Low Interest Rates and Risk Taking: Evidence from Individual Investment Decisions*

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Abstract

How do low interest rates affect investor behavior? We demonstrate that individuals "reach for yield," that is, have a greater appetite for risk taking when interest rates are low. Using randomized investment experiments holding fixed risk premia and risks, we show low interest rates lead to significantly higher allocations to risky assets among diverse populations. The behavior is not easily explained by conventional portfolio choice theory or institutional frictions. We then propose and provide evidence for mechanisms related to investor psychology, including reference dependence and salience. We also present results using observational data on household investment decisions.

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1 Introduction

Since the global financial crisis, central banks in major developed countries have set benchmark interest rates to historic lows. A widely discussed question is whether such low interest rates increase investors' appetite for risk taking, a phenomenon often referred to as "reaching for yield."[1] Increased risk taking may help stimulate the economy, but may also pose challenges for financial stability. Policy makers and investors have highlighted the importance of reaching for yield (Bernanke, 2013; Stein, 2013; Rajan, 2013; Fink, 2016). Researchers also posit the "risk-taking channel" of monetary policy (Borio and Zhu, 2012; Bruno and Shin, 2015; Brunnermeier and Schnabel, 2016).

What drives reaching for yield? Recent work offers insights based on institutional frictions, including agency problems (Feroli, Kashyap, Schoenholtz, and Shin, 2014; Morris and Shin, 2015; Acharya and Naqvi, 2016) and financial intermediaries' funding conditions (Diamond and Rajan, 2012; Drechsler, Savov, and Schnabl, 2018). A number of studies also provide empirical evidence that banks, mutual funds, and pension funds invest in riskier assets when interest rates are low (Maddaloni and Peydró, 2011; Jiménez, Ongena, Peydró, and Saurina, 2014; Chodorow-Reich, 2014; Hanson and Stein, 2015; Choi and Kronlund, 2016; Di Maggio and Kacperczyk, 2017; Andonov, Bauer, and Cremers, 2017).

In this paper, we present evidence that reaching for yield is not confined to institutions. Rather, it can be driven by preferences and psychology, and arise from the way people perceive and evaluate return and risk trade-offs in different interest rate environments.

Specifically, we show that individuals demonstrate a stronger preference for risky assets when the risk-free rate is low. We first document this phenomenon in a simple randomized experiment. In Treatment Group 1, participants consider investing between a risk-free asset with 5% returns and a risky asset with 10% average returns (the risky payoffs are approximately normally distributed with 18% volatility). In Treatment Group 2, participants consider investing between a risk-free asset with 1% returns and a risky asset with 6% average returns (the risky payoffs are again approximately normally distributed with

[1] The term "reaching for yield" is sometimes used in different ways. For instance, Becker and Ivashina (2015) document that insurance companies have a general propensity to buy riskier assets, and refer to this behavior as "reaching for yield." In recent discussions of monetary policy and financial markets, "reaching for yield" refers more specifically to the notion that investors may have a higher propensity to take risks *when interest rates are low*, which is what we focus on. The "reaching for yield" behavior we study in this paper, most precisely, is that people invest more in risky assets when interest rates are low, holding fixed the risks and excess returns of risky assets.

18% volatility). In other words, across the two treatment conditions, we keep the risk premium (i.e. average excess returns) and the risks of the risky asset fixed, and only make a downward shift in the risk-free interest rate. Participants are randomly assigned to one of the two conditions. The investment decision in each condition represents the simplest mean-variance analysis problem, where the solution should not be affected by the risk-free rate based on the textbook mean-variance benchmark (Markowitz, 1952; Sharpe, 1964).

We find robust evidence that people in the low interest rate condition (Treatment Group 2) invest significantly more in the risky asset than people in the high interest rate condition (Treatment Group 1). The average investment share in the risky asset increases by about 8 percentage points. This finding holds among large and diverse groups of participants (several thousand participants from the US general population through Amazon's Mechanical Turk platform as well as four hundred Harvard Business School MBA students), and across different settings (hypothetical questions as well as incentivized experiments). Such behavior by individuals is not explained by institutional frictions. It is also hard to square with standard portfolio choice theory under fairly general conditions (specifically, absolute risk aversion is weakly decreasing in wealth).

We conjecture two categories of mechanisms that may contribute to reaching for yield in individual investment decisions. The first category captures the observation that people may form reference points of investment returns. When interest rates fall below the reference level, people experience discomfort, and become more willing to invest in risky assets to seek higher returns. The reference point can be shaped by what people have become used to over past experiences. The observation connects to the popular view among investors that 1% interest rates are "too low," compared to what they are accustomed to. This intuition can be formalized in the framework of reference dependence (Kahneman and Tversky, 1979), where the reference point may be history-dependent (Kahneman and Miller, 1986; Bordalo, Gennaioli, and Shleifer, 2017; DellaVigna, Lindner, Reizer, and Schmieder, 2017).

The second category of mechanisms postulates that reaching for yield could be affected by the salience of the higher average returns on the risky asset in different interest rate environments. Specifically, 6% average returns relative to 1% risk-free returns may appear more attractive than 10% average returns relative to 5% risk-free returns. This intuition can be formalized by a version of the Salience Theory (Bordalo, Gennaioli, and Shleifer, 2013b). It also connects to the well documented phenomenon, often referred to as Weber's law, that people tend to evaluate stimuli by proportions (i.e. 6/1 is much larger than 10/5) rather than by differences.

We design a set of additional tests to investigate these potential mechanisms, and find support for both. First, we document considerable non-linearity in how investment decisions respond to interest rates. We examine allocations across a wider range of interest rate conditions, from -1% to up to 15% (holding fixed the excess returns of the risky asset as before), and randomly assign participants to one of these conditions. We find that reaching for yield is particularly pronounced as interest rates decrease below historical norms prior to the Great Recession, and dissipates when interest rates are sufficiently high. The non-linear response to interest rates further suggests the psychological foundations of reaching for yield. The patterns are consistent with history-dependent reference points. They are also broadly consistent with salience, as the proportions change more with interest rates when rates are low.

Second, as further evidence for history-dependent reference points, we find that investment history has a significant impact on investment decisions. For instance, when participants first make investment decisions in the high interest rate condition and then make decisions in the low interest rate condition, they invest substantially more in the risky asset in the low rate condition.

Third, as further evidence for salience, risk taking decreases and reaching for yield is dampened if investment payoffs are presented using gross returns (e.g. instead of saying 6%, we say that one gets 1.06 units for every unit invested). In this case, the proportion of average returns shrinks (from 6/1 and 10/5, to 1.06/1.01 and 1.1/1.05), especially in the low interest rate condition, and becomes similar across the two conditions. As the higher average returns of the risky asset become much less salient, risk-taking in the low interest rate condition diminishes.

Our study uses an experimental approach as experiments allow us to cleanly isolate the effect of changes in the risk-free rate, and hold fixed the excess returns and risks of the risky asset. It is otherwise challenging to find large exogenous variations in interest rates (Ramey, 2016). It can also be difficult to measure investors' beliefs about returns and risks of assets in capital markets (Greenwood and Shleifer, 2014), which further complicates the analysis. In addition, experiments help us test the underlying mechanisms in detail, and better understand what drives the reaching for yield behavior we observe.

We supplement our experimental results with suggestive evidence from observational data. We use data from several sources and find consistent results. We start with monthly portfolio allocations data reported by members of the American Association of Individual Investors (AAII) since late 1987. We find that allocations to stocks decrease with interest rates and allocations to safe interest-bearing assets increase with interest rates, controlling for proxies of returns and risks in the stock market and general economic conditions. The magnitude is close to what we find in the benchmark experiment. We also use data on flows into equity and high yield corporate bond mutual funds, and find higher inflows when interest rates fall.

Our study contributes to several strands of research. First, we present novel evidence on reaching for yield in individual investment decisions, and reveal two psychological mechanisms at play. Recognizing these intrinsic individual-level tendencies is important for understanding the impact of low interest rates. Such tendencies can affect the investments of households, who are the end investors that allocate savings between safe and risky assets (Campbell, 2006; Frazzini and Lamont, 2008; Lou, 2012; Célérier and Vallée, 2017). Households' preferences can also shift investment decisions by financial institutions, which often cater to clients' tastes. Moreover, the preferences and psychology we document may affect professional investors as well. Reaching for yield is significant among financially well-educated individuals like HBS MBAs, and does not appear to diminish with wealth, investment experience, or work experience in finance.

Second, we demonstrate the importance of insights in behavioral economics for questions in monetary economics (i.e. impact of interest rates on investor behavior). We draw upon several mechanisms studied in different settings, including reference dependence (Kahneman and Tversky, 1979; Benartzi and Thaler, 1995; Camerer, Babcock, Loewenstein, and Thaler, 1997; Barberis, Huang, and Santos, 2001; Pope and Schweitzer, 2011), salience (Bordalo et al., 2013b; Hastings and Shapiro, 2013), and history dependence (Kahneman and Miller, 1986; Simonsohn and Loewenstein, 2006; Malmendier and Nagel, 2011; DellaVigna et al., 2017; Bordalo et al., 2017). Our contribution is to show how they help understand the key problem of investors' response to interest rates. Our findings have also been replicated by regulators to inform their policy analyses (Ma and Zijlstra, 2018).

Third, our paper relates to experimental studies on decision under risk and uncertainty. A number of experiments test elements that affect risk taking (Holt and Laury, 2002; Gneezy and Potters, 1997; Cohn, Engelmann, Fehr, and Maréchal, 2015; Kuhnen, 2015; Beshears, Choi, Laibson, and Madrian, 2016), often using abstract gambles. Little is known about the impact of interest rates, which are an essential component in most monetary risk decisions in practice (e.g. investment decisions of households and firms). We use experimental methods to study this applied question and present new findings. In a contemporaneous experiment with hypothetical questions, Ganzach and Wohl (2017) also find increased risk taking when interest rates are low. We provide a large set of evidence across many different settings, isolate behavior that departs from standard benchmarks, and test the underlying mechanisms in detail.

The remainder of the paper is organized as follows. Section 2 presents results of the benchmark experiment. Section 3 discusses possible explanations for the reaching for yield behavior we observe, and Section 4 tests these mechanisms. Section 5 provides results using historical data on household investment decisions. Section 6 concludes.

2 Benchmark Experiment

This section describes our benchmark experiment that tests low interest rates and risk taking. We conduct this experiment in different settings and with different groups of participants, which yield similar results. In the benchmark experiment, participants consider investing between a risk-free asset and a risky asset. Half of the participants are randomly assigned to the high interest rate condition and half to the low interest rate condition. In the high interest rate condition, the risk-free asset offers 5% annual returns and the risky asset offers 10% average annual returns. In the low interest rate condition, the risk-free asset offers 1% annual returns and the risky asset offers 6% average annual returns. In both conditions, the risky asset's excess returns are the same and approximately normally distributed. We truncate a normal distribution into nine outcomes to help participants understand the distribution more easily; the volatility of the risky asset's returns is 18% (about the same as the volatility of the US stock market). In other words, across the two conditions, we keep the excess returns of the risky asset fixed and make a downward shift of the risk-free rate. We document that participants invest significantly more in the risky asset in the low interest rate condition, and the result is robust to experimental setting, payment structure, and participant group.

2.1 Experiment Design and Sample Description

Our experiment takes the form of an online survey that participants complete using their own electronic devices (e.g. computers and tablets). The survey has two sections: Section

1 presents the investment decision, and Section 2 includes a set of demographic questions. Each experiment has 400 participants, who are randomly assigned to the two interest rate conditions. The survey forms are available in the Survey Appendix.

We conduct the benchmark experiment among two groups of participants. The first group consists of adults in the US from Amazon's Mechanical Turk (MTurk) platform. MTurk is an online platform for surveys and experiments, which is increasingly used in economic research (Kuziemko, Norton, Saez, and Stantcheva, 2015; Ambuehl, Niederle, and Roth, 2015; D'Acunto, 2015; Cavallo, Cruces, and Perez-Truglia, 2017; DellaVigna and Pope, 2017a,b). It allows access to a diverse group of participants from across the US, completes large-scale enrollment in a short amount of time, and provides response quality similar to that of lab experiments (Casler, Bickel, and Hackett, 2013). These features are very helpful for our study. As we show later, our MTurk participants have similar demographics as the US general population, with fewer elderlies and a higher level of education. Figure 1 shows the geographic location of participants in the benchmark experiments, which is representative of the US population. Our experiments on MTurk provide relatively high payments compared to the MTurk average to ensure quality response.

