacy on expected returns and risk, conditioning on subject characteristics. Table 8 reports these differences and associated p-values for tests that the differences are zero.

Estimated models predict a significantly higher probability of loss across all asset classes in the low-trust manager condition than in the high-trust manager condition. The same pattern applies when switching from low to high financial literacy. Taking U.S. large cap stock funds as an example, the average predicted value of probability of loss was 5.29 percentage points higher in the condition where the fund was labeled with the low-trust manager name (34.63%) compared with the high-trust manager name (29.34%). Differences in probabilities of loss were even larger in size, and again statistically significant, for other types of funds. Moving along the row to column 8 shows that the difference in the average predicted probability of loss for the U.S. large cap fund was 6.96 percentage points higher if the subject had low financial literacy (35.76%) compared with high financial literacy (28.81%). The second panel in the table compares predictions in low-trust versus high-trust manager conditions, holding level of subjects' financial literacy constant. This comparison shows that a significantly higher probability of loss in the low-trust manager condition is associated with low financial literacy for funds in all asset classes apart from global stocks. At the same time, manager-trust effects are significant when financial literacy is high for U.S. small cap (5.98) and global stocks (9.64). Organizational trust significantly impacts expectations of high-financial-literacy subjects for the U.S. small cap and global stock index funds.

We find similar, although less consistent, patterns with expected returns. The third panel in Table 8 shows that the average predicted value of expected return is higher for the high-trust condition, than for the low-trust condition, and significantly so for U.S. large cap and global stock funds. Taking the the U.S. large cap funds as an example, subjects in the high-trust condition expected a 3.24 percentage point higher one year return on average (7.79%) than subjects in the low-trust manager condition (4.56%). Subjects with high financial literacy report higher expected returns for all asset classes and these differences were significant for U.S small cap and global stocks funds. This mixed pattern is clarified by the results in panel four, where organizational trust effects are conditioned on subject financial literacy. This panel shows that low financial literacy subjects assign significantly higher expected returns to high-trust manager funds in all asset classes apart from global stocks is conditional, whereas the expected returns for the high-trust and low-trust manager fund conditions are not significantly different for high financial literacy subjects.

Overall these regression results confirm that organization labels significantly influence subjects' expectations of investment outcomes at the one-year horizon. Subjects expect that losses are less likely if the label shows the name of a manager high in organizational trust and this expectation is more prevalent among subjects with low financial literacy for more asset classes. At the same time, subject financial literacy is also important, with low financial literacy subjects expecting losses to be less likely for money market, U.S. bonds and U.S. stock funds that have a high-trust-manager label. Similarly, low financial literacy subjects expect returns to be higher for high-trust-manager labeled funds. At the next stage in the analysis, we look at whether these differences in expectations of returns and losses feed into investment allocations.

Table 7: **Variable Descriptions**

This table reports definitions of variables used in estimation. Variables are computed from responses to an online survey of 952 members of the Understanding America Study (UAS) through the University of Southern California conducted in October 24 - November 15, 2018. A full description of the survey and complete data dictionary is available at `https://uasdata.usc.edu/index.php`

Variable Name		**Description**
Experiment indicators		
Condition	C	A categorical variable equal to: 1 if the subject was assigned to the high-trust manager (versus 'generic' white label) condition; 2 if the subject was assigned to the low-trust manager (versus 'generic' white label) condition; 3 if the subject was assigned to the employer white label versus 'pure' white label Condition; and 4 if the subject was assigned to only the 'pure' white label Condition (control).
Outcome variables		
Org. Label only		An indicator variable that equals 1 if the subject allocates all of their retirement funds to high-trust manager options (Condition 1) or low-trust manager options (Condition 2) or employer white-label options (Condition 3), 0 otherwise.
Mixed		An indicator variable that equals 1 if the subject allocates some of their retirement funds to high-trust manager options (Condition 1) or low-trust manager options (Condition 2) or employer white-label options (Condition 3) and some to generic white label options, 0 otherwise.
White Label only		An indicator variable that equals 1 if the subject allocates none of their retirement funds to high-trust manager options (Condition 1) or low-trust manager options (Condition 2) or employer white label options (Condition 3), 0 otherwise.
Percent allocation to org. labeled fund	$Y_{i,j}$	Fraction of retirement funds the subject allocates to manager-labelled options for money market, bonds, large-cap equities, small-cap equities or global equities index funds (Conditions 1 and 2) or equivalent employer white-label options (Condition 3).
Probability of Loss	$L_{i,j}$	Count of balls (out of 100) subject i assigns to the loss domain bins 1-3 ($0-$99,999) in distribution builder task for each asset j.
Expected return	$R_{i,j}$	Approximate expected rate of return in percent p.a. calculated as the probability weighted rate of return to $100,000 investment for each asset. Returns are the ratios of mid-points of dollar ranges for each bin over the $100,000 initial investment. Probabilities are the proportion of 100 balls the subject assigns to each bin.
Subject Characteristics		
Male		An indicator variable that equals 1 if the subject is male, 0 otherwise.
Marital status		An indicator variable that equals 1 if the subject is married and living with their spouse, 0 otherwise (spouse living elsewhere, separated, divorced, widowed, never married.
Age		Age in years at the start of the survey; All subjects are between 19 and 80 years of age.
College degree		An indicator variable that equals 1 if the subject has a college degree or higher degree, 0 otherwise.
High income		An indicator variable that equals 1 if the subject's household income is at or above the sample median ($75,000 p.a.).
White		An indicator variable that equals 1 if the subject identifies as racially only white, 0 otherwise.

Continued

Table 7 – *Continued*

Variable Name		**Description**
High Financial Literacy	FL	An indicator variable that equals 1 if the subject answered 11 of 14 financial literacy questions correctly, 0 otherwise. The financial literacy questions test simple interest, time value of money, inflation, knowledge of financial securities (e.g., stock and bonds) and diversification. Responses are taken from UAS 121 `https://uasdata.usc.edu/index.php`.
Stock owner		An indicator variable that equals 1 if the subject answers yes to the question "Do you or your spouse/partner have any shares of stock or stock mutual funds?", 0 otherwise (No, Dont know). Responses are taken from UAS 117 `https://uasdata.usc.edu/index.php`.
High Finance Trust		An indicator that equals 1 if the subject scores above the median in predicted trust in finance, 0 otherwise. Predicted trust in finance is the individual prediction from a factor model of responses to five questions on a seven point scale where 1 is 'Don't trust at all' and 7 is 'Trust completely'. The questions ask about trust in the stock market, banks, insurance companies, stock brokers and investment advisers.
Employer Trust (High, Medium, Low)	ET	Responses to question on the degree to which subjects trust their employer on a seven point scale where 1 is 'Don't trust at all' and 7 is 'Trust completely'. 1-4 = Low employer trust; 5 = Medium employer trust; and 6-7 = High employer trust.
Inattention		An indicator that equals 1 if the subject assigns the same probability of loss to every asset class (i.e., the same number of balls in the loss bins) and also assigns the same expected return to every asset class (i.e., the same pattern of balls in each bin), 0 otherwise

Table 8: **Estimated effects of organizational trust and financial literacy on expected returns and risk.**

The table reports average predicted values and results of tests that marginal differences are zero from regressions of proxies for risk and return on condition indicators (high or low trust manager conditions), financial literacy indicators (high and low financial literacy) and interactions, and demographic controls (equation 3). High-trust manager condition: N=223; Low-trust manager condition: N=231. Standard errors are calculated via the delta method. *** indicates p-value < 0.01; ** indicates p-value < 0.05; * indicates p-value < 0.1.