We also conduct the benchmark experiment with Harvard Business School MBA students. HBS MBA students are a valuable group of participants who are financially well-educated, and who are likely to become high net worth individuals that are the most important end investors in financial markets. A significant fraction of HBS MBAs also work in financial institutions. Their participation helps us study whether reaching for yield exists among these important financial decision-makers. Payments in our experiment with HBS MBAs are comparable to previous financial investing experiments with finance professionals (Cohn et al., 2015; Charness and Gneezy, 2010).

Below we provide detailed descriptions of the benchmark experiment in three different settings and the sample characteristics.

Experiment B1: MTurk, Hypothetical

In Experiment B1, participants consider a question about investing total savings of \$100,000 between the risk-free asset and the risky asset, and report their most preferred allocation. The investment horizon is one year. Participants are recruited on MTurk in June 2016. They receive a fixed participation payment of \$1. The experiment takes about 15 minutes to complete, and we allow a maximum duration of 60 minutes for all of our

MTurk experiments.

Table 1 Panel A shows the summary statistics of participant demographics in Experiment B1. Roughly half of the participants are male. About 75% of participants report they have college or graduate degrees; the level of education is higher than the US general population (Ryan and Bauman, 2015). The majority of participants are between 20 to 40 years old. Their attitudes toward risk taking, as measured by choices among simple binary gambles, are relatively conservative: the majority prefer safe lotteries with lower expected payoffs to risky lotteries with higher expected payoffs.[2] In the demographic section, we also ask participants' subjective evaluation of risk tolerance, and the majority select they are "somewhat risk averse but willing to hold some risky assets." About 60% of participants have financial wealth (excluding housing) above $10,000; roughly 10% to 15% of participants are in debt, while 5% to 10% have financial wealth more than $200,000. The wealth distribution is largely in line with the US population (the 2016 Survey of Consumer Finances shows median household financial assets of $23,500). Most participants have some amount of investment experience; 56.5% own stocks, slightly higher than the stock ownership rate of 51.9% from the 2016 Survey of Consumer Finances.

In the final three columns of Table 1, we also check whether the random assignment balances participant characteristics across the two treatment conditions. For each characteristic (e.g. gender), we compute the difference in the share of participants in a given category across the two conditions (e.g. difference in the share of males), and the t-statistics associated with the difference. Because many characteristics have several categories (e.g. education has graduate school, college, high school), in the final column we also make an overall assessment by comparing the distribution across the two treatment conditions. We use the non-parametric and ordinal Mann-Whitney-Wilcoxon (rank-sum) test and report the p-value. In Experiment B1, most characteristics are fairly balanced, except that the high interest rate condition happens to have more men.

Experiment B2: MTurk, Incentivized

In Experiment B2, participants consider allocating an experimental endowment of 100,000 Francs between the risk-free asset and the risky asset. The investment horizon is one year.

[2] Specifically, at the end of the demographics section, we ask a question where participants report their favorite lottery among six options: a) 50% chance receive $22 and 50% chance receive $22; b) 50% chance receive $30 and 50% chance receive $18; c) 50% chance receive $38 and 50% chance receive $14; d) 50% chance receive $46 and 50% chance receive $10; e) 50% chance receive $54 and 50% chance receive $6; f) 50% chance receive $60 and 50% chance receive $0. We categorize risk tolerance as low if participants choose option a) or b), medium if they choose option c) or d), and high if they choose option e) or f).

Participants are recruited on MTurk in February 2016. They receive a participation payment of $0.7, and could earn a bonus payment proportional to their investment outcomes, with every 8,950 Francs converted to one dollar of bonus payment.[3] The bonus payment is on the scale of $12, which is very high on MTurk. After the experiment is completed, participants see the investment outcome (the return of the safe asset is fixed and the return of the risky asset is randomly drawn based on the distribution). We follow prior investment experiments and implement the decision of 10% randomly selected participants, who will receive the bonus payment. The payment structure is clearly explained throughout the experiment. Cohn et al. (2015) review payment schemes with random implementation and argue "there is solid evidence showing that these schemes do not change behavior."[4] We verify that results are unchanged whether the bonus payment is provided to all participants or a random subset of participants. Internet Appendix Table A10 shows comparison experiments that test robustness to payment structure. Given the one year investment horizon, in our baseline specification the bonus payment is delivered a year after participation. In Table A10, we also verify that behavior is not affected by the delayed bonus.

Table 1 Panel B shows the demographics in Experiment B2. Experiment B2 has slightly more male participants; participants are also slightly wealthier, and have a higher stock ownership rate (64% in Experiment B2, compared to 56.5% in Experiment B1). Overall the demographics are similar to those in Experiment B1. Participant characteristics across the two treatment conditions are fairly balanced in Experiment B2.

Experiment B3: HBS MBA, Incentivized

In Experiment B3, participants consider allocating an experimental endowment of 1,000,000 Francs to the risk-free asset and the risky asset. The investment horizon is one year. Participants are recruited via email from all HBS MBA students in April 2016. They receive a $12 dining hall lunch voucher in appreciation for their participation, and could earn a bonus payment proportional to their investment outcome, with every 4,950 Francs converted to one dollar of bonus payment. Thus the bonus payment is on the scale of $210. Similar to Experiment B2, we implement the decision of 10% randomly selected participants and they receive the bonus payment. Financial offices at Harvard process the bonus payment,

[3] We use an experimental currency called Francs (and then convert final payoffs to dollars) following prior experimental studies on investment decisions (Camerer, 1987; Lei, Noussair, and Plott, 2001; Bossaerts, Plott, and Zame, 2007; Smith, Lohrenz, King, Montague, and Camerer, 2014). Francs in larger scales helps to make the investment problem easier to think about.

[4] From an ex ante perspective, participants should make their optimal decisions, in case they are chosen and their choices are implemented.

scheduled for approximately a year after the experiment to adhere to the one year horizon.

Table 1 Panel C shows that about 60% of participants are male, roughly 70% are from the US (and 30% are international students), and roughly 70% have primary educational background in social science or science and engineering. The MBA participants have a higher level of risk tolerance than MTurk participants, according to both lottery choice-based assessment and subjective assessment. More than 40% report having some or extensive investment experience. The vast majority, 80%, own stocks; a significant fraction, 40%, have worked in finance. Participant characteristics across the two treatment conditions are generally balanced in Experiment B3.

2.2 Results

Table 2 reports results of the benchmark experiment. The first four columns in Panel A show mean allocations to the risky asset in the high and low interest rate conditions, the difference between the two conditions, and the *t*-stat that the difference is significantly different from zero. We find that the mean allocation to the risky asset is about 7 to 9 percentage points higher in the low interest rate condition. Specifically, the mean allocation to the risky asset increases from 48.15% in the high rate condition to 55.32% in the low rate condition in Experiment B1 (difference is 7.17%), from 58.58% to 66.64% in Experiment B2 (difference is 8.06%), and from 66.79% to 75.61% in Experiment B3 (difference is 8.83%). It is natural that the general level of risk tolerance can vary across these experiments depending on the subject pool and the setting (e.g. HBS MBAs are more risk tolerant than MTurk participants; MTurk participants are more risk tolerant investing experimental endowments than investing a significant amount of savings), so the *level* of mean allocations is different in Experiments B1 to B3. However, these differences in risk tolerance do not seem to affect the pattern of reaching for yield (i.e. the treatment effect).

Panel A columns (5) to (9) report additional tests. Column (5) shows *p*-values from non-parametric Mann-Whitney-Wilcoxon tests (all significant at the 5% level). The remaining columns report mean differences in allocations controlling for individual characteristics, through OLS regressions as well as propensity score matching (estimates of average treatment effects are reported). The covariates include gender, education, age, risk tolerance, wealth, investment experience in the MTurk samples; and gender, risk tolerance, investment experience, and work experience in finance in the HBS MBA sample. The treatment effect is very similar with controls.[5] Figure 2 plots the distribution of allocations to the risky asset in the high and low interest rate conditions for Experiments B1 to B3. The distributions are fairly smooth, with an upward shift in allocations in the low rate condition relative to the high rate condition.

Table 2 Panel B presents the regression results for each sample, with coefficients on control variables:

$$Y_i = \alpha + \beta Low_i + X_i'\gamma + \epsilon_i \tag{1}$$

where Y_i is individual i's allocation to the risky asset, Low_i is a dummy variable that takes value one if individual i is in the low interest rate condition, and X_i is a set of demographic controls. The treatment effect of the low interest rate conditions, β, is the same as results in Panel A column (6). Among the demographic controls, males tend to invest more in the risky assets in most samples, while education, age, and wealth do not show a significant impact. Investment experience and work experience in finance have some positive effects on overall risk taking, though not statistically significant. Participants' risk tolerance is significantly positively correlated with risk taking (here risk tolerance is measured through choices among simple lotteries; results are similar using subjective evaluations of risk preferences). In terms of magnitude, the treatment effect of the low interest rate condition (allocations to the risky asset higher by 8 percentage points) is roughly the same as risk tolerance increasing by one category, or by about a tercile of individuals in each sample.

The increase of mean allocations to the risky asset of around 8 percentage points is economically meaningful. It is a roughly 15% increase on the base of about 60% allocations to the risky asset. We also translate the differences in portfolio shares to equivalents in terms of changes in the effective risk premium. Specifically, we calculate, for a given coefficient of relative risk aversion γ, how much the risk premium (i.e. average excess returns) on the risky asset, μ, needs to change to induce this much shift in portfolio allocations, ϕ, in a conventional mean-variance analysis problem if we apply the formula $\phi = \mu/\gamma\sigma^2$. For $\gamma = 3$,[6] for instance, the treatment effect is equivalent to μ changing by about 0.7 percentage points (on a base of about 5 percentage point risk premium).[7]

[5] To check for robustness to extreme observations, in addition to the non-parametric test in Panel A column (5), we also run least absolute deviation regressions with controls (same specification as Panel A column (6) and Equation (1)). The coefficient on the low interest rate condition in Experiments B1, B2, B3 is 6.56, 12.70, 10.00 ($t-$stat 1.74, 3.80, 3.17) respectively. The results are similar to those with OLS.

[6] $\gamma = 3$ is roughly consistent with the average level of allocation in the risky asset in Experiment B1.

[7] In the experiment, participants make decisions about investing a fixed amount of money. In practice, interest rates may also affect the consumption/saving decision and therefore the amount of money people

Our results on reaching for yield are consistent in different settings and subject pools. Some previous studies find the influence of psychological forces and certain biases may diminish with education and experience (List and Haigh, 2005; Cipriani and Guarino, 2009; Kuchler and Zafar, 2017), while others do not find such an effect or find the opposite (Haigh and List, 2005; Abbink and Rockenbach, 2006; Cohn et al., 2015). In our data, HBS MBAs and MTurks reach for yield by a similar degree. Nor do we find that reaching for yield declines with wealth, investment experience, or education among MTurks, or with investment and work experience in finance among MBAs, as shown in Internet Appendix Table A9. Among the HBS MBAs who have worked in finance (42% of the sample), for example, the difference in mean allocations to the risky asset between the high and low interest rate conditions is 10 percentage points (t-stat 2.47).

Stake Size in Incentivized Experiments

One constraint of incentivized investment experiments is the stakes are modest compared to participants' wealth, given researchers' budget limits. For the typical stake size in incentivized experiments, participants should be risk neutral. In our data, only about 25% of participants in Experiment B2 (MTurk) and about 30% of participants in Experiment B3 (MBA) invest everything in the risky asset, in line with previous studies that participants are typically risk averse with respect to modest stakes.

We make three observations in light of concerns about modest stake size. First, this issue does not affect the hypothetical experiment. The treatment effect is consistent across hypothetical and incentivized tests, which suggests the robustness of the result. Second, to the extent that small stakes make participants more risk neutral and decrease variations in investment decisions, it works against us finding significant differences between different interest rate conditions. Third, experimental research finds that risk preferences with respect to small stakes are meaningful and consistent with participants' risk preferences in general (Holt and Laury, 2002). Previous studies find informative results based on experimental stakes (Andersen, Harrison, Lau, and Rutström, 2008; Andreoni and Sprenger, 2012; Charness, Gneezy, and Imas, 2013; Bossaerts et al., 2007; Cohn et al., 2015), and we use stake size in line with prior work. We also find that participants' risk tolerance in the incentivized experiments is significantly correlated with allocations of their household financial wealth,

decide to invest in the first place. Prior empirical studies, however, often do not find significant responses of consumption and savings to interest rates (Mankiw, Rotemberg, and Summers, 1985; Hall, 1988; Campbell and Mankiw, 1989). In Section 5, we also present suggestive evidence that lower interest rates appear to be associated with both higher portfolio shares and higher dollar amounts invested in risky assets.

as shown in Internet Appendix Table A11.

In sum, we find investments in the risky asset increase significantly in the low interest rate condition. Such reaching for yield behavior is remarkably stable in different settings and populations. In the next section, we discuss potential explanations of this result.

3 Potential Mechanisms

In this section, we discuss potential explanations of our findings in Section 2. We first show that conventional portfolio choice theories may not easily explain the reaching for yield behavior we document. We then suggest two categories of possible explanations, reference dependence and salience, which we test in Section 4.

3.1 Conventional Portfolio Choice Theory

The investment decision in our benchmark experiment corresponds to a standard static portfolio choice problem with one risk-free asset and one risky asset. An investor considers allocating wealth w between a safe asset with returns r_f, and a risky asset with returns $r_f + x$, where x is the excess returns with mean $\mu = \mathbb{E}x > 0$. Let ϕ denote the proportion of wealth allocated to the risky asset, and $1 + r_p = 1 + r_f + \phi x$ the portfolio returns. The investor chooses optimal $\phi^* \in [0, 1]$ to maximize expected utility:

$$\phi^* = \arg \max_{\phi \in [0,1]} \mathbb{E}u\left(w\left(1 + r_p\right)\right) \tag{2}$$

We start with the case of mean-variance analysis, the widely used approximation to the general portfolio choice problem, and then discuss the general case.

Mean-Variance Analysis. Conventional portfolio choice analysis often uses the mean-variance approximation, in which case the investor trades off the average returns and variance of the portfolio, and obtains

$$\phi^*_{mv} \triangleq \arg \max_{\phi \in [0,1]} \ \mathbb{E}r_p - \frac{\gamma}{2} Var\left(r_p\right) = \min\left(\frac{\mathbb{E}x}{\gamma Var\left(x\right)}, 1\right), \tag{3}$$

where $\gamma = \frac{-wu''(w)}{u'(w)}$ denotes the coefficient of relative risk aversion.

When we hold fixed the distribution of the excess returns x, the risk-return trade-off stays the same in mean-variance analysis, and investment decisions should not change with the level of the risk-free rate r_f.[8]

General Case. The optimal mean-variance portfolio allocation ϕ^*_{mv} in Equation (3) is a second-order approximation to the optimal allocation to the risky asset ϕ^* defined in Equation (2). Now we analyze the general case which also takes into account the potential impact of higher order terms. We consider how the optimal allocation to the risky asset ϕ^* changes with the risk-free rate r_f for a given distribution of the excess returns x.

Proposition 1. *We assume the investor's utility function u is twice differentiable and strictly concave, with (weakly) decreasing absolute risk aversion. Then, for a given distribution of the excess returns x, the optimal allocation to the risky asset ϕ^* is (weakly) increasing in r_f.*[9]

The intuition for this result is that, for a given distribution of x, when r_f increases the investor effectively becomes wealthier. If absolute risk aversion is decreasing in wealth, the investor would be less risk averse and more willing to invest in the risky asset. In other words, the investor would "reach against yield," which is the opposite of what we document in Section 2. This wealth effect, however, is not first order and it drops out in the mean-variance approximation.[10]

Proposition 1 assumes weakly decreasing absolute risk aversion, a property shared by commonly used utility functions (e.g. CRRA). The prediction of Proposition 1 would be reversed if investors instead have increasing absolute risk aversion. Is this a possible explanation for the reaching for yield phenomenon we document? In studies of choice under

[8]For our incentivized experiments, would wealth outside the experiment affect predictions of the conventional portfolio choice analysis? We make three observations. First, if the investor's outside wealth w_o has a non-stochastic return r_o, we can just redefine the utility function $\tilde{u}(w(1+r_p)) = u(w_o(1+r_o)+w(1+r_p))$ and the same analysis applies. Second, even if the return on outside wealth is stochastic, as long as it is independent of the returns in the experiment, we can show that the optimal allocation based on mean-variance analysis (a second-order approximation to the problem in (2)) still should not change with respect to the interest rate. Finally, as Barberis, Huang, and Thaler (2006) point out, narrow framing (which refers to investors' tendency to consider investment problems in isolation, rather than mingling them with other risks) is key to explaining many phenomena, including the lack of risk neutrality to modest risks which holds in our experiments. To the extent that investors frame narrowly, the analysis here also applies directly.

[9]In Section 3, we focus on the partial derivative of investment allocations with respect to the risk-free rate, holding inflation and inflation expectations constant, as in our randomized experiment. We discuss other issues related to inflation outside of the experiment in Internet Appendix B.7.

[10]Why do we only need decreasing *absolute* risk aversion, instead of decreasing *relative* risk aversion, for ϕ^* to be increasing in r_f? Note that the investor's final wealth is given by $w(1+r_f+\phi x)$. An increase of r_f, for a given ϕ, increases the absolute level of his final wealth but does not change the absolute amount of risk he is taking. In contrast, an increase in w, for a given ϕ, would increase the absolute amount of risk the investor is taking. Accordingly, for ϕ^* to increase with r_f, decreasing *absolute* risk aversion is sufficient (whereas for ϕ^* to increase with w, decreasing *relative* risk aversion is required).

uncertainty, increasing relative risk aversion is sometimes observed, but (weakly) decreasing absolute risk aversion appears to be a consensus (Holt and Laury, 2002). Moreover, increasing absolute risk aversion is hard to square with additional experimental results we present in Section 4 to test mechanisms.

In the above we follow the experiment in Section 2 and study a static portfolio choice problem in (2). The static design helps us cleanly tease out the behavioral mechanisms that may generate reaching for yield behavior. In Internet Appendix B.1, we discuss the impact of interest rates on portfolio allocations more generally, such as in dynamic portfolio choice problems with hedging or life-cycle motives. These explanations do not seem to explain the experimental results in Section 2 and further tests of mechanisms in Section 4.

3.2 Reference Dependence

In the following, we discuss two categories of mechanisms that can lead to reaching for yield in personal investment decisions.

The first category of mechanisms comes from the observation that people may form reference points of investment returns, and strive to achieve the reference returns. When the risk-free rate falls below the reference level, people experience discomfort and become more willing to invest in risky assets to seek higher returns. This connects to the popular view among investors that 1% interest rates are "too low" (where the notion "too low" suggests comparison to some reference level and discomfort in light of that).

One way to specify reference dependence is through a framework of loss aversion around the reference point, as formulated in the Prospect Theory (Kahneman and Tversky, 1979). In the following, we first use this type of framework to analyze the investment decision and predictions for reaching for yield. We then discuss reference point formation in our setting and additional empirical implications.

We use the same set-up as in (2), but now we assume the utility function u features loss aversion captured by a kink around the reference point:

Assumption 1.

$$u\left(w\left(1+r_p\right)\right)=\begin{cases} w\left(r_p-r_r\right) & r_p \geq r_r \\ -\lambda w\left(r_r-r_p\right) & r_p < r_r \end{cases} \tag{4}$$

where r_r is the reference point (in returns) and $\lambda > 1$ reflects the degree of loss aversion below the reference point.

Here we only include the reference point component, without additional features of the Prospect Theory such as diminishing sensitivity and probability reweighting, as the gist of our observation relates to the reference point and loss aversion around the reference point. We discuss the case with diminishing sensitivity in Internet Appendix B.2.[11] Probability reweighting does not affect our key result in Proposition 2 about responses to changes in the risk-free rate; see He and Zhou (2011) for a more detailed discussion. We also discuss other functional forms for modeling reference dependence in Internet Appendix Section B.

Proposition 2. *Under Assumption 1, for a given distribution of the excess returns x:*

i. The optimal allocation to the risky asset ϕ^* is (weakly) decreasing in r_f if $r_f < r_r$.

ii. The optimal allocation to the risky asset ϕ^* is (weakly) increasing in r_f if $r_f > r_r$.

Proposition 2 shows that when the risk-free rate r_f is below the reference point r_r, the investor invests more in the risky asset as interest rates fall. The intuition is that when interest rates are below the reference point and drop further, investing in the safe asset will make the investor bear the entire increase in the first-order loss (i.e. utility loss from loss aversion). The risky asset, however, provides some chance to avoid the increase in the first-order loss. As a result, the lower the interest rates, the higher the incentive to invest in the risky asset. This result suggests a potential explanation for the findings in Section 2 that participants in the low interest rate condition invest more in the risky asset.

On the other hand, when the risk-free rate r_f is above the reference point r_r, the optimal allocation to the risky asset ϕ^* is (weakly) increasing in r_f. In other words, the investor would "reach against yield." The intuition is that when the risk-free rate is above the reference point, investing in the safe asset can avoid the first-order loss with certainty. If interest rates fall but stay above the reference point, the safe asset still does not generate any first-order loss, but there is a higher chance that the risky investment gets into the region with the first-order loss.

Proposition 2 focuses on how investment decisions change with the risk-free rate r_f, fixing the reference point r_r. The mirror image is how decisions change with the reference point r_r, for a given level of interest rate r_f.

[11] As Internet Appendix B.2 explains in detail, the theoretical prediction of whether diminishing sensitivity contributes to reaching for yield is ambiguous We then evaluate the results numerically based on standard Prospect Theory parameter values (Tversky and Kahneman, 1992). We find it seems hard for diminishing sensitivity *alone* to account for the evidence in Section 2 without the loss aversion component. Some recent research also questions diminishing sensitivity, especially the convexity of the utility function in the loss domain, in the investment context (Bracha, 2016).

Corollary 1. *Under Assumption 1, for a given level of excess returns x, we have:*

i. The optimal allocation to the risky asset ϕ^* is (weakly) increasing in r_r if $r_f < r_r$.

ii. The optimal allocation to the risky asset ϕ^* is (weakly) decreasing in r_r if $r_f > r_r$.

Corollary 1 shows that if the risk-free rate r_f is below the reference point r_r, the higher the reference point, the higher the allocation to the risky asset. The intuition follows that of Proposition 2: an investor with a higher reference point bears the full increase in the first-order loss if he invests in the safe asset; however, he only bears a partial increase in the first-order loss if he invests in the risky asset which has some chance of escaping the loss region. Thus higher reference points lead to stronger appetite for the risky asset.

Reference Point Formation

A natural question is where investors' reference points come from. In the following, we discuss the leading theories of reference points, and explain why people's past experiences may be the main contributor to the type of reference dependence that generates reaching for yield. We provide proofs and more discussions in Internet Appendix Section B.4.

In Kahneman and Tversky (1979), the reference point is the status quo wealth level ($r_r = 0$). However, as long as the interest rate is non-negative, it would be higher than the status quo $r_f \geq r_r = 0$. This falls into the second case of Proposition 2, and does not explain the reaching for yield behavior in our benchmark experiment.[12]

Later work introduces reference points that are equal to the risk-free rate (Barberis et al., 2001), as well as reference points that are rational expectations of outcomes in people's choice set (Kőszegi and Rabin, 2006; Pagel, 2017). In both cases, when the risk-free rate changes while excess returns are held fixed, returns on the safe asset, returns on the risky asset, and the reference point move in parallel. Accordingly, the trade-offs in the investment decision remain unchanged, and allocations should not be different across the treatment conditions in our benchmark experiment.[13]

Another form of reference point that can be important in our setting highlights the impact of past experiences (Simonsohn and Loewenstein, 2006; Bordalo et al., 2017; DellaVigna

[12]That said, we do not suggest that loss aversion at zero does not matter. It could be important for many behavior (e.g. aversion to small risks), but it does not appear to be the key driver of reaching for yield, if not partially offsetting it.

[13]For expectations-based reference points, this result applies when the reference point is entirely determined by forward-looking rational expectations, which is the emphasis of Kőszegi and Rabin (2006). It is also possible that expectations-based reference points are influenced by past experiences and have a backward looking component. This alternative case is analogous to the final category of history-dependent reference points we discuss below.

et al., 2017). Specifically, people form reference investment returns that they have become accustomed to. When the risk-free rate drops below what they are used to, people experience discomfort and become more willing to invest in risky assets.[14] This falls in the first case of Proposition 2, which predicts reaching for yield. Given the economic environment in the decades prior to the Great Recession, reference points from past experiences appear in line with investors' view that 1% or 0% interest rates are "too low."[15]

Together with Corollary 1, history-dependent reference points suggest a novel implication: the degree of reaching for yield may depend on prior economic conditions. How much investors shift to risky assets when interest rates are low may be different if they used to live in an environment of high interest rates compared to if they are used to high interest rate environments versus medium interest rate environments.