	Probability of Loss							
	Average predicted value (%)		Difference (%)	p-value	Average predicted value (%)		Difference (%)	p-value
	Low-trust manager	High trust manager			Low Financial Literacy	High Financial Literacy		
Money Market	27.88	22.20	5.68	**	29.01	21.71	7.29	**
U.S. Bonds	31.25	24.07	7.19	***	31.78	24.20	7.58	**
U.S. Large Cap	34.63	29.34	5.29	**	35.76	28.81	6.96	***
U.S. Small Cap	40.41	33.98	6.43	***	42.58	32.68	9.90	***
Global Stocks	42.92	36.21	6.71	***	44.36	35.54	8.82	***
	Probability of Loss | Low Financial Literacy				Probability of Loss | High Financial Literacy			
	Low-trust manager	High-trust manager			Low-trust manager	High-trust manager		
Money Market	33.60	24.46	9.14	**	23.12	20.32	2.79	
U.S. Bonds	37.58	26.03	11.55	***	25.98	22.43	3.55	
U.S. Large Cap	39.30	32.26	7.04	*	30.73	26.90	3.83	
U.S. Small Cap	46.08	39.11	6.97	*	35.68	29.70	5.98	**
Global Stocks	45.96	42.78	3.18		40.39	30.74	9.64	***
	Expected Return							
Money Market	3.17	5.18	-2.01		2.99	5.18	-2.19	
U.S. Bonds	2.33	4.36	-2.03		2.16	4.35	-2.19	
U.S. Large Cap	4.56	7.79	-3.24	***	4.85	7.29	-2.44	
U.S. Small Cap	1.07	3.20	-2.14		-0.81	4.59	-5.40	***
Global Stocks	1.55	4.40	-2.85	***	0.97	4.67	-3.69	**
	Expected Return | Low Financial Literacy				Expected Return | High Financial Literacy			
	Low-trust manager	High-trust manager			Low-trust manager	High-trust manager		
Money Market	0.34	5.61	-5.27	*	5.54	4.82	0.71	
U.S. Bonds	-0.76	5.05	-5.81	**	4.91	3.79	1.12	
U.S. Large Cap	1.51	8.17	-6.66	**	7.10	7.49	-0.39	
U.S. Small Cap	-2.89	1.25	-4.14	*	4.36	4.83	-0.47	
Global Stocks	-0.74	2.66	-3.40		3.46	5.86	-2.39	

4.1.3 Organizational trust effects on portfolio allocations

Subjects' allocations of their retirement funds should depend on their subjective expected returns and expected loss probability. To test this proposition across the high and low organizational trust conditions, we estimate the effects of individual expected return and loss probabilities on allocations using panel models.

$$Y_{i,j,c} = \beta_1 M_{i,j,c} + \beta_2 M_{i,j,c} * FL_i + \beta_3 M_{i,j,c} * FL_i * C + \alpha_i + \gamma_k + \varepsilon_{i,j} \tag{4}$$

for $j = 1, \ldots, 5$, $i = 1, \ldots, N$, and $k = 1, \ldots, 3$ where $Y_{i,j,c}$ is the allocation of participant i to asset class j for condition c, $M_{i,j,c}$ are participant, asset class and condition-specific expected returns or loss probabilities, $M_{i,j,c} * FL_i$ is the interaction between subject financial literacy (low versus high) and expected returns or loss probabilities, $M_{i,j,c} * FL_i * C$ is the three-way interaction between the indicator for the experimental condition (high-trust manager versus low-trust manager), subject financial literacy (low versus high) and expected returns or loss probabilities, α_i are participant-level fixed effects, γ_k are asset class fixed effects (money market, bonds and stocks)[18] and $\varepsilon_{i,j}$ is the individual and asset-class specific error. For Condition 1, $M_{i,j,c}$ and $Y_{i,j,c}$ relate to the high-trust-manager label options and for Condition 2 they relate to the low-trust-manager label options.

We estimate the effect of $R_{i,j,c}$ and $L_{i,j,c}$ on allocations separately because the variables are highly negatively correlated ($\rho = -0.7716$). Tables 9 and 10 shows the results from panel estimations of equation 4. Models estimate the percentage allocation of subject i to the manager-labeled fund in asset class j conditioning on subjects' one-year expected probability of loss $L_{i,j,c}$ (Models 1 and 2), financial literacy (Model 3 and 4) and a high- or low-trust manager condition indicator (Model 4). Models 1-4 include individual fixed effects. Models 2-4 also include fixed effects for money market, bond and stock asset classes.

Estimates reported in Table 9 show that a 10-percentage point increase in the expected probability of loss for a manager-labeled fund is associated with a 0.5 percentage point decrease in allocation to that fund. The marginal effects of financial literacy and condition are not significant once P(Loss) and fixed effects are included. We find similarly small and significant effects for expected returns. Table 10 reports estimates that predict a 2.4 percentage point increase in allocation to a manager-labeled fund for every 10 percentage point increase in expected one year return. We also find that high financial literacy subjects raise allocations more in response to higher expected returns than do low financial literacy subjects.

Overall, the panel models confirm theoretical predictions that investors will allocate more to funds with higher expected returns and less risk, and importantly, show that subjects' expectations collected through the balls and bins exercise in task 2 significantly explain their choices of investments in task 1. The sizes of expectations effects we find here are small, consistent with earlier research

[18] We estimate one fixed effect for the three stock classes for efficiency reasons. Sparse allocations to U.S. small cap and global stock funds meant that three separate fixed effects for stock funds were not well identified.

(Giglio et al., 2021). Coupled with the results shown in Table 8, the results here are evidence for an indirect impact of organizational trust on allocation decision, via expected returns and losses.

Table 9: **Panel Estimates of Allocation to Manager-labelled Option: Effect of Expected Probability of Loss**

The table reports estimation results from fixed effects panel models of allocations to manager-labeled investment options in conditions 1 and 2. In task 2, subjects allocated 100% of their hypothetical retirement balance to 10 fee-free index funds in 5 asset classes (Money Market, U.S. Bonds, U.S. Large cap stocks, U.S. Small cap stocks and Global stocks) where funds within asset classes had either a manager label or a white label. Models estimate the percentage allocation of subject i to the manager-labeled fund in asset class j conditioning on subjects' one-year expected probability of loss $L_{i,j,c}$, financial literacy and a high- or low-trust manager condition indicator. Models 1-4 include individual fixed effects. Models 2-4 also include fixed effects for money market, bond and stock asset classes. Standard errors are in parentheses. Columns 5 and 7 report marginal effects with delta-method standard errors. *** indicates p-value < 0.01; ** indicates p-value < 0.05; * indicates p-value < 0.1.

	Model					
% Allocation to Manager Option	(1)	(2)	(3)	(3) Pred. Marg	(4)	(4) Pred. Marg
Probability of Loss P(Loss)	-0.063***	-0.052**	-0.079***	-0.044**	-0.088*	-0.046**
	(0.020)	(0.021)	(0.030)	(0.020)	(0.045)	(0.021)
High Fin Lit x P(Loss)			0.064*			
			(0.038)			
Low Fin Lit x Low Trust x P(Loss)					0.019	
					(0.057)	
High Fin Lit x High Trust x P(Loss)					0.048	
					(0.063)	
High Fin Lit x Low Trust x P(Loss)					0.090*	
					(0.051)	
High Fin Lit				2.071*		1.959
				(1.222)		(1.208)
Low Trust Manager						0.971
						(1.270)
Participant FE	Yes	Yes	Yes		Yes	
Asset class FE	No	Yes	Yes		Yes	
R-squared	0.006	0.032	0.033		0.034	
Observations	2310	2310	2310		2310	

We assume that participants make their asset allocation decision in a sequential manner. Participants first decide how much of of their retirement funds to allocate to a broad asset class k (money market, bonds, total stocks). Then they decide on how much to allocate to the organizationally labelled fund within each asset class versus the white-labeled option, conditional on the total allocation decided upon in the first step. We model this two-stage decision making structure as follows:

$$\begin{aligned} Y_{i,k} &= \alpha_{1,k} + \Gamma X_i + \beta_{1,k} C_i + \beta_{2,k} FL_i + \beta_{3,k} FL_i * C_i + \varepsilon_i \\ Y_{i,k,c} &= \alpha_{2,j} + \Upsilon X_i + \beta_{4,k} C_i + +\beta_{5,k} FL_i + \beta_{6,k} FL_i * C_i + \beta_{7,k} Y_{i,k} + u_i \end{aligned} \tag{5}$$

Where i denotes participants, k denotes broad asset class, and c high or low trust manager options, X_i is a vector of individual expected returns and probability of losses for asset class k. Our goal is estimate the marginal effect of the change in condition from low to high trust manager on the allo-

Table 10: **Panel Estimates of Allocation to Manager-labelled Option: Effect of Expected Returns**

The table reports estimation results from fixed effects panel models of allocations to manager-labeled investment options in conditions 1 and 2. In task 2, subjects allocated 100% of their hypothetical retirement balance to 10 fee-free index funds in 5 asset classes (Money Market, U.S. Bonds, U.S. Large cap stocks, U.S. Small cap stocks and Global stocks) where funds within asset classes had either a manager label or a white label. Models estimate the percentage allocation of subject i to the manager-labeled fund in asset class j conditioning on subjects' one-year expected return $R_{i,j,c}$, financial literacy and a high- or low-trust manager condition indicator. Models 1-4 include individual fixed effects. Models 2-4 also include fixed effects for money market, bond and stock asset classes. Standard errors are in parentheses. Columns 5 and 7 report marginal effects with delta-method standard errors. *** indicates p-value < 0.01; ** indicates p-value < 0.05; * indicates p-value < 0.1.