3.3 Salience and Proportional Thinking

The second category of mechanisms is that investment decisions could be affected by the salience of the higher average returns of the risky asset, which may vary with the interest rate environment. Specifically, 6% average returns might appear to be more attractive compared to 1% risk-free returns than 10% average returns compared to 5% risk-free returns. This intuition can be formalized by a version of the Salience Theory of Bordalo et al. (2013b). It also connects to the well documented phenomenon that people tend to evaluate stimuli by proportions (i.e. 6/1 is much larger than 10/5) rather than by differences (Weber's law; Tversky and Kahneman (1981); Kőszegi and Szeidl (2013); Cunningham (2013); Bushong, Rabin, and Schwartzstein (2016)).

Equation (5) outlines a representation of this idea, which uses a variant of the mean-variance analysis in Equation (3). The investor still trades off a portfolio's expected returns and risks. The relative weight between these two dimensions, however, depends not only

[14]The reference point could also come from saving targets that people aim for to cover certain expenses, which are likely formed based on past experiences and leads to a similar reduced form formulation.

[15]In the incentivized experiments, if participants mingle the experimental returns with other returns and monetary payoffs in their lives, one question is whether they compare the experimental returns or the sum of all monetary payoffs with respect to their reference points. As Barberis et al. (2006) highlight, narrow framing—the tendency to consider an investment problem in isolation as opposed to mingling it with other risks (e.g. labor income risks, other investments)—appears to be a robust element of investor behavior. To the extent that participants are inclined to frame narrowly and evaluate the investment problem on its own, we can directly apply the predictions of the reference dependence mechanisms studied in this section. The same holds for the salience and proportional thinking mechanism in Section 3.3.

on the investor's relative risk aversion, but also on the ratio of the assets' average returns:

$$\phi_s^* \triangleq \arg\max_{\phi\in[0,1]} \ \delta\mathbb{E}r_p - \frac{\gamma}{2}Var\left(r_p\right), \tag{5}$$

where δ is a function of the properties of the two assets, and is increasing in the ratio of the average returns of the two assets $(r_f + \mathbb{E}x)/r_f$.

Equation (5) embeds the idea that investors' perception of the risky asset's compensation for risk is not exactly the *difference* between the average returns on the risky asset and the risk-free rate (as in the conventional mean-variance analysis). Instead, it is also affected by the *proportion* of the average returns of the two assets. When the proportion is large, investors perceive compensation for risk taking to be better, and behave as if the return dimension in Equation (5) gets a higher weight.

In the language of the Salience Theory of Bordalo et al. (2013b), δ captures the salience of the expected return dimension relative to the risk dimension. When the proportion of the average returns of the two assets is larger, the expected return dimension becomes more salient, and gets a higher weight in portfolio decisions.[16] We adopt a specification of δ following Bordalo et al. (2013b).

Assumption 2. *We require the risk-free rate $r_f > 0$ throughout this subsection. Following Bordalo et al. (2013b), define*

$$\delta(r_f + \mathbb{E}x, r_f, Var\left(x\right), 0) = f\left(\left|\frac{(r_f + \mathbb{E}x) - r_f}{(r_f + \mathbb{E}x) + r_f}\right| - \left|\frac{Var\left(x\right) - 0}{Var\left(x\right) + 0}\right|\right), \tag{6}$$

where $f : [-1, 1] \to R^+$ is an increasing function.

This definition is a generalization of the formulation in Bordalo et al. (2013b) and Bordalo, Gennaioli, and Shleifer (2016).[17] δ is increasing in the ratio of the average returns

[16] In our context, the Salience Theory and proportional thinking are broadly the same. In the Internet Appendix Section B.6, we discuss a subtle difference between the way "salience" is defined in Bordalo et al. (2013b) and proportional thinking. We also explain the relationship between our framework and other related models such as Bordalo, Gennaioli, and Shleifer (2012), Bordalo, Gennaioli, and Shleifer (2013a), Bushong et al. (2016), and Kőszegi and Szeidl (2013).

[17] In the original set-up, either the risk dimension is more salient or the return dimension is more salient, and the more salient dimension receives a fixed weight. When there is a risk-free asset, the risk dimension is always more salient, by a fixed amount. Accordingly, returns of the risk-free asset do not change the salience of the return dimension relative to the risk dimension. We generalize Bordalo et al. (2013b) to a continuous salience function that allows salience to move even when there is a risk-free asset. Our formulation nests the original salience function as a special case $f\left(t\right) = \begin{cases} \beta & t > 0 \\ \frac{1}{\beta} & t < 0 \end{cases}$, where $\beta > 1$. In addition, the decision problem in Bordalo et al. (2013b) and Bordalo et al. (2016) is a discrete choice problem. We generalize it to continuous decisions. See Internet Appendix Section B.6 for more discussions.

between the two assets (through the first term in the parenthesis), and decreasing in the ratio of their variance (through the second term in the parenthesis). Our focus here is how changes in the average returns of the assets affect investment decisions; we hold fixed the risk properties (the second term in the parenthesis is always one).

Proposition 3. *Under Assumption 2, for a given distribution of the excess returns x, the optimal allocation to the risky asset, ϕ_s^*, is (weakly) decreasing in the risk-free rate r_f.*

The intuition of Proposition 3 is straightforward. Holding average excess returns $\mathbb{E}x$ constant, the proportion of the average returns $(r_f + \mathbb{E}x)/r_f$ increases as r_f decreases. Accordingly, δ is larger and the investor is more willing to invest in the risky asset.

4 Testing Mechanisms

In this section, we perform three additional experiments to test explanations for the reaching for yield behavior discussed in Section 3. We find evidence supportive of both reference dependence and salience.

4.1 Experiment T1 (Non-Linearity)

In Experiment T1, we extend the benchmark experiment and test investment allocations across a wider set of interest rate conditions, with the risk-free rate ranging from -1% to 15%. The excess returns of the risky asset are the same as before and the average excess returns is 5%. We randomly assign participants to one of these conditions.

Through this experiment, we would like to examine two main questions. The first is whether reaching for yield exhibits non-linearity, and is most pronounced when interest rates are low. Both reference dependence and salience/proportional thinking predict such non-linearity. In the model of reference point and loss aversion in Section 3.2, reaching for yield occurs when interest rates are below the reference point. In the model of salience/proportional thinking in Section 3.3, allocations to the risky asset would be more sensitive to interest rates when interest rates are low, where the ratio of the average returns $(r_f + \mathbb{E}x)/r_f$ changes more with the risk-free rate. The second question is whether we observe "reaching against yield" (i.e. allocations to the risky asset increasing in the risk-free rate) when interest rates are sufficiently high, as predicted by the traditional Prospect Theory formulation in Proposition 2.

We conduct Experiment T1 in June 2016. Participants are recruited on MTurk. As in the benchmark experiments, each interest rate condition has 200 participants. Similar to Experiment B2 (Benchmark Incentivized, MTurk), participants consider allocating experimental endowment of 100,000 Francs to the risk-free asset and the risky asset. The payment structure follows Experiment B2. The participation payment is \$0.7. Participants may also receive a bonus payment proportional to their investment outcomes, with every 8,950 Francs converted to one dollar (so the bonus payment is on the scale of \$12). We implement the decision of 10% randomly chosen participants and they receive the bonus payment. Table A14 in the Internet Appendix shows the demographics of participants in Experiment T1, which are similar to those in the benchmark experiments. In all of our experiments, we use participants who did not participate in any of our previous experiments.[18]

Table 3 presents the results of Experiment T1. The mean allocation to the risky asset is 78% when the risk-free rate is -1%, 70% when the risk-free rate is 0%, 65% when the risk-free rate is 1%, and 58% when the risk-free rate is 3%. As interest rates rise further, allocations change more slowly. The mean allocation to the risky asset is 57% when the risk-free rate is 5%, which is roughly the same as when the risk-free rate is 3%. It declines to 50% when the risk-free rate is 10%, and stays about the same when the risk-free rate is 15%. Mean allocations across different interest rate conditions are also plotted in Figure 3.

Results in Experiment T1 suggest notable non-linearity in how investment decisions respond to interest rates. Reaching for yield is particularly pronounced when interest rates are low, roughly below 3%. Statistical tests can reject linearity with high significance.[19] The shape of the non-linear response is in line with reasonable reference points based on the average level of interest rates and investment returns most participants were used to prior to the Great Recession. The pattern is also generally consistent with salience/proportional thinking, as the ratio of the average returns $(r_f + \mathbb{E}x)/r_f$ becomes significantly less sensitive to r_f when r_f is high.

On the other hand, the substantial non-linearity we observe is hard to square with con-

[18]For incentivized experiments in Section 4, participants receive their bonus payments shortly after participation. Delaying the bonus by one year requires us to collect MTurk participants' contact information, in case they no longer work on MTurk in one year's time. In Section 2 and Internet Appendix Table A10, we have tested that the results are robust to payment timing. Therefore, in the additional experiments we pay the bonus within one week to simplify the logistics.

[19]For instance, in a quadratic specification of $Y_i = \alpha + \beta r_{f,i} + \gamma r_{f,i}^2 + \epsilon_i$, where Y_i is individual i's allocation to the risky asset and $r_{f,i}$ is the risk-free rate in individual i's assigned condition, the t-stat on γ not equal to zero is 5.67 (p-value < 0.001). We can also test the null that the piece-wise slopes between all the adjacent interest rate conditions are the same, and the null can be rejected with p-value < 0.001.

ventional portfolio choice theories with increasing absolute risk aversion, life cycle motives, or hedging motives. In these cases, it is not clear why differences in allocations are substantial between conditions with 0% versus 5% interest rates, for instance, but are absent between conditions with 10% versus 15% interest rates.

In addition, while we see clear patterns of reaching for yield when interest rates get into the low range, we do not observe reaching against yield when interest rates approach the high end. In Section 3 Proposition 2, we show the baseline Prospect Theory formulation does predict reaching against yield when the risk-free rate is higher than the reference point. One possibility is that reaching against yield is modest in magnitude, and our sample size of 200 per condition does not have enough power to detect it; this effect could be further dampened by salience/proportional thinking. Another possibility is that the reaching against yield prediction is not very robust, and is specific to the functional form in the traditional Prospect Theory formulation. For example, an alternative formulation of reference dependence is that people experience discomfort/loss aversion when the average return of the portfolio is below the reference point (as opposed to experiencing loss aversion for each state where the realized return is below the reference point, as in the traditional formulation in Section 3.2). This alternative formulation predicts reaching for yield when interest rates are low, but does not predict reaching against yield when interest rates are high. We present this alternative formulation in Internet Appendix B.3.[20]

The results of reaching for yield and non-linearity are robust across different settings and different populations. In August 2017, the Dutch Authority for the Financial Markets replicated the test using 900 Dutch households. They used the hypothetical version of our protocol (translated into Dutch) and six interest rate conditions from -1% to 10%. The Dutch results are available in Internet Appendix C.2 and in Ma and Zijlstra (2018).

4.2 Experiment T2 (History Dependence)

In Experiment T2, we examine how investment history and reference dependence affect investment decisions. Specifically, participants in this experiment make two rounds of

[20]One may want to use the experimental results to formally estimate what investors' reference returns are. This analysis faces several challenges. For instance, as we discuss above, the predictions of reference dependence (e.g. whether there is "reaching against yield) can depend on the functional forms. Reference points may also be heterogeneous among investors. In addition, the existence of salience/proportional thinking may complicate the analysis. Even though reference dependence may predict, as Proposition 2 shows, that investors reach against yield when interest rates are above the reference return, salience/proportional thinking still predicts reaching for yield, which adds difficulties to estimating the reference point.

investment decisions: half of the participants (Group 1) first make decisions in the high interest rate condition (5% safe returns and 10% average risky returns, same as the benchmark experiment), and then make decisions in the low interest rate condition (1% safe returns and 6% average risky returns); the other half of the participants (Group 2) do the reverse. Group 1 mimics the situation where people move from a high interest rate environment to a low interest rate environment, which is a particularly relevant case for the recent discussions about investor reactions to low interest rates. After being placed in the high interest rate condition, participants in Group 1 are likely to carry a relatively high reference point when they move to the low interest rate condition. As Section 3.2 suggests, allocations to the risky asset in a low rate environment would increase when people have higher reference points. Accordingly, participants in Group 1 may invest more aggressively in the risky asset in the low interest rate condition.

We conduct two versions of Experiment T2. In the incentivized version, in each round participants consider allocating experimental endowment of 100,000 Francs to the safe asset and the risky asset (the outcomes of the risky asset in the two rounds are uncorrelated). Participants are recruited on MTurk in June 2016. They receive a participation payment of $1.2. They may also receive a bonus payment proportional to their investment outcome in one randomly chosen round, with every 8,950 Francs converted to one dollar (so the bonus payment is on the sale of $12). Investment outcomes for both rounds are displayed after the entire experiment is completed. Participants are then informed which round the bonus payment would depend on, and whether they are among the 10% randomly selected participants to receive the bonus payment. Making payments based on randomly chosen outcomes is standard in prior experimental work (e.g. Holt and Laury (2002); Frydman and Mormann (2016)).[21] To check the robustness of this result, we also report results from a hypothetical version. In the hypothetical version, in each round participants consider hypothetical questions about investing total savings of $10,000 between the safe asset and the risky asset. Participants are recruited from MTurk in August 2015. They receive $0.5 for participation. In both versions, there are 200 participants in Group 1 and 200 participants in Group 2. Internet Appendix Table A15 shows the demographics in Experiment T2.

Table 4 and Figure 4 present the results, which show several findings. First, there is

[21]Consider for example the decision in the second round: there is a 1/2 chance that the first round will be chosen so the second round does not matter, and a 1/2 chance that the second round will be chosen so the first round does not matter. Thus the decision in the second round should not depend on what happens in the first round, and vice versa, for the purpose of maximizing expected utility as long as utility functions are additively separable across different states.

reaching for yield both within group and across groups. Within each of Group 1 and Group 2, allocations to the risky asset are higher in the low rate condition than in the high rate condition. Across Group 1 and Group 2, when making the first decision, the group facing the low rate condition (Group 2) has significantly higher allocations to the risky asset. This is analogous to the benchmark experiment.

Second and importantly, participants in Group 1—who consider the high rate condition first—have particularly high allocations to the risky asset in the low rate condition. On average, they invest roughly 10 percentage points more in the low rate condition than participants in Group 2. These results are in line with predictions of reference dependence in Section 3.2 Corollary 1 and history-dependent reference points.[22]

Internet Appendix Section B.5 presents alternative designs to test history dependence, which produce similar findings. In these tests, all participants face the same interest rate environment in the final round, but prior to that, one group starts with an environment with higher interest rates, while another group starts with an environment with lower interest rates. Our discussant Cary Frydman performed a hypothetical experiment on MTurk. We performed an incentivized version with slightly different interest rate specifications. The results show a consistent pattern: when participants consider the final medium interest rate condition, those who start in a high interest rate setting invest more aggressively in the risky asset than those who start in a low interest rate setting.

These findings point to potential path dependence of reaching for yield. Experiences of high interest rate environments, which likely increase people's reference points, may intensify reaching for yield behavior. With some extrapolation, the evidence hints at a novel implication that the degree of reaching for yield in a low interest rate setting may depend on the previous economic environment. It could be more pronounced if the prior environment had relatively high interest rates. This observation connects to recent research that highlights the importance of past experiences in economic decision making (Malmendier and Nagel, 2011, 2016; Bordalo et al., 2017).

History-dependent reference points could be affected by both short-term and long-term

[22]In this experiment, we do not find that experiences of the low rate condition have a significant influence on allocations in the high rate condition. According to Corollary 1, with the traditional Prospect Theory formulation, a decrease in the reference point should increase risk taking when the reference point is lower than the risk-free rate. In this case, Group 2 would be expected to invest more in the risky asset in the high rate condition, which we do not observe in the data. Since Corollary 1 follows from Proposition 2, this prediction is equivalent to the reaching against yield prediction we discussed in Experiment T1. Thus it shares the same explanations for the lack of evidence in our data, as elaborated at the end of Section 4.1.

experiences.[23] Experiment T2 studies the mechanism by exploiting differences in short-term experiences. We make two observations about the impact of long-term experiences. First, as discussed in Section 4.1, the non-linearity in Experiment T1 is in line with reference points from prior life experiences. Second, we also test whether heterogeneity in lifetime experiences, which may result in different reference points, can help explain differences in investment decisions. In our experiments, due to relative homogeneity in age, variations in lifetime experiences are limited (the interquartile difference is average experienced interest rates, for example, is about 1%). Moreover, given we only have one cross-section, we cannot separate experience effects from age effects. To shed further light on this issue, in Internet Appendix Section C.3.2 we use panel data from the Survey of Consumer Finances and apply the empirical strategy of Malmendier and Nagel (2011). We present suggestive evidence that, at each point in time, individuals who experienced higher interest rates over their lifetime appear less satisfied with safe assets and exhibit a higher propensity to invest in risky assets like stocks. While there are several caveats in the observational data (e.g. hard to fully control for potential differences in perceived risks and returns of risky assets), the overall pattern seems consistent with history-dependent reference points.

4.3 Experiment T3 (Salience and Proportional Thinking)

In Experiment T3, we examine the influence of salience and proportional thinking. In particular, we study whether results vary when we present investment payoffs using net returns (Baseline Framing) versus gross returns (Gross Framing), as explained below.

The baseline framing is what we use in the benchmark experiments and in Experiments T1 and T2. Specifically, we first explain the (average) returns of the investments, in terms of net returns (e.g. 1%, 5% etc.) which are most common in financial markets. We then further explain the risky asset's payoffs using examples. The descriptions read as follows:

> **Investment A**: Investment A's return is **5%** for sure.
>
> For example, suppose you put 100 Francs into this investment, you will get 105 Francs.
>
> ...
>
> **Investment B**: Investment B has nine possible outcomes. Its average return is **10%**. The volatility of the investment returns is 18%. The nine possible outcomes are shown

[23] An analogy is a person's reference point for weather (e.g. winter temperature). This can be affected by both long-term experiences: whether $30°F$ is cold is different for a New Yorker vs. a Floridian; and short-term experiences: $30°F$ may feel particularly cold if a New Yorker just returned from a vacation in Florida, which temporarily changes his reference points. Experiment T2 isolates the mechanism by creating different short-term experiences. It is analogous to randomly assigning New Yorkers to winter vacations in Florida vs. Montreal, who will come back with different temporary reference points about weather.

by the chart below, where the number inside each bar indicates the probability of that particular outcome.

For example, suppose you put 100 Francs into this investment, you will get 110 Francs on average. There is uncertainty about the exact amount of money you will get. The first row of the chart below describes the nine possible outcomes: there is a 19% chance that you will get 120 Francs, there is a 12% chance that you will get 90 Francs, etc. ...

In the gross framing experiments, instead of using the commonly used net returns, we describe the investments' payoffs using gross returns. Instead of 5%, we say for every Franc invested one would get 1.05 Francs. We keep everything else the same. The descriptions read as follows:

Investment A: For every Franc you put into Investment A, you will get **1.05** Francs for sure.

For example, suppose you put 100 Francs into this investment, you will get 105 Francs. ...

Investment B: Investment B has nine possible outcomes. For every Franc you put into Investment B, you will get **1.1** Francs on average. The volatility of the investment returns is 18%. The nine possible outcomes are shown by the chart below, where the number inside each bar indicates the probability of that particular outcome.

For example, suppose you put 100 Francs into this investment, you will get 110 Francs on average. There is uncertainty about the exact amount of money you will get. The first row of the chart below describes the nine possible outcomes: there is a 19% chance that you will get 120 Francs, there is a 12% chance that you will get 90 Francs, etc.

The comparison between baseline framing and gross framing tests the influence of salience and proportional thinking. A corollary of Proposition 3 is that for any given interest rate, allocations to the risky asset would be higher with baseline framing than with gross framing, and this difference would be more pronounced in the low interest rate condition (see Internet Appendix Lemma A1). Intuitively, the ratio of average returns between the risky asset and the risk-free asset with gross framing (e.g. 1.06/1.01) is much smaller than its counterpart with baseline framing (e.g. 6/1). This change is larger for the low rate condition (i.e. 6/1 to 1.06/1.01) than for the high rate condition (i.e. 10/5 to 1.1/1.05). Correspondingly, salience and proportional thinking could lead to less reaching for yield with gross framing than with baseline framing, as the proportions of average returns become very similar across the two conditions with gross framing.[24]

[24]To understand how the reaching for yield behavior may change with framing, we also test another framing which we refer to as "net framing." In the net framing conditions, we explain the investments' headline returns in net returns, just like with the baseline framing. When we explain the distribution of the risky asset's returns through examples, instead of describing them as getting a certain amount of Francs for every 100 Francs invested, we describe them as gaining or losing a certain amount of Francs. For instance, the description of Investment A becomes: "Investment A's return is **5%** for sure. For example, suppose you put 100 Francs into this investment, you will earn 5 Francs." We find that the reaching for yield behavior is similar using net framing and baseline framing, shown in Internet Appendix Table A13.

Additionally, Experiment T3 also helps further differentiate our findings from conventional portfolio choice theories with increasing absolute risk aversion, life cycle motives, or hedging motives, which do not predict variations based on framing.

In Experiment T3, we randomly assign participants to different framing conditions and different return conditions (i.e. baseline high, baseline low, gross high, gross low), with 200 participants in each condition. Participants are recruited on MTurk in June 2015. Experiment T3 and Experiment T1 are run together; all procedures and payment structures are the same. Internet Appendix Table A16 shows the demographics in Experiment T3.

Table 5 and Figure 5 present results of Experiment T3. With baseline framing, the mean allocation to the risky asset is 57.13% in the high interest rate condition, and 64.51% in the low interest rate condition. With gross framing, the mean allocation to the risky assets is 52.65% and 54.44% in the high and low interest rate conditions respectively. Allocations to the risky asset are lower with gross framing than with baseline framing, especially in the low rate condition. The mean allocation in the risky asset decreases by 4.47% from baseline framing to gross framing in the high interest rate condition, and by 10.06% in the low interest rate condition. This result is consistent with predictions of salience and proportional thinking. Correspondingly, reaching for yield is dampened with gross framing.[25]

Taken together, results in Experiments T1 to T3 suggest that both reference dependence and salience contribute to reaching for yield. The findings are not easily explained by conventional portfolio choice theory. In the experiments, we ask participants to explain their investment decisions; the explanations also echo both categories of mechanisms.

5 Suggestive Evidence from Observational Data

In this section, we complement the experimental results with suggestive evidence from observational data. Using data on household investment decisions from three different sources, we show that low interest rates are associated with increased investments in risky assets. The pattern and magnitude are in line with findings in our experiments.

[25] What is the relationship between results in Experiment T3 and reference dependence? One observation is that since reference points from the natural environment are most likely about net returns, gross framing may dampen the influence of reference points. Specifically, when using net returns, 1% interest rates may appear particularly low relative to experience, but this comparison could be less instinctive when investment payoffs are described in gross returns. Thus results in Experiment T3 may not be inconsistent with reference dependence. Can reference dependence and the observation above fully *explain* results in Experiment T3? Probably not, given that allocations to the risky asset in the high interest rate condition are also higher with baseline framing than with gross framing.

There are two important challenges in the analysis using observational data. First, it is hard to assess investors' beliefs about the returns and risks of risky assets. Ideally, we would like to control for investors' expectations of excess returns and risks of the risky asset, and isolate the impact of shifts in the risk-free rate. Even if investors have rational expectations, it could be hard to find exact measures of asset properties. Moreover, recent research documents that households' subjective expectations of stock returns differ from model-based expected returns (Greenwood and Shleifer, 2014; Amromin and Sharpe, 2013). In light of this issue, we control for both model-based measures and subjective expectations from investor surveys. Second, interest rate variations can be correlated with other drivers of investment decisions, such as general economic conditions and investors' risk tolerance. To the extent that investors are more risk averse in recessions, this bias would work against us. We include controls of economic conditions (e.g. GDP growth, credit spreads (Gilchrist and Zakrajšek, 2012)). In the data, these controls strengthen our results.[26]

Main Variables. We measure household investment decisions using data from three sources. The first data source is monthly portfolio allocations reported by members of the American Association of Individual Investors (AAII). We have time series data on the mean allocation to stocks (direct holdings and mutual funds) and "cash" (which in investor terminology refers to interest-bearing liquid assets, such as savings accounts, CDs, money market funds as explained in the AAII survey form), available since November 1987. A nice feature of this dataset is that it documents portfolio shares, which correspond to quantities in our experiment. The second data source is monthly flows into risky assets including equity mutual funds and high-yield corporate bond mutual funds since 1985, from the Investment Company Institute (ICI). The third data source is quarterly household sector flows into stocks and interest-bearing safe assets since 1985, from the Flow of Funds (FoF). Because interest rate variations occur over time, in this analysis we use long and relatively high frequency time-series data on investment allocations (instead of panel data with limited time periods such as the SCF or brokerage accounts data from Barber and Odean (2001)).