	Model					
% Allocation to Manager Option	(1)	(2)	(3)	(3) Pred. Marg	(4)	(4) Pred. Marg
Expected Return E(R)	0.165***	0.158***	0.076	0.232***	0.099	0.236***
	(0.044)	(0.043)	(0.051)	(0.048)	(0.077)	(0.047)
High Fin Lit x E(Ret.)			0.287***			
			(0.092)			
Low Fin Lit x Low Trust x E(R)					-0.057	
					(0.094)	
High Fin Lit x High Trust x E(R)					0.358***	
					(0.128)	
High Fin Lit x Low Trust x E(R)					0.192	
					(0.138)	
High Fin Lit				1.082***		1.228***
				(0.347)		(0.367)
Low Trust Manager						-0.525
						(0.448)
Participant FE	Yes	Yes	Yes		Yes	
Asset class FE	No	Yes	Yes		Yes	
R-squared	0.012	0.039	0.046		0.047	
Observations	2310	2310	2310		2310	

cation to the manager-labelled option $\frac{\partial Y}{\partial C}$, which represents the effect of trust on allocation to manager labeled funds within asset class k. Consistent with our estimation of asset class fixed effects in the previous models, we group together different equity options into a single "equity" asset class. In these models, we have three asset classes in total: equity, money market, and bonds.

Estimating Equation 5 via OLS results in a biased estimates if ε_i and u_i are correlated. In other words, if unobserved factors affecting a subject's total allocation to money market funds are correlated with that subject's allocation to manager labeled money market funds, then estimating Equation 5 via OLS has an endogeneity bias. To address this endogeneity bias, we construct an instrumental variable using a method similar to the "split-sample IV" approach of Angrist and Krueger (1995).

We construct our instrument using the portfolio choices elicited from subjects in Condition 4 (i.e., the control group whose menu contained only generic white label funds - one for each broad asset class). By using only subjects in the control group, we eliminate any potential organizational trust effects from influencing the first-stage allocation decision. Our goal is to construct a model that explains subjects' portfolio allocations to two of the three asset classes: equity funds and money market funds (we leave the allocation to bond funds as a residual). We consider this to be a classical "prediction problem" and use a variety of demographic features and elicited risk preferences and beliefs to explain subjects' allocations. We test a variety of machine learning algorithms (specifically: the elastic net, adaptive splines, gradient-boosted linear models, and random forests) and compared their predictive accuracy using 10-fold cross-validation.[19] In our case, the most accurate algorithm was the random forest algorithm, which had an out-of-sample root-mean-squared-error of approximately 26 percentage points for both equity and money market allocations.

We then use the random forest algorithm to predict equity and money market shares for subjects in the high/low trust manager and employer label conditions. These predicted allocations are used as an instrument for the overall equity and money market shares for these subjects in the regression to examine the effects of trust on allocation to manager labeled versus generic white labeled funds. Our method creates synthetic matches for the manager or employer labeled conditions from the white-label only condition and simulates the decisions that the subjects in the manager (employer) labeled conditions would have taken had they been allocated to the white-label-only control from the ML predictions. The ML predictions of allocation to asset class $\widehat{Y_{i,k}}$ can thus be treated as independent of the error term in equation 5, u_i, assuming the variables on which ML predictions are based support a matching (prediction) that accounts for endogeneity bias.

Table 11 reports second stage Generalized Method of Moments (GMM) estimates of equation 5 where the endogeneous variable (allocation to overall asset class) is instrumented using ML predictions. The table shows estimates and marginal effects conditioning on total asset class allocation,

[19] k-fold cross-validation is a way of estimating out-of-sample prediction error while making efficient use of a relatively small sample of data. In k-fold cross-validation, the sample is partitioned into k groups; model parameters are estimated using data from $k - 1$ groups and then out-of-sample prediction error is calculated for observations in the k'th group. This process is repeated k times, which generates k out-of-sample prediction error estimates. The average of these values is taken as the estimate of out-of-sample prediction error.

condition indicator (high or low trust manager label), subject financial literacy (high or low) and subjects' expected returns or probabilities of loss. Models 1 and 3 estimate percentages allocated to manager labeled money market funds and Models 2 and 4 estimate total percentages allocated to all manager labeled stock funds. Results show a significant and large effect of high organization trust on allocations, at 4.8 (4.6) percentage points, measured by marginal effects for models 1 and 3. The effect for stock allocations is also significant: switching from the low to the high trust manager conditions causes a 13.7 (13.5) percentage points higher overall allocation to stock funds. In other words, once subjects have decided on their allocations to broad asset classes, choices between manager-labeled and white-labeled options within those classes are still strongly affected by trusted manager labels.

Table 11: **IV Estimates of Allocation to Manager-labelled Option**

This table reports second stage Generalized Method of Moments (GMM) estimates and marginal effects from equation 5 for conditions 1 and 2. Models 1 and 3 estimate percentages allocated to manager-labeled money market funds and Models 2 and 4 estimate total percentages allocated to all manager-labeled stock funds.

	(1)	(1)	(2)	(2)	(3)	(3)	(4)	(4)
% Manager-labeled Option	Money Market		Stocks		Money Market		Stocks	
		Marg. Eff		Marg. Eff		Marg. Eff		Marg. Eff
Total Money Market allocation	0.458***	0.458***			0.498***	0.498***		
	(0.131)	(0.131)			(0.140)	(0.140)		
Total Stocks Allocation			0.647***	0.647***			0.616***	0.616***
			(0.165)	(0.165)			(0.178)	(0.178)
High Trust Manager	4.362	4.785***	7.037***	13.689***	4.105	4.609***	7.201***	13.519***
	(2.693)	(1.458)	(2.665)	(2.216)	(2.683)	(1.451)	(2.696)	(2.250)
High Fin Lit	-3.211	-2.822	-10.173**	-4.050	-3.084	-2.620	-9.582**	-3.765
	(2.869)	(2.448)	(4.010)	(3.297)	(2.834)	(2.386)	(4.069)	(3.345)
High Trust x High Fin Lit	0.774		12.195***		0.923		11.584***	
	(3.050)		(4.334)		(3.039)		(4.342)	
E(R) Money Market	0.015	0.015						
	(0.057)	(0.057)						
E(R) U.S. Large Cap			0.070	0.070				
			(0.082)	(0.082)				
E(R) U.S. Small Cap			0.054	0.054				
			(0.091)	(0.091)				
E(R) Global Stocks			-0.072	-0.072				
			(0.079)	(0.079)				
P(Loss) Money Market					-0.031	-0.031		
					(0.034)	(0.034)		
P(Loss) U.S. Large Cap							0.004	0.004
							(0.052)	(0.052)
P(Loss) U.S. Small Cap							-0.040	-0.040
							(0.048)	(0.048)
P(Loss) Global Stocks							-0.020	-0.020
							(0.056)	(0.056)
Constant	1.576		-8.610			1.332		-4.579
	(4.937)		(8.132)			(4.862)		(10.892)
R-squared	0.457		0.309			0.469		0.314
Observations	462	462	462	462	462	462	462	462
First stage statistics								
Underidentification (K-P LM)	27.47		28.36			25.27		27.04
Weak Identification (K-P Wald)	30.39		32.72			28.91		31.17

4.2 Study Two: Comparing High, Medium, and Low Trust Employer White Labels

In Condition 3, subjects chose from a menu consisting of generic white-label funds and employer-named white-label funds. At the beginning of the survey, each subject entered a proxy name for their employer, and UAS piped their employer proxy name into the screens for both the investment allocation and distribution builder tasks. Subjects also submitted personal ratings of their trust in their employer. As was the case for Conditions 1 and 2, the labels apply to no-fee index funds and subjects should be indifferent between employer-white-label and generic-white-label funds, regardless of their assessment of the trustworthiness of their employer organization. Condition 3 thus offers another test of organizational trust, where the possible association is the trustworthiness of their employer instead of an asset manager.

4.2.1 Distributions of expected returns and losses

Fitted probability densities of expected returns and losses show a pattern consistent with Table 5 for Study Two (Condition 3). Figure 8 compares densities for high and low trust conditions for money market, bond and large cap stock indices, this time divided into high, medium and low employer trust sub-samples. Expected return densities (Panel a) for the high-employer-trust sub-sample (solid line) again have more mass around zero than for the low and medium trust sub-sample (dashed and dotted lines). Turning to losses, Panel (b) shows less mass over higher losses for the high-employer-trust condition. However, the sub-samples are small and the null hypothesis of equal distributions is only rejected in two of the ten Kolmogorov-Smirnov tests when comparing expected return and probability of loss distributions for employer-labeled funds for subjects with low versus high self-reported trust in their employer (see Table 12).

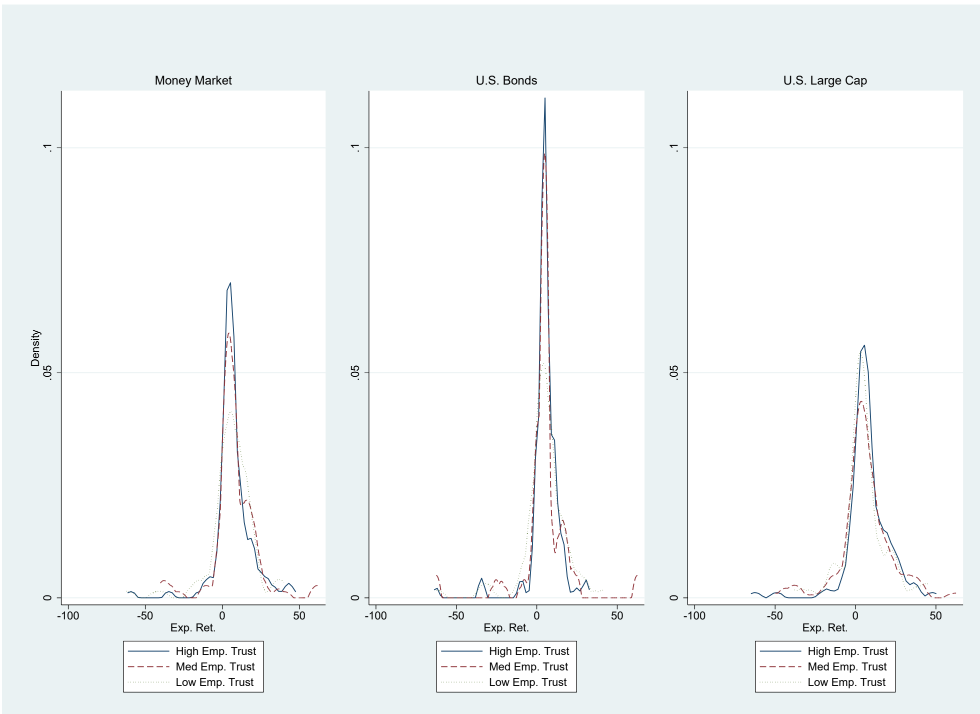
Table 12: **Kolmogorov-Smirnov two-sample test results**

The table reports p-values for Kolmogorov-Smirnov tests that samples are drawn from the same distribution. P-values < 0.1 indicate that the null that the distributions are the same is rejected at the 10% level or less.

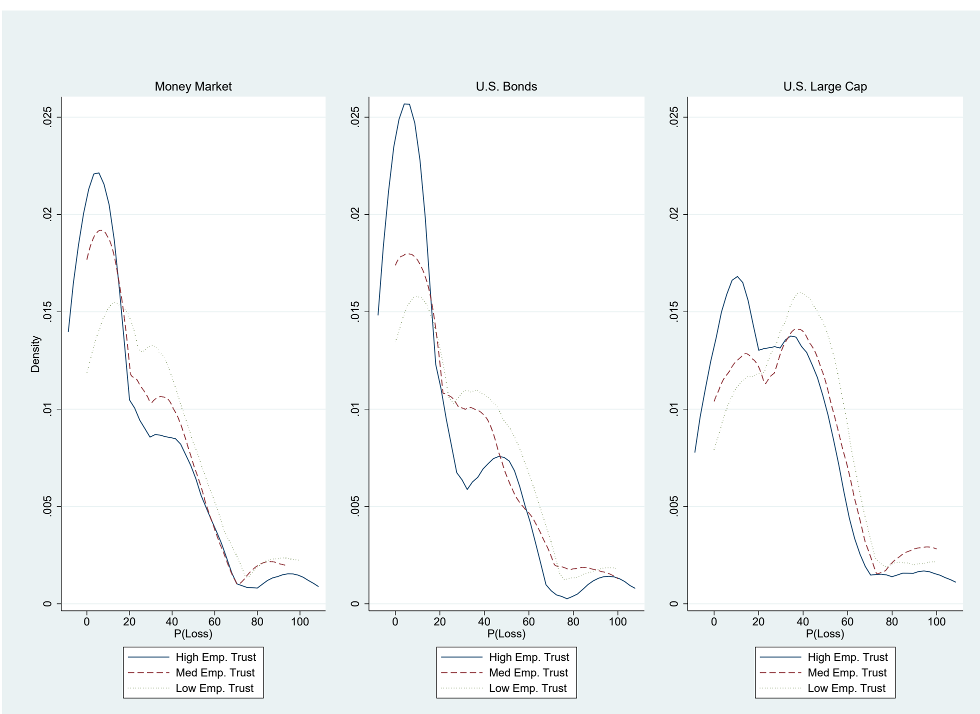
	High v. Low Employer Trust				
	Money Market	US Bonds	US Large Cap	US Small Cap	Global Stock
	Combined KS p-value				
Expected Return densities	0.514	0.428	0.121	0.628	0.796
Probability of Loss densities	0.025	0.045	0.132	0.625	0.323

Figure 8: **Fitted densities: Expected returns and probabilities of loss by low, medium, and high self-reported trust in employer**

Panel (a) Shows kernel densities for expected one-year returns to a $100,000 investment in employer-labeled money market, US Bond index and US Large Cap index funds. The solid line is the fitted density for the expected returns of subjects in Condition 3 who self-reported high trust in their employer, the dashed line is the fitted density for subjects who self-reported medium trust in their employer, and the dotted line is the fitted density for subjects who self-reported low trust in their employer. Panel (b) shows the kernel densities for the one-year probability of loss to a $100,000 investment of the same groups of subjects.



(a) Fitted density of expected returns by high/medium/low trust in their employer



(b) Fitted density of probability of loss by high/medium/low trust in their employer

4.2.2 Effects of self-reported employer organizational trust and financial literacy on expected returns and losses

Again following Study One, we compute marginal effects from OLS regressions:

$$M_{i,j} = \alpha_{1,j} + \Gamma X_i + \beta_{1,j} ET_i + \beta_{2,j} FL_i + \beta_{3,j} ET_i * FL_i + \varepsilon_{i,j} \tag{6}$$

where the dependent variable is either a measure of expected return or probability of loss ($M_{i,j} \ : \ R_{i,j}; L_{i,j}$) for subject i and asset class j, ET_i is a categorical variable indicating high, medium or low employer trust for subject i, FL_i is an indicator for high financial literacy (versus low financial literacy) and X_i is a vector of control variables comprising gender, marital status, age, education, household income, race, stock ownership, trust in the finance sector and attention to the survey. We use estimates of equation 6 to compute differences in predictive margins for the effects of employer organizational trust and financial literacy on expected returns and risk, conditioning on subject characteristics.

Table 13 reports results from these tests. We find that direction of effects, by and large, are the same as as reported in Table 8, with low employer trust associated with higher probabilities of loss and lower expected returns than high employer trust. The same pattern as in Table 8 also applies for low and high financial literacy where low financial literacy is associated with higher probabilities of loss and (mostly) lower expected returns. However very few differences are statistically significant due to the small sample size within the condition.

Table 13: **Estimated effects of self-reported employer trust and financial literacy on expected returns and risk.**

The table reports average predicted values and results of tests that marginal differences are zero from regressions of proxies for risk and return on self-reported employer trust bins (low, medium, or high employer trust), financial literacy indicators (high and low financial literacy) and interactions, and demographic controls (equation 3). High-trust employer sample: N=112; Medium-trust employer sample: N=86; Low-trust employer sample: N=62. Standard errors are calculated via the delta method. *** indicates p-value < 0.01; ** indicates p-value < 0.05; * indicates p-value < 0.1.