[26]One may also consider using monetary policy shocks as instruments. In our sample period, monetary policy shocks by Romer and Romer (2004) and Gertler and Karadi (2015) are strong instruments for interest rate changes at the monthly frequency (our data on household investment allocations are at monthly or quarterly frequencies). We find results with slightly larger coefficients but less power using the Romer and Romer (2004) and Gertler and Karadi (2015) shocks, shown in Internet Appendix Table A20. A caveat is, to the extent that monetary policy shocks may affect stock market conditions, they are not perfect instruments unless we can find precise measures of expectations of stock returns and risks. In addition, it could also be hard to rule out that monetary policy shocks may affect investors' risk tolerance for other reasons (e.g. by influencing economic conditions).

We use the three-month Treasury rate for the risk-free rate. For control variables, we use several model-based measures of expected stock returns, including the Campbell-Shiller price-earnings ratio (P/E10), the surplus consumption ratio ($Surp$) of Campbell and Cochrane (1999), as well as predicted next twelve-month excess stock returns (estimated using past twelve-month stock returns and surplus consumption).[27] In addition, we control for proxies of subjective expectations using investor sentiment measured in the AAII survey, as in Greenwood and Shleifer (2014). Finally, we control for VIX^2 (the square of VIX, which measures expected variance of the S&P 500 index), and commonly used proxies for general economic conditions: past year real GDP growth, and the credit spread (Gilchrist and Zakrajšek, 2012). We lag all the right hand side variables by one period, as opposed to using contemporaneous ones, since allocation decisions may affect contemporaneous asset prices (so using contemporaneous controls could be problematic).

Internet Appendix Section D provides a summary of variable definitions and data sources. Table 6 presents summary statistics of the main variables used in this section.

Results. Table 7 presents results using portfolio allocations data from AAII. We find that lower interest rates are associated with higher allocations to stocks and lower allocations to "cash." A one percentage point decrease in interest rates is associated with a roughly 1.4 to 2 percentage points increase in allocations to stocks and a similar size fall in allocations to "cash." In our benchmark experiments, the treatment is a 4 percentage points difference in the level of interest rates, which is associated with a roughly 8 percentage points change in the mean allocation to the risky asset. The magnitude of investment allocations' response to interest rates appears similar in the experiment and in the observational data. In Internet Appendix Table A19, we present regressions using changes in allocations and changes in interest rates, which show similar results. We also find that results are weaker using real interest rates, suggesting nominal interest rates may play a more important role.

Table 8 presents results using investment flows from ICI and Flow of Funds. As flows are analogous to changes in allocations, here we use changes in interest rates on the right hand side. Across different data sources, decreases in interest rates are consistently associated with flows into risky assets and out of safe interest-bearing assets.[28]

[27] A caveat of the price-earnings ratio (or dividend yield) is it is linked to expected returns (Campbell and Shiller, 1988; Campbell, 1991), not expected *excess* returns. However, the additional measures (surplus consumption ratio and predicted future excess stock returns) are linked to expected *excess returns*.

[28] In the past two decades, stock market participation rate declined secularly while interest rates fell. The falling stock market participation rate can be driven by a number of demographic factors (e.g. inequality, income and unemployment conditions), and appears most pronounced among young households based

We also use standard structural VAR (sVAR) to study the impulse response of investment decisions to innovations in interest rates, presented in Internet Appendix Figure A10 and Figure A11. The sVAR analysis yields the same results. The impulse response suggests persistent impact in the medium run.

Who takes the other side of households' investment flows? In Internet Appendix Table A21, we use data from the Flow of Funds to study net flows into equities by households and other sectors, as well as net equity issuance by firms (net inflows are equal to net issuance by accounting identity). Table A21 shows that following a fall in interest rates, the financial sector tends to have higher inflows to equities, although the increase is not statistically significant. The inflows from US households and institutions are partly accommodated by investors in the rest of the world, who reduce their holdings of US equities. The main player on the other side of the inflows appears to be US corporate issuers, whose net equity issuance increases. We also examine changes in asset prices to verify that the flows are driven by higher demand for equities (as opposed to higher supply). Internet Appendix Figure A12 plots the response of *excess* stock returns to interest rate movements. Lower interest rates are associated with higher excess stock returns in the first few months (i.e. positive price impact due to inflows), followed by lower excess returns in the long term, consistent with findings by Bernanke and Kuttner (2005) and Bianchi, Lettau, and Ludvigson (2017).

In sum, results using different types of historical data show consistent patterns of increased risk taking by households when interest rates fall. The findings are in line with our experimental evidence on investment decisions. Given the challenges and limitations discussed above, we hold results in the observational data as suggestive and complementary to our core experimental results.

6 Conclusion

In this paper, we document intrinsic reaching for yield behavior at the individual level and analyze its drivers. Using simple randomized experiments of investment decision making, we show that allocations to the risky asset are significantly higher when interest rates are low, holding fixed the excess returns of the risky asset. We find consistent results in different settings, and in diverse subject pools including MTurk workers and HBS MBAs.

on the SCF data. However, both investment by stock market participants and aggregate stock market participation in dollar terms do not seem to secularly decline. Drops in interest rates do seem to prompt aggregate household inflows to risky assets such as high yield bonds and stocks.

We propose two categories of explanations, reference dependence and salience, and provide evidence that both contribute to the reaching for yield behavior. Despite challenges and caveats, we find complementary evidence in observational data that risk taking in household investment decisions increases as interest rates fall.

Since the Great Recession, central banks in many countries adopted extraordinary monetary policies. A large volume of research studies how these policies affect borrowers (Di Maggio, Kermani, Keys, Piskorski, Ramcharan, Seru, and Yao, 2017; Auclert, 2016; Greenwald, 2018; Wong, 2018; Beraja, Fuster, Hurst, and Vavra, 2017). There has been less focus on savers. Our findings, along with other recent research (Hartzmark and Solomon, 2017), suggest there is also much to be understood about savers' behavior. Savers' reaching for yield behavior can also influence financial institutions' actions: institutions may invest in riskier assets to cater to clients' demand, or may design securities that highlight returns and shroud risks to further exploit these preferences (Célérier and Vallée, 2017).

Taken together, we provide new perspectives for understanding investor behavior in low interest rate environments, and the potential "risk-taking channel" of monetary policy. Besides monetary policy, low interest rates can arise from a confluence of factors (such as low productivity growth (Gordon, 2015), weak aggregate demand (Summers, 2015), or shortage of assets (Caballero, Farhi, and Gourinchas, 2008)), for which our findings may also be relevant. Investors' reaching for yield behavior could have implications for the link between key macroeconomic issues and capital market dynamics and financial stability.

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Main Figures and Tables

Figure 1: Geographic Distribution of MTurk Participants

This plot shows the geographic distribution of MTurk participants in the benchmark experiments (Experiments B1 and B2). The dots indicate participant locations. The background shade is colored based on log population density in each county.

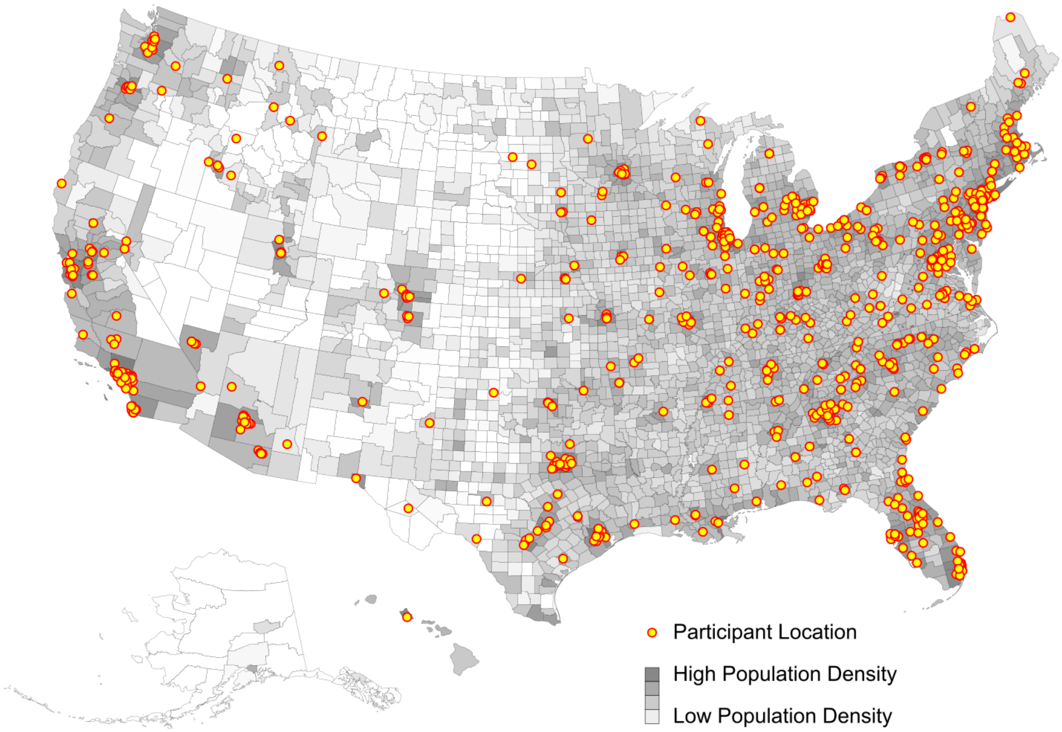
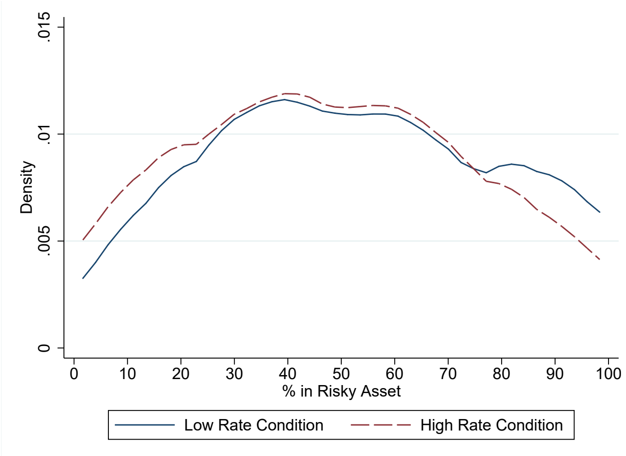


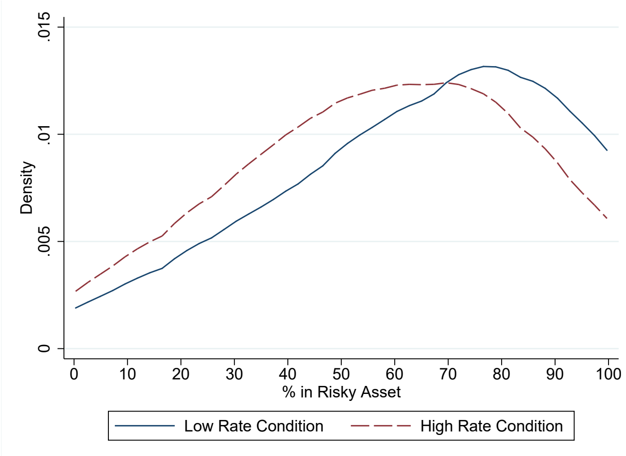
Figure 2: Distribution of Allocations to the Risky Asset in Benchmark Experiments

Density plots of allocations to the risky asset in the benchmark experiments. Panels A, B, and C present plots for Experiments B1, B2, and B3 respectively. The solid line is the distribution of allocations to the risky asset in the low interest rate condition, and the dashed line is that in the high interest rate condition.

Panel A. Experiment B1: MTurk, Hypothetical



Panel B. Experiment B2: MTurk, Incentivized



Panel C. Experiment B3: HBS MBA, Incentivized

Figure 3: Mean Allocations Across Interest Rate Conditions

Mean allocations to the risky asset across various interest rate conditions in Experiment T1. Each condition has 200 participants. The x-axis shows the risk-free rate in each condition. The mean excess returns on the risky asset is 5% in all conditions. The y-axis is the mean allocation to the risky asset. The vertical bar shows the 95% confidence interval for the mean allocation.