Probability of Loss									
	Average predicted value (%)			Difference	p-value	Average predicted value		Difference	p-value
	Low Trust	Medium Trust	High Trust	Low - High		Low Financial Literacy	High Financial Literacy	Low - High	
Money Market	26.85	23.05	20.97	5.88		26.35	21.04	5.31	
U.S. Bonds	23.17	23.55	19.95	3.22		27.22	18.64	8.57	*
U.S. Large Cap	32.78	33.86	28.74	4.03		32.10	30.96	1.14	
U.S. Small Cap	34.01	35.39	34.40	-0.40		38.34	32.36	5.99	
Global Stocks	38.87	38.34	37.53	1.34		39.13	37.49	1.64	

	Probability of Loss | Low Financial Literacy					Probability of Loss | High Financial Literacy				
	Average predicted value (%)			Difference	p-value	Average predicted value			Difference	p-value
	Low Trust	Medium Trust	High Trust	Low - High		Low Trust	Medium Trust	High Trust	Low - High	
Money Market	25.99	26.12	26.72	-0.73		27.39	21.16	17.43	9.95	**
U.S. Bonds	30.64	27.16	25.37	5.26		18.58	21.34	16.61	1.96	
U.S. Large Cap	33.29	35.72	28.67	4.62		32.46	32.72	28.79	3.68	
U.S. Small Cap	35.58	39.62	38.89	-3.32		33.04	32.80	31.64	1.40	
Global Stocks	41.98	40.75	36.32	5.66		36.96	36.86	38.27	-1.31	

Expected Return									
	Average predicted value (%)			Difference	p-value	Average predicted value		Difference	p-value
	Low Trust	Medium Trust	High Trust	Low - High		Low Financial Literacy	High Financial Literacy	Low - High	
Money Market	6.18	7.55	7.38	-1.20		6.67	7.45	-0.79	
U.S. Bonds	5.80	4.58	4.64	1.16		3.84	5.54	-1.70	
U.S. Large Cap	6.69	5.45	7.11	-0.43		7.02	6.11	0.91	
U.S. Small Cap	4.17	2.92	4.31	-0.15		1.93	4.98	-3.05	
Global Stocks	3.30	3.81	4.26	-0.97		3.96	3.84	0.12	

	Expected Return | Low Financial Literacy					Expected Return | High Financial Literacy				
	Average predicted value (%)			Difference	p-value	Average predicted value			Difference	p-value
	Low Trust	Medium Trust	High Trust	Low - High		Low Trust	Medium Trust	High Trust	Low - High	
Money Market	5.61	8.41	5.91	-0.30		6.53	7.03	8.29	-1.76	
U.S. Bonds	3.71	4.41	3.47	0.24		7.09	4.68	5.36	1.73	
U.S. Large Cap	7.47	5.52	7.93	-0.45		6.20	5.40	6.61	-0.41	
U.S. Small Cap	3.65	0.48	2.09	1.56		4.48	4.42	5.68	-1.20	
Global Stocks	4.17	3.21	4.41	-0.24		2.76	4.18	4.17	-1.41	

4.2.3 Employer organizational trust effects on portfolio allocation

Tables 14 and 15 present estimates using the specification in 4 with investment options labeled with the name of the subject's employer (Condition 3). The results are consistent with those in Tables 9 and 10 but with larger standard errors, which may reflect the smaller sample size in Condition 3 as well as the inability to experimentally stratify by trust in one's employer. Higher probabilities of loss predict lower allocations to the employer-labeled option and higher expected returns predict higher allocations to the employer labeled option. However we estimate a significant effect of employer trust for models including expected returns and not for models including probabilities of loss.

Table 14: **Panel Estimates of Allocation to Employer-labelled Option: Effect of Expected Probability of Loss**

The table reports estimation results from fixed effects panel models of allocations to employer-labeled investment options in Study Two. In task 2, subjects allocated 100% of their hypothetical retirement balance to 10 fee-free index funds in 5 asset classes (Money Market, U.S. Bonds, U.S. Large cap stocks, U.S. Small cap stocks and Global stocks) where funds within asset classes had either a label for the participant's employer or a white label. Models estimate the percentage allocation of subject i to the employer-labeled fund in asset class j conditioning on subjects' one-year expected probability of loss $L_{i,j,c}$, financial literacy, and a high-, medium- or low-trust employer condition indicator. Models 1-4 include individual fixed effects. Models 2-4 also include fixed effects for money market, bond and stock asset classes. Standard errors are in parentheses. Columns 5 and 7 report marginal effects with delta-method standard errors. *** indicates p-value < 0.01; ** indicates p-value < 0.05; * indicates p-value < 0.1.

	Model					
% Allocation to Employer Option	(1)	(2)	(3)	(3)	(4)	(4)
				Pred. Margin		Pred. Margin
Probability of Loss P(Loss)	-0.0890**	-0.0923**	-0.127**	-0.0861**	-0.183	-0.0892**
	(0.0348)	(0.0402)	(0.0637)	(0.0390)	(0.117)	(0.0374)
High Fin Lit x P(Loss)			0.0660		0.237*	
			(0.0723)		(0.128)	
Med Emp. Trust x P(Loss)					0.136	
					(0.164)	
High Emp. Trust x P(Loss)					0.00166	
					(0.143)	
High Fin Lit x Med Emp Trust x P(Loss)					-0.271	
					(0.189)	
High Fin Lit x High Emp Trust x P(Loss)					-0.151	
					(0.164)	
High Fin Lit				1.967		2.625
				(2.155)		(2.059)
Med Emp. Trust						-0.296
						(2.659)
High Emp. Trust						-2.375
						(2.338)
Participant FE	Yes	Yes	Yes		Yes	
Asset class FE	No	Yes	Yes		Yes	
R-squared	0.010	0.038	0.039		0.044	
Observations	1300	1300	1300		1300	

Table 15: **Panel Estimates of Allocation to Employer-labelled Option: Effect of Expected Returns**

The table reports estimation results from fixed effects panel models of allocations to employer-labeled investment options in Study Two. In task 2, subjects allocated 100% of their hypothetical retirement balance to 10 fee-free index funds in 5 asset classes (Money Market, U.S. Bonds, U.S. Large cap stocks, U.S. Small cap stocks and Global stocks) where funds within asset classes had either a label for the participant's employer or a white label. Models estimate the percentage allocation of subject i to the employer-labeled fund in asset class j conditioning on subjects' one-year expected return $R_{i,j,c}$, financial literacy, and a high-, medium- or low-trust employer condition indicator. Models 1-4 include individual fixed effects. Models 2-4 also include fixed effects for money market, bond and stock asset classes. Standard errors are in parentheses. Columns 5 and 7 report marginal effects with delta-method standard errors. *** indicates p-value < 0.01; ** indicates p-value < 0.05; * indicates p-value < 0.1.

	Model					
% Allocation to Manager Option	(1)	(2)	(3)	(3) Pred. Marg	(4)	(4) Pred. Marg
Expected Return E(R)	0.280***	0.252***	0.192**	0.336***	0.253**	0.338***
	(0.0765)	(0.0748)	(0.0838)	(0.0929)	(0.117)	(0.0840)
High Fin Lit x E(R)			0.232		-0.298*	
			(0.164)		(0.180)	
Med Emp. Trust x E(R)					-0.182	
					(0.150)	
High Emp. Trust x E(R)					0.104	
					(0.203)	
High Fin Lit x Med Emp Trust x E(R)					0.910***	
					(0.325)	
High Fin Lit x High Emp Trust x E(R)					0.324	
					(0.309)	
High Fin Lit				1.218		0.800
				(0.861)		(0.802)
Med Emp. Trust						2.418**
						(1.085)
High Emp. Trust						1.749*
						(0.920)
Participant FE	Yes	Yes	Yes		Yes	
Asset class FE	No	Yes	Yes		Yes	
R-squared	0.023	0.047	0.050		0.058	
Observations	1300	1300	1300		1300	

To estimate direct organizational trust effects, we follow Study One and again assume that participants make their asset allocation decision in a sequential manner. For subjects in Condition 3, we implement the IV model in equation 5 using the ML generated instrument that predicts their broad asset class allocations.

Table 16 reports results for participants in Condition 3 who were shown white label options alongside options labeled with their (proxy) employer's name. The effects of high (self-reported) trust in one's employer display similar patterns to those for the high-trust asset manager in Table 11, although the effects of organizational trust are only significant when comparing participants with high self-reported trust in their employers relative to participants with low self-reported trust. For example, the effect of having a high-trust employer increases the allocation to employer-labeled money market funds (stock funds) by approximately 5.2 (5.0) percentage points. Note, however, that the effects of having high employer trust are not significant in Model 4.

In summary, analysis of responses from Condition 3 offer some evidence for organizational trust influences on allocation decisions, limited by small sub-sample sizes. Findings reveal a significant indirect and direct effect of high employer trust on money market and stock allocations when models include subjects' expected returns. Models including expected probabilities of loss show a direct effect of high employer trust on money market allocations while effects on stock allocations are in the expected direction but estimated with large standard errors.

5 Conclusion

With the growing prevalence of white-label funds in retirement plan menus, employers have widening discretion over the way that investment options are labeled. As a result, there is the potential for them to, intentionally or unintentionally, steer participants' investment choices. While rational investors will ignore irrelevant signals, earlier findings have shown that participants can be affected by factors that should not matter, such as cosmetic choices of investment fund names.

Our study demonstrates that organizational trust, or confidence in a firm to deliver an expected outcome, as signaled via investment fund labels, may play a large role in retirement plan asset allocations. Our incentivized experiment shows that participants' expectations of investment returns and losses to a fund depend on the perceived trustworthiness of the organization on the label and these expectations indirectly influence allocation decisions. We also find that organizational trust directly influences allocation choices, in addition to the impact of expectations. Specifically, in Study One we find that options showing highly-trusted asset manager names are more attractive than equivalent white-label options, and that the reverse holds for poorly-trusted names. These allocations are partly motivated by participants' expectations that funds labeled with trusted manager names will deliver higher returns and lower losses than funds with less-trusted manager names. Participants with low financial literacy are more prone to these inferences. In Study Two we find weaker evidence that trusted employer's names are also attractive to plan participants.

In the experiment, there is no advantage or disadvantage to choosing an organizationally labelled investment option relative to a generic option. However, in a more realistic setting, agency conflicts between the retirement plan sponsor, asset managers, and other financial intermediaries may make choosing an organizationally labelled fund suboptimal for investors if those asset managers use their positive name association to extract rents via contracts with intermediaries that are unobservable to retirement plan sponsors or participants (see, e.g., Pool et al. (2022)). Even if skilled asset managers do not extract all surplus through fees, organizational trustworthiness is likely to be a poor signal for asset management skill (Sialm and Tham, 2016). Moreover, retirement plan sponsors may not be able to adjust their menus quickly enough to account for changes in organizational trust due to frictions in the administrative process.

In sum, our research has important implications for plan sponsors and investment companies. Our study provides further evidence that menu design matters and that careful consideration must be given before introducing new options into plan menus. In addition, the naming of fund options is not a trivial task. Our study also highlights the importance of fund labeling and organizational trust and demonstrates the potential impact on fund flows. While naming white label funds after the employer is a common practice among retirement plans (Bare et al., 2017), this paper provides, for the first time, guidance to companies regarding whether or not adding their name to their fund labels will discourage or promote flows to their funds.

Table 16: **IV Estimates of Allocation to Employer-labelled Option**

This table reports second stage Generalized Method of Moments (GMM) estimates and marginal effects from equation 5 for conditions 3. Models 1 and 3 estimate percentages allocated to manager-labeled money market funds and Models 2 and 4 estimate total percentages allocated to all manager-labeled stock funds.

	(1)	(1)	(2)	(2)	(3)	(3)	(4)	(4)
% Employer-labeled Option	Money Market		Stocks		Money Market		Stocks	
		Marg. Eff		Marg. Eff		Marg. Eff		Marg. Eff
Total Money Market allocation	0.811***	0.811***			0.838***	0.838***		
	(0.144)	(0.144)			(0.167)	(0.167)		
Total Stocks Allocation			0.390	0.390			0.190	0.190
			(0.323)	(0.323)			(0.405)	(0.405)
Med Emp. Trust	5.612	2.033	-3.092	4.580	5.398	1.869	-3.344	3.953
	(4.471)	(2.517)	(5.427)	(4.385)	(4.555)	(2.577)	(5.815)	(4.520)
High Emp. Trust	10.25***	5.187**	8.626*	8.128*	10.11***	4.978**	7.414	7.194
	(3.606)	(2.058)	(5.239)	(4.348)	(3.733)	(2.196)	(6.028)	(4.549)
High Fin Lit	4.882	-0.552	0.950	4.702	5.182	-0.273	3.885	7.629
	(4.591)	(2.783)	(8.541)	(6.658)	(4.772)	(2.904)	(9.249)	(7.718)
High Fin Lit x Med Emp. Trust	-5.780		12.39		-5.699		11.78	
	(5.328)		(8.273)		(5.442)		(8.503)	
High Fin Lit x High Emp. Trust	-8.175*		-0.805		-8.288*		-0.357	
	(4.353)		(8.120)		(4.465)		(8.575)	
E(R) Money Market	-0.0328	-0.0328						
	(0.0459)	(0.0459)						
E(R) U.S. Large Cap			0.101	0.101				
			(0.147)	(0.147)				
E(R) U.S. Small Cap			0.0213	0.0213				
			(0.155)	(0.155)				
E(R) Global Stocks			-0.0557	-0.0557				
			(0.192)	(0.192)				
P(Loss) Money Market					-0.0129	-0.0129		
					(0.0417)	(0.0417)		
P(Loss) U.S. Large Cap							-0.115	-0.115
							(0.0922)	(0.0922)
P(Loss) U.S. Small Cap							-0.0283	-0.0283
							(0.112)	(0.112)
P(Loss) Global Stocks							-0.0119	-0.0119
							(0.0824)	(0.0824)
Constant	-9.237		6.671		-9.905		23.00	
	(6.317)		(15.82)		(6.603)		(25.51)	
R-squared	0.603		0.252		0.591		0.196	
Observations	260	260	260	260	260	260	260	260
First stage statistics								
Underidentification (K-P LM)	15.55		11.35		12.61		7.23	
Weak Identification (K-P Wald)	14.77		11.60		12.61		7.15	

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A Survey Sample Demographics

Table A.1: **Descriptive Statistics by Condition**

			Condition 1		**Condition 2**		**Condition 3**		**Condition 4**	
	All		**High Trust**		**Low Trust**		**Employer White Label**		**White Label**	
	Count	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
N	952		233		231		260		228	
Male	474	50%	121	52%	118	51%	134	52%	101	44%
Married	637	67%	169	73%	146	63%	169	65%	153	67%
Age										
19 to 29 years old	35	4%	5	2%	12	5%	9	3%	9	4%
30 to 39 years old	225	24%	56	24%	47	20%	75	29%	47	21%
40 to 49 years old	279	29%	73	31%	72	31%	66	25%	68	30%
50 to 59 years old	266	28%	65	28%	66	29%	66	25%	69	30%
60 to 70 years old	132	14%	31	13%	30	13%	40	15%	31	14%
70 to 80 years old	14	1%	3	1%	4	2%	4	2%	3	1%
Missing	1	0%	0	0%	0	0%	0	0%	1	0%
Total	951	100%	233	100%	231	100%	260	100%	228	100%
Education										
Less than High School	15	2%	1	0%	1	0%	4	2%	9	4%
High School	123	13%	37	16%	24	10%	28	11%	34	15%
Some College	168	18%	39	17%	49	21%	41	16%	39	17%
College (Assoc. or Bachelor)	443	47%	92	39%	120	52%	133	51%	98	43%
Post Graduate Degree	203	21%	64	27%	37	16%	54	21%	48	21%
Total	952	100%	233	100%	231	100%	260	100%	228	100%
Household Income										
Less than $5,000	5	1%	2	1%	0	0%	1	0%	2	1%
$5,000 to $7,499	1	0%	1	0%	0	0%	0	0%	0	0%
$7,500 to $9,999	3	0%	2	1%	1	0%	0	0%	0	0%
$10,000 to $12,499	6	1%	0	0%	2	1%	0	0%	4	2%

Continued

Table A.1 – *Continued*

			Condition 1		**Condition 2**		**Condition 3**		**Condition 4**	
	All		**High Trust**		**Low Trust**		**Employer White Label**		**White Label**	
	Count	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**	**Count**	**%**
$12,500 to $14,999	6	1%	1	0%	2	1%	2	1%	1	0%
$15,000 to $19,999	10	1%	1	0%	0	0%	4	2%	5	2%
$20,000 to $24,999	21	2%	4	2%	5	2%	5	2%	7	3%
$25,000 to $29,999	25	3%	8	3%	5	2%	5	2%	7	3%
$30,000 to $34,999	37	4%	8	3%	9	4%	9	3%	11	5%
$35,000 to $39,999	40	4%	8	3%	7	3%	16	6%	9	4%
$40,000 to $49,999	62	7%	13	6%	20	9%	16	6%	13	6%
$50,000 to $59,999	87	9%	22	9%	30	13%	16	6%	19	8%
$60,000 to $74,999	114	12%	32	14%	32	14%	32	12%	18	8%
$75,000 to $99,999	173	18%	43	18%	42	18%	44	17%	44	19%
$100,000 to $149,999	212	22%	50	21%	46	20%	73	28%	43	19%
$150,000 or more	149	16%	38	16%	30	13%	36	14%	45	20%
Missing	1	0%	0	0%	0	0%	1	0%	0	0%
Total	952	100%	233	100%	231	100%	260	100%	228	100%
Race										
White	809	85%	201	86%	195	84%	226	87%	187	82%
Black	71	7%	17	7%	17	7%	17	7%	20	9%
Other	70	7%	14	6%	18	8%	17	7%	21	9%
Missing	2	0%	1	0%	1	0%	0	0%	0	0%
Total	950	100%	233	100%	231	100%	260	100%	228	100%
Labor Status										
Currently Working	948	100%	233	100%	229	99%	258	99%	228	100%
On Sick or Other Leave	1	0%	0	0%	1	0%	0	0%	0	0%
Unemployed-Looking	2	0%	0	0%	0	0%	2	1%	0	0%
Retired	1	0%	0	0%	1	0%	0	0%	0	0%
Total	952	100%	233	100%	231	100%	260	100%	228	100%