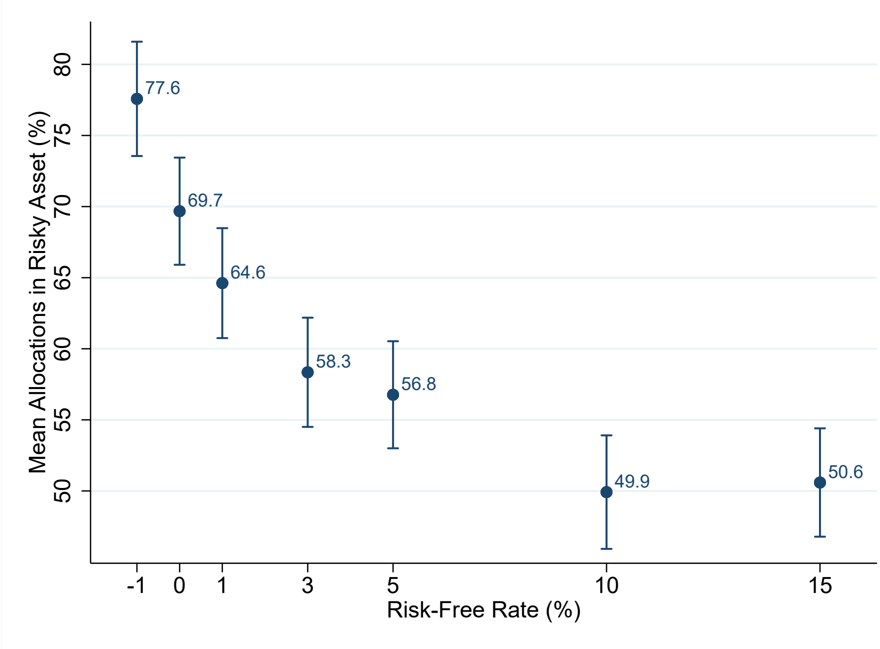


Figure 4: Path Dependence of Investment Decisions

This plot shows mean allocations in Experiment T2. In Group 1, participants first make investment decisions in the high interest rate condition (5% risk-free rate and 10% average risky returns), and then make decisions in the low interest rate condition (1% risk-free rate and 6% average risky returns). In Group 2, participants first make investment decisions in the low rate condition, and then make decisions in the high rate condition. The circles are mean allocations in the high interest rate condition; the diamonds are mean allocations in the low interest rate condition. The vertical bar shows the 95% confidence interval for the mean allocation. We perform this experiment using both hypothetical questions and incentivized tests.

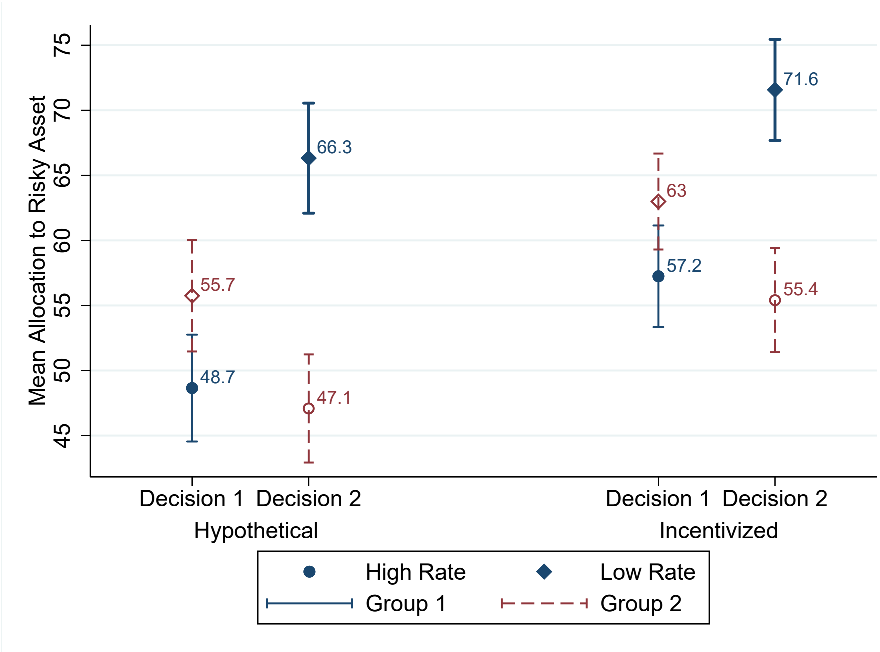


Figure 5: Mean Allocations with Baseline and Gross Framing

Mean allocations to the risky asset in Experiment T3. The circles are mean allocations in the high interest rate condition; the diamonds are mean allocations in the low interest rate condition. The vertical bar shows the 95% confidence interval for the mean allocation.

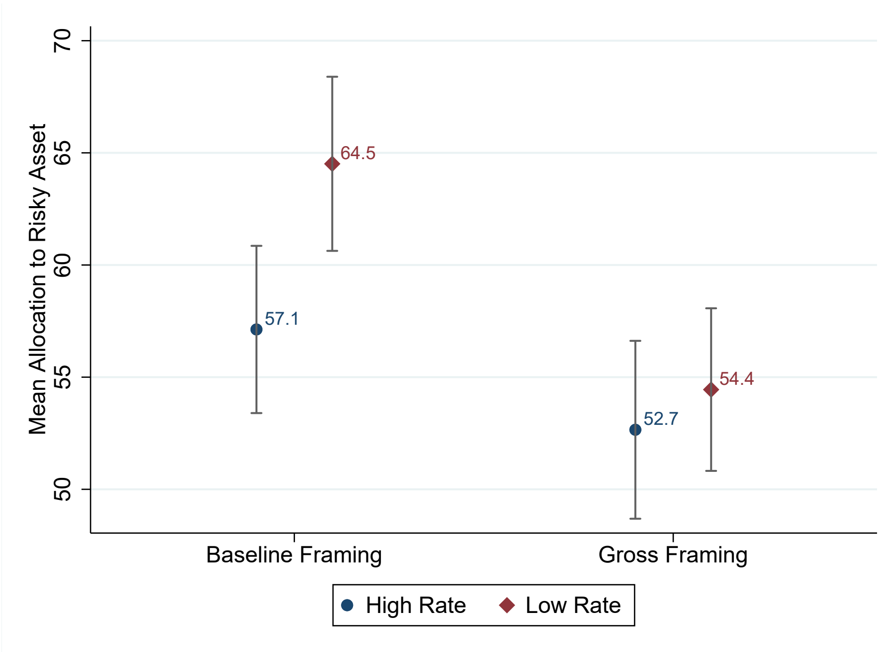


Table 1: Demographics of Benchmark Experiment Samples

Panels A, B, C tabulate demographics for Experiments B1, B2, B3 respectively. In the Low condition, the risk-free rate is 1%; in the High condition, the risk-free rate is 5%. The mean excess returns of the risky asset is 5% in both conditions. The final three columns show repetitively: the difference in the percentage of participants in a certain category, the t-statistic associated with the difference, and the p-value from the Mann-Whitney-Wilcoxon test against the null that the distribution of characteristics across the two conditions are the same. For the MBA sample, we do not collect age because of homogeneity, and do not collect wealth as it might be sensitive information. Risk tolerance is measured through a question that asks participants to choose their favorite lottery from six options increasing in risks and expected payoffs. We group risk tolerance into low, medium, and high based on the lottery chosen.

Panel A. Experiment B1: MTurk, Hypothetical

		Low		High		Low - High		
		N	%	N	%	%	[t]	U test (p)
Gender	Male	82	40.0	102	52.3	-12.3	[-2.48]	0.01
	Female	123	60.0	93	47.7	12.3	[2.48]	
Education	Graduate school	38	18.5	30	15.4	3.2	[0.84]	0.99
	College	112	54.6	118	60.5	-5.9	[-1.19]	
	High school	53	25.9	45	23.1	2.7	[0.62]	
Age	Below 30	103	50.2	98	50.3	-0.0	[-0.00]	0.97
	30–40	63	30.7	56	28.7	2.0	[0.44]	
	40–50	16	7.8	25	12.8	-5.0	[-1.65]	
	Above 50	23	11.2	16	8.2	3.0	[1.02]	
Risk tolerance	High	32	15.6	35	18.0	-2.3	[-0.62]	0.54
	Medium	67	32.7	64	32.8	-0.1	[-0.03]	
	Low	106	51.7	96	49.2	2.5	[0.49]	
Financial wealth (ex. housing)	200K+	10	4.9	17	8.7	-3.8	[-1.52]	0.65
	50K–200K	56	27.3	56	28.7	-1.4	[-0.31]	
	10K–50K	57	27.8	43	22.1	5.7	[1.33]	
	0–10K	59	28.8	51	26.2	2.6	[0.59]	
	In debt	23	11.2	28	14.4	-3.1	[-0.94]	
Investing experience	Extensive	7	3.4	6	3.1	0.3	[0.19]	0.69
	Some	61	29.8	60	30.8	-1.0	[-0.22]	
	Limited	88	42.9	75	38.5	4.5	[0.91]	
	No	49	23.9	54	27.7	-3.8	[-0.86]	
Total		205		195				

Panel B. Experiment B2: MTurk, Incentivized

		Low		High		Low - High		
		N	%	N	%	%	[t]	U test (p)
Gender	Male	116	56.6	111	56.9	-0.3	[-0.07]	0.98
	Female	89	43.4	84	43.1	0.3	[0.07]	
Education	Graduate school	30	14.6	33	16.9	-2.3	[-0.63]	0.13
	College	122	59.5	125	64.1	-4.6	[-0.94]	
	High school	53	25.9	37	19.0	6.9	[1.65]	
Age	Below 30	103	50.2	88	45.1	5.1	[1.02]	0.57
	30–40	54	26.3	66	33.9	-7.5	[-1.64]	
	40–50	30	14.6	23	11.8	2.8	[0.84]	
	Above 50	18	8.8	18	9.2	-0.5	[-0.16]	
Risk tolerance	High	33	16.1	27	13.9	2.3	[0.63]	0.71
	Medium	73	35.6	72	36.9	-1.3	[-0.27]	
	Low	99	48.3	96	49.2	-1.0	[-0.19]	
Financial wealth (ex. housing)	200K+	25	12.2	22	11.3	1.0	[0.28]	0.36
	50K–200K	47	22.9	55	28.2	-5.3	[-1.21]	
	10K–50K	60	29.3	58	29.7	-0.5	[-0.10]	
	0–10K	42	20.5	35	17.9	2.5	[0.64]	
	In debt	31	15.1	25	12.8	2.3	[0.66]	
Investing experience	Extensive	6	2.9	6	3.1	-0.2	[-0.09]	0.98
	Some	68	33.2	66	33.9	-0.7	[-0.14]	
	Limited	83	40.5	75	38.5	2.0	[0.41]	
	No	48	23.4	48	24.6	-1.2	[-0.28]	
Total		205		195				

Panel C. Experiment B3: HBS MBA, Incentivized

		Low		High		Low - High		
		N	%	N	%	%	[t]	U test (p)
Gender	Male	117	58.2	129	64.8	-6.7	[-1.36]	0.17
	Female	84	41.8	70	35.2	6.7	[1.36]	
Past 15 years of life	US	140	69.7	133	66.8	2.8	[0.60]	0.55
	Abroad	61	30.4	66	33.2	-2.8	[-0.60]	
Primary educational field	Humanities	26	12.9	23	11.6	1.4	[0.42]	0.04
	Social science	64	31.8	43	21.6	10.2	[2.32]	
	Science & engineering	80	39.8	95	47.7	-7.9	[-1.60]	
	Other	31	15.4	38	19.1	-3.7	[-0.97]	
Risk tolerance	High	116	57.7	107	53.8	3.9	[0.79]	0.55
	Medium	48	23.9	56	28.1	-4.3	[-0.97]	
	Low	37	18.4	36	18.1	0.3	[0.08]	
Investment experience	Extensive/professional	22	10.9	25	12.6	-1.6	[-0.50]	0.47
	Some	71	35.3	60	30.2	5.2	[1.10]	
	Limited	70	34.8	68	34.2	0.7	[0.14]	
	No	38	18.9	46	23.1	-4.2	[-1.03]	
Worked in finance	Yes	84	41.8	86	43.2	-1.4	[-0.29]	0.77
	No	117	58.2	113	56.8	1.4	[0.29]	
Total		201		199				

Table 2: Low Interest Rates and Risk Taking: Benchmark Experiment Results

This table presents results of the benchmark experiments. In Panel A, the first four columns show mean allocations to the risky asset in the high and low interest rate conditions, the difference in mean allocations between the two conditions, and the corresponding t-statistics. Column (5) shows p-values from the Mann–Whitney–Wilcoxon test, against the null that allocations in the high and low interest rate conditions are the same. Columns (6) and (7) show the mean difference in allocations controlling for individual characteristics through OLS; columns (8) and (9) show the difference through propensity score matching (ATE). In the MTurk samples, covariates include dummies for gender, age group, education level, risk tolerance, investment experience, wealth level. In the HBS MBA sample, covariates include dummies for gender, risk aversion level, investment experience, and work experience in finance. Panel B presents the OLS regressions displaying coefficients on the controls. The absorbed groups are female, below 30, high school or below, low risk tolerance, in debt, no or limited investment experience, did not work in finance.