B Fractional Multivariate Logit Results

In this Appendix we present results from estimating a multivariate model where the dependent variable is the vector of each subject's portfolio share, rather than the individual elements consisting of the allocation to each of the funds. Doing so allows us to incorporate the portfolio constraint (i.e. that the sum of shares is 100% for each individual in the data) into the estimation procedure. As with the instrumental variable estimates in the main text, we aggregate across equity funds and the outcome of interest is the six-element vector of portfolio allocations to branded and white label funds the three broad asset classes (money market, bonds, equities) for each respondent in Study One. To model the vector of shares, we employ a multinomial logit framework analogous to Papke and Wooldridge (1996). While this framework has the advantage of enforcing the adding-up constraint; to the best of our knowledge, the econometric properties of this estimator in settings such as ours where the data contain a meaningful number of portfolio shares at the boundary (i.e. individual allocations of 0% or 100%) have not been studied. Table B.1 presents coefficient estimates from the estimation procedure. Note that the table contains only five columns even though there are six elements to the vector of portfolio shares. This is because the coefficient estimates for the first element, the allocation to branded bond funds, are normalized to one; thus, the coefficient estimates for the other five outcomes are relative to the base outcome.[20]

As with multinomial logit estimates, the coefficient estimates themselves are hard to interpret, therefore we present the average partial effects in Table B.2, which are akin to the marginal effects estimates from a traditional multinomial model (and are presented for all six funds). Note that the sum of the average partial effects is equal to zero across the six funds. This is enforced by the estimation procedure and reflects the constraint that the impact of a unit change in a covariate on one outcome must be offset by the effects on the other outcomes. The results in Table B.2 are very similar to those found in the panel and IV models in the main text; a high trust brand is associated with a higher allocation within the given asset class. Also reflecting the unconditional results in Table 3, the positive effect of a high trust brand to the allocation within that asset class is almost completely offset by a reduction to the white label fund within that asset class (e.g. moving from the low trust to the high trust condition increases the allocation to a branded bond fund by roughly 3.5 percentage points, but decreases the allocation to a white label bond fund by roughly 3.2 percentage points).

[20]This is analogous to a multinomial logit model, where the coefficient estimates for some "base outcome" are unidentified and typically normalized to one.

Table B.1: **Fractional Multivariate Logit Estimates of Portfolio Allocation: Coefficient Estimates**

The table reports estimation results from a multivariate fractional logit model for subjects in Study One. In task 2, subjects allocated 100% of their hypothetical retirement balance to 10 fee-free index funds in 5 asset classes (Money Market, U.S. Bonds, U.S. Large cap stocks, U.S. Small cap stocks and Global stocks) where funds within asset classes had either a manager label or a white label. Models estimate the percentage allocation of respondent i to the manager- or white-labeled fund in one of three asset classes: money market, bond, or stocks (aggregating across large cap, small cap, and global). Standard errors are in parenthesis. *** indicates p-value $<$ 0.01; ** indicates p-value $<$ 0.05; * indicates p-value $<$ 0.1.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	WL Bond Allocation	Manager Equity Allocation	WL Equity Allocation	Manager Money Market Allocation	WL Money Market Allocation
High Trust Manager	-0.557*	-0.00505	-0.632**	0.0211	-0.487
	(0.323)	(0.251)	(0.296)	(0.289)	(0.339)
High Fin Lit	0.987***	0.439*	0.902***	-0.192	0.305
	(0.343)	(0.250)	(0.308)	(0.312)	(0.349)
High Trust x High Fin Lit	-0.836*	-0.137	-0.697*	-0.214	-0.719
	(0.453)	(0.333)	(0.412)	(0.381)	(0.455)
Constant	-0.152	0.541	0.638	0.303	0.0820
	(0.654)	(0.551)	(0.601)	(0.618)	(0.663)
Participant Controls	Yes	Yes	Yes	Yes	Yes
Observations	462	462	462	462	462

Table B.2: **Fractional Multivariate Logit Estimates of Portfolio Allocation: Average Partial Effects**

The table reports average partial effects from a multivariate fractional logit model for the estimates in Table B.1. Note that the sum of average partial effects across columns within a row equal to zero; this reflects the portfolio constraint. Standard errors are calculated via the delta method. *** indicates p-value < 0.01; ** indicates p-value < 0.05; * indicates p-value < 0.1.

	(1)	(2)	(3)	(4)	(5)	(6)
	Manager Bond Share	WL Bond Share	Manager Equity Share	WL Equity Share	Manager Money Market Share	WL Money Market Share
High Trust Manager	0.0353***	-0.0315***	0.129***	-0.143***	0.0534***	-0.0433**
	(0.0123)	(0.00859)	(0.0248)	(0.0247)	(0.0191)	(0.0172)
High Fin Lit	-0.0178	0.0212*	0.0361	0.0794***	-0.0807***	-0.0382*
	(0.0126)	(0.0110)	(0.0290)	(0.0294)	(0.0245)	(0.0224)
Observations	462	462	462	462	462	462

C Participant Financial Uncertainty

Recent work (e.g. Liang (2024)) has documented that some individuals' subjective uncertainty over financial concepts, rather than simply being wrong, is predictive of financial decision-making. In this Appendix we present results incorporating participants' stated uncertainty. To do this, we use k-means cluster analysis to separate participants into three groups based on their responses to multiple-choice financial literacy questions contained in the Understanding America Study. We find that the clusters are highly imbalanced: 623 (65.6%) fall into the largest cluster (Cluster #1); 271 (28.6%) participants fall into the second-largest cluster (Cluster #2); and the remaining 55 (5.8%) fall into the smallest cluster (Cluster #3).[21] The k-means clustering analysis uncovers an intuitive pattern in the data. The participants grouped into Cluster #1 on average have a higher number of correct answers to the fourteen financial literacy questions, followed by Cluster #2 and Cluster #3, a pattern visible in Figure C.1, below.

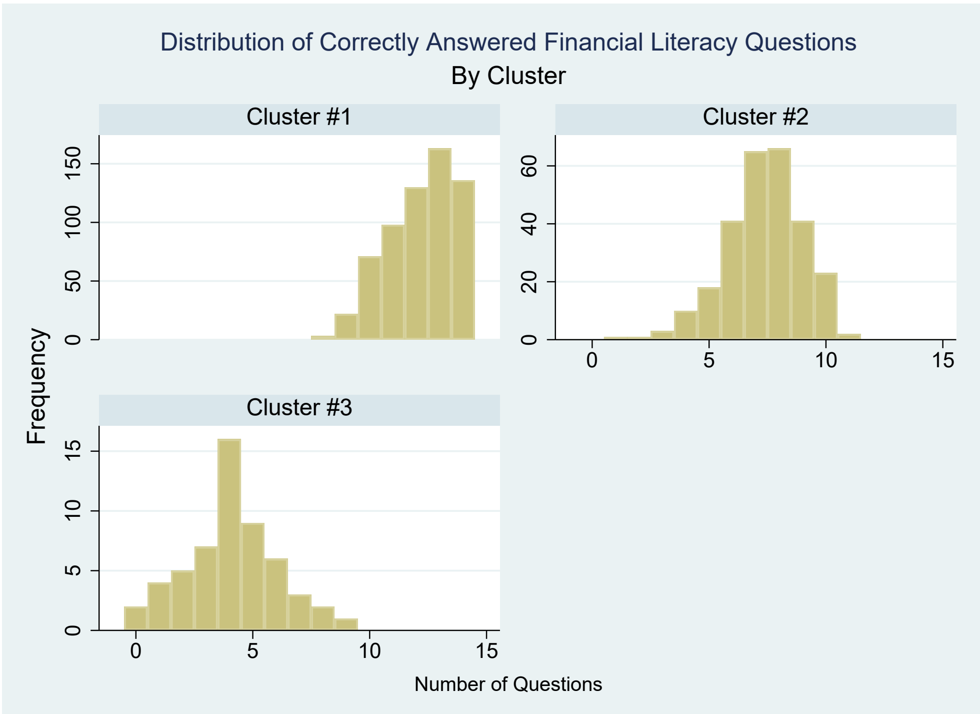
While the clusters clearly are correlated with the number of correct answers to financial literacy questions, cluster #3 also contains individuals who seem to be more willing to state their ignorance or uncertainty over financial literacy concepts. The median number of "I don't know" responses in Cluster #3 is six, whereas the median number of "I don't know" responses in Clusters #1 and # are zero and two, respectively. The distributions of expected returns and one-year probabilities of loss for participants in each of the three clusters is shown below in Figure C.2. The distribution of expected returns and probabilities of loss is much more diffuse (i.e. flatter) for those participants who are willing to admit they do not know the answers to financial literacy questions or answer incorrectly.

These results are suggestive that participants' subjective risk and return expectations may differ based on whether they respond to financial literacy questions by stating their uncertainty as opposed to answering incorrectly. However, we are unable to examine stated uncertainty as a mediator for trust due to the relatively small number of participants who answer "I don't know" in response to financial literacy questions. Out of the 55 participants in Cluster #3, only 24 are included in Study One and 10 are included in Study Two.

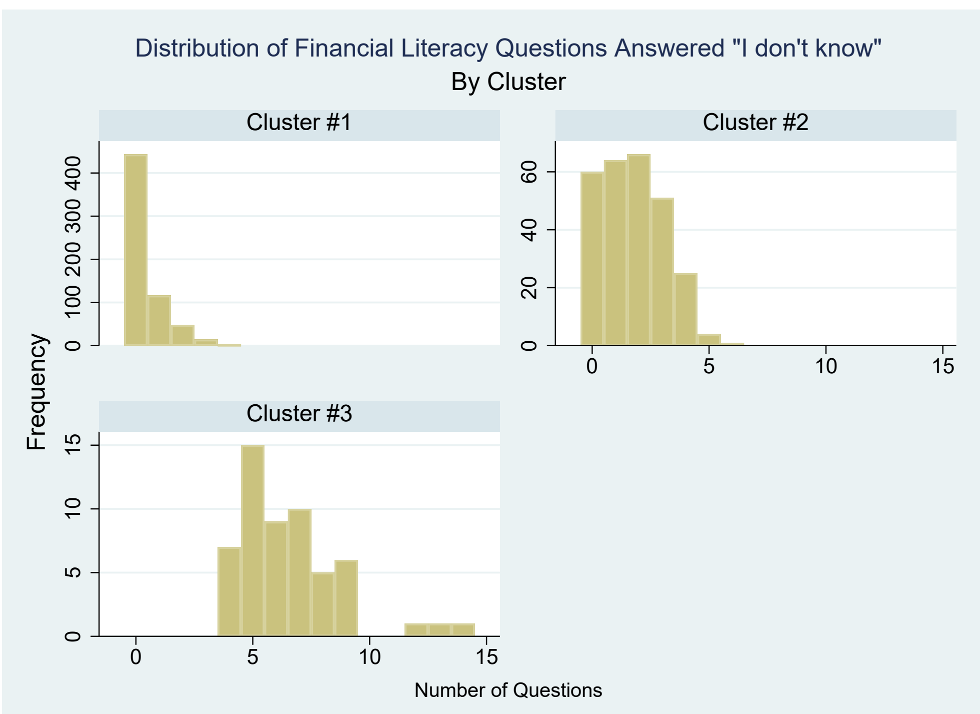
[21] The numbering of the clusters is arbitrary and is purely for expositional convenience.

Figure C.1: **Histograms: Number of correctly answered financial literacy questions and questions answered "I don't know" by cluster**

Panel (a) shows a histogram of the number of correctly answered questions for participants grouped into three clusters based on k-means analysis based on responses to financial literacy questions administered in the Understanding America Study. Panel (b) shows a histogram of the number of financial literacy questions to which participants answered "I don't know."



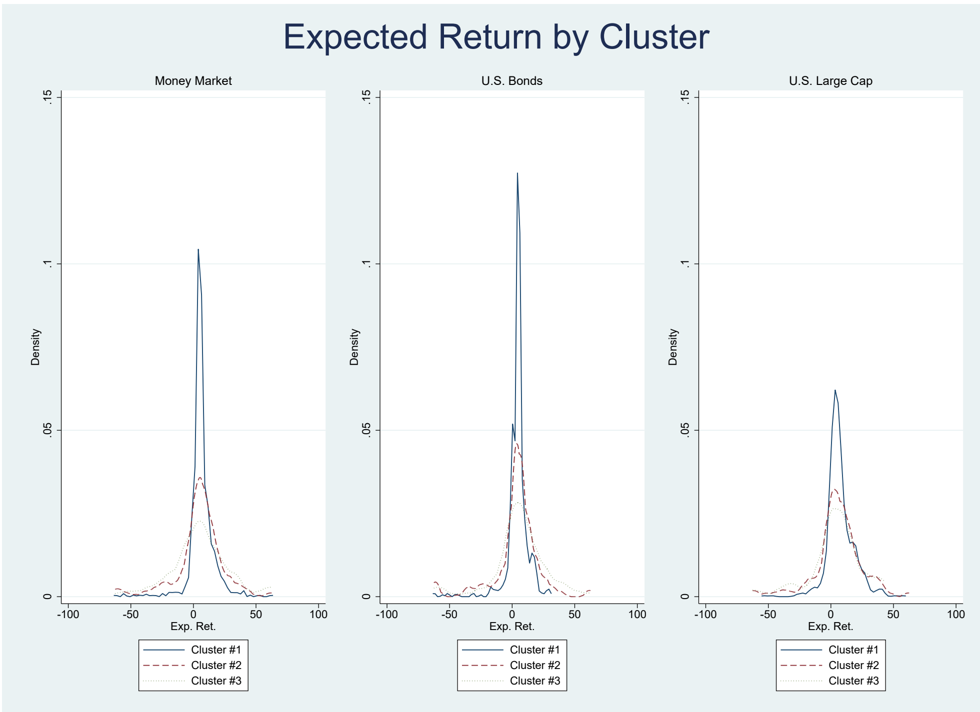
(a) Histogram of correct financial literacy responses by cluster



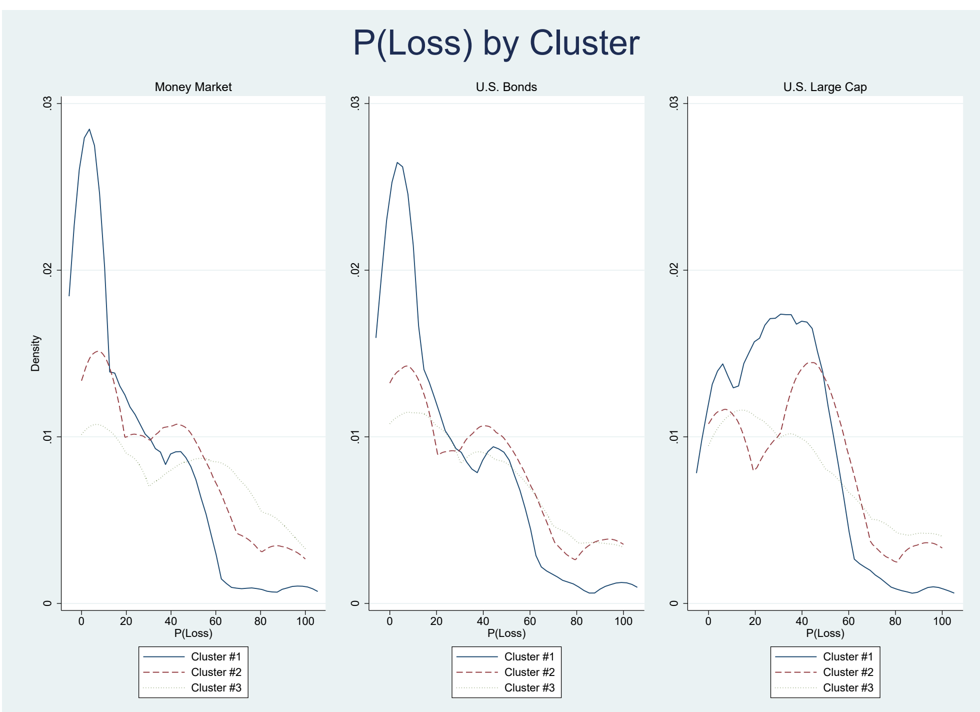
(b) Histogram of "I don't know" responses to financial literacy questions by cluster

Figure C.2: **Fitted densities: Expected returns and probabilities of loss by cluster**

Panel (a) shows kernel densities for expected one-year returns to a $100,000 investment in money market, US Bond index, and US Large Cap index funds. The solid line is the fitted density for expected returns of subjects grouped into Cluster #1, the dashed line is the fitted density for subjects grouped into Cluster #2, and the dotted line is the fitted density for subjects who grouped into Cluster #3 using k-means analysis based on responses to financial literacy questions administered in the Understanding America Study.



(a) Fitted density of expected returns by cluster



(b) Fitted density of probability of loss by cluster