Panel A. Allocations to Risky Asset (%)

	High (1)	Low (2)	**Dif** (Raw) (3)	[t] (4)	U test (p) (5)	**Dif** (OLS) (6)	[t] (7)	**Dif** (Match) (8)	[t] (9)
B1: MTurk, Hypo.	48.15	55.32	7.17	[2.52]	(0.02)	7.69	[2.74]	7.27	[2.66]
B2: MTurk, Incen.	58.58	66.64	8.06	[3.06]	(0.00)	8.14	[3.23]	8.66	[2.81]
B3: HBS MBA, Incen.	66.79	75.61	8.83	[3.13]	(0.00)	8.76	[3.19]	8.91	[3.30]

Panel B. Regressions with Individual Characteristics

	% Allocated to Risky Asset		
	B1 (MTurk)	B2 (MTurk)	B3 (HBS)
Low Rate Condition	**7.69**	**8.14**	**8.76**
	[2.74]	[3.23]	[3.19]
Male	-1.04	6.63	6.25
	[-0.36]	[2.49]	[2.14]
College	-3.09	3.32	
	[-0.92]	[1.00]	
Grad School	0.51	1.31	
	[0.11]	[0.29]	
Age (30—40)	3.69	0.86	
	[1.16]	[0.29]	
Age (40—50)	7.51	1.87	
	[1.48]	[0.47]	
Age (50+)	1.26	6.63	
	[0.22]	[1.35]	
Risk Tolerance Med	12.30	10.15	5.56
	[3.97]	[3.62]	[1.36]
Risk Tolerance High	18.22	15.28	15.39
	[4.46]	[4.25]	[4.01]
Wealth (0—10K)	-6.07	-8.69	
	[-1.41]	[-1.88]	
Wealth (10K—50K)	0.27	-4.87	
	[0.06]	[-1.13]	
Wealth (50K—200K)	-5.29	-2.85	
	[-1.20]	[-0.63]	
Wealth (200K+)	0.75	3.40	
	[0.11]	[0.67]	
More Experience	5.80	2.95	4.41
	[1.71]	[1.05]	[1.28]
Worked in Finance			3.34
			[1.00]
Constant	41.03	54.44	55.81
	[8.91]	[9.82]	[14.27]
Obs	400	400	400
R^2	0.118	0.136	0.115

Robust t-statistics in brackets

Table 3: Allocations in Various Interest Rate Conditions

This table presents results of Experiment T1. It shows mean allocations to the risky asset in different interest rate conditions. Each condition has 200 participants. Each column presents results for one condition. The first two rows show the properties of the investments in a given condition: the first row is the returns on the safe asset; the second row is the mean returns on the risky asset. The excess returns of the risky asset are the same in all conditions. The third row shows mean allocations to the risky asset in each condition, and the fourth row shows the 95% confidence interval.

Risk-Free Rate	-1%	0%	1%	3%
Mean Returns of Risky Asset	4%	5%	6%	8%
Mean Allocations to Risky Asset (%)	77.58	69.67	64.62	58.34
95% CI	(73.53, 81.62)	(65.88, 73.46)	(60.72, 68.51)	(54.48, 62.21)

Risk-Free Rate	5%	10%	15%
Mean Returns of Risky Asset	10%	15%	20%
Mean Allocations to Risky Asset (%)	56.77	49.92	50.59
95% CI	(52.98, 60.55)	(45.90, 53.93)	(46.76, 54.43)

Table 4: Path Dependence of Investment Decisions

This table presents results of Experiment T2. Half of the participants are randomly assigned to Group 1, and they first make investment decisions in the high interest rate condition (5% risk-free rate and 10% average risky returns), and then make decisions in the low interest rate condition (1% risk-free rate and 6% average risky returns). The other half of the participants are assigned to Group 2, and they first make investment decisions in the low rate condition, and then make decisions in the high rate condition. We perform this experiment using both hypothetical questions and incentivized tests.

G1	High: 5—10	Low: 1—6
Mean Alloc. to Risky	48.65	**66.33**
G2	Low: 1—6	High: 5—10
Mean Alloc. to Risky	55.75	47.08
G1 (Low) - G2 (Low)	Difference 10.58	[t] [3.44]

(a) Hypothetical

G1	High: 5—10	Low: 1—6
Mean Alloc. to Risky	57.24	**71.57**
G2	Low: 1—6	High: 5—10
Mean Alloc. to Risky	62.99	55.40
G1 (Low) - G2 (Low)	Difference 8.58	[t] [3.14]

(b) Incentivized

Table 5: Baseline and Gross Framing

This table presents results of Experiment T3. The first half of Panel A reports mean allocations to the risky asset in the high and low interest rate conditions, the difference in mean allocations between the two conditions, and the t-statistics associated with the test that the difference is different from zero. p-values from the Mann–Whitney–Wilcoxon test are also included. The bottom half of Panel A compares allocations with baseline framing to allocations with gross framing. Panel B presents differences in allocations controlling for individual characteristics, both through OLS and through propensity score matching (ATE). The individual characteristics include dummies for gender, education level, age group, risk tolerance, investment experience, and wealth level. The first half of Panel B compares allocations in the high and low interest rate conditions for a given framing. The second half of Panel B compares allocations with baseline and gross framing for a given interest rate condition.

Panel A. Mean Allocations to Risky Asset (%)

	High: 5—10	Low: 1—6	Difference	[t]	U test (p-val)
Baseline	57.13	64.51	7.38	[2.69]	(0.00)
Gross	52.65	54.44	1.79	[0.65]	(0.47)
Baseline - Gross	4.47	10.06	5.59	-	-
[t]	[1.61]	[3.72]	[1.44]	-	-
U test (p-val)	(0.14)	(0.00)	-	-	-

Panel B. Differences Controlling for Individual Characteristics

	Dif (OLS)	[t]	Dif (ATE)	[t]
Baseline: Low − High	5.90	[2.25]	6.75	[2.47]
Gross: Low − High	1.93	[0.70]	0.68	[0.21]
High: Baseline − Gross	5.08	[1.94]	5.43	[1.97]
Low: Baseline − Gross	9.65	[3.61]	11.37	[4.30]

Table 6: Summary Statistics of Observational Data

Summary statistics for observational data. Mean, median, standard deviation, quartiles, and data time periods are presented. Variables include: allocations to stocks and "cash" (interest-bearing liquid assets, such as savings accounts, CDs, money market funds) using data from the American Association of Individual Investors (AAII); equity and high yield corporate bond mutual fund flows, normalized by respective net asset value, using data from the Investment Company Institute (ICI); household sector flows into stocks (both direct holdings and mutual fund holdings) and interest-bearing safe assets (include time and saving deposits, money market mutual funds, and commercial paper), normalized by household sector financial wealth, using data from the Flow of Funds; interest rates; stock market sentiment (% Bullish−% Bearish) from AAII, Campbell-Shiller P/E10, Campbell-Cochrane surplus consumption ratio, VIX^2, past four quarter GDP growth, and the credit spread (BAA−10-year Treasury).

	Mean	Std. Dev.	25%	50%	75%	Start	End	N
Portfolio Share Data from AAII								
% in Stocks	60.18	8.35	53.27	61.25	66.91	1987M11	2014M12	326M
% in "Cash" (AAII)	23.96	6.32	19.00	22.69	28.00	1987M11	2014M12	326M
Mutual Fund Flow Data from ICI								
Equity Fund Flows/NAV (%)	0.39	0.77	-0.12	0.28	0.90	1985M1	2014M12	360M
HY CB Fund Flows/NAV (%)	0.65	1.90	-0.58	0.75	1.77	1985M1	2014M12	360M
Household Investment Flows Data from FoF								
Flows into Stocks/HH Fin. Ast. (%)	-0.19	0.82	-0.72	-0.22	0.27	1985Q1	2014Q4	120Q
Flows into Deposits/HH Fin. Ast. (%)	0.71	0.87	0.15	0.75	1.36	1985Q1	2014Q4	120Q
Interest Rates								
3-Month Treasury Rate	3.66	2.53	1.13	4.31	5.53	1985M1	2014M12	360M
Controls								
Stock Market Sentiment (AAII)	8.57	15.30	-1.81	9.36	18.75	1987M8	2014M12	329M
P/E10	23.44	7.54	18.31	22.41	26.46	1985M1	2014M12	360M
$Surp$	0.113	0.098	0.081	0.157	0.185	1985M1	2014M12	360M
VIX^2	0.049	0.051	0.023	0.035	0.056	1986M1	2014M12	348M
Past 4Q GDP Growth	2.70	1.68	1.80	3.02	3.96	1985Q1	2014Q4	360M
Credit Spread	2.31	0.74	1.73	2.17	2.75	1985M1	2014M12	360M

Table 7: Interest Rates and AAII Portfolio Allocations

Monthly time series regressions:

$$Y_t = \alpha + \beta r_{f,t-1} + X'_{t-1}\gamma + \epsilon_t$$

where r_f is 3-month Treasury rate; X includes P/E10 in column (2), the surplus consumption ratio in column (3), and predicted next 12-month excess stock returns in column (4) (estimated using surplus consumption and past 12-month excess stock returns), as well as AAII stock market sentiment, VIX^2, real GDP growth in the past four quarters, and the credit spread. Y is mean allocations to stocks in Panel A and mean allocations to "cash" in Panel B. Monthly from November 1987 to December 2014. Standard errors are Newey-West, using the automatic bandwidth selection procedure of Newey and West (1994).

Panel A. Interest Rates and Mean Allocations to Stocks

	Mean Allocations to Stocks			
	(1)	(2)	(3)	(4)
L.r_f	-0.38	-1.47	-1.92	-2.00
	[-0.51]	[-4.49]	[-2.46]	[-2.57]
L.P/E10		0.84		
		[9.16]		
L.$Surp$			6.79	
			[0.40]	
L.$E[rx^{12}_{stk}]$				-0.12
				[-0.60]
L.AAII Sentiment		0.04	0.17	0.16
		[1.66]	[4.01]	[3.67]
L.VIX^2		-6.34	-14.45	-5.73
		[-0.78]	[-0.96]	[-0.27]
L.Past 12M GDP Growth		0.34	2.11	2.17
		[0.85]	[2.61]	[2.77]
L.Credit Spread		-3.87	-2.64	-3.37
		[-4.02]	[-1.34]	[-1.46]
Constant	61.47	52.58	66.01	68.87
	[19.30]	[14.59]	[10.88]	[9.03]
Observations	326	326	326	326

Newey-West t-statistics in brackets

Panel B. Interest Rates and Mean Allocations to "Cash"

	Mean Allocations to "Cash"			
	(1)	(2)	(3)	(4)
L.r_f	0.62	1.51	1.19	1.28
	[1.21]	[3.85]	[2.26]	[1.99]
L.P/E10		-0.47		
		[-4.22]		
L.$Surp$			20.56	
			[1.78]	
L.$E[rx^{12}_{stk}]$				-0.21
				[-1.27]
L.AAII Sentiment		-0.02	-0.13	-0.13
		[-1.00]	[-4.29]	[-3.41]
L.VIX^2		9.69	11.01	27.02
		[1.10]	[1.06]	[1.52]
L.Past 12M GDP Growth		-0.01	-1.33	-1.10
		[-0.01]	[-2.45]	[-1.63]
L.Credit Spread		3.83	2.82	1.69
		[3.56]	[2.11]	[0.86]
Constant	21.85	21.32	15.14	19.50
	[9.99]	[4.97]	[3.69]	[3.02]
Observations	326	326	326	326

Newey-West t-statistics in brackets

Table 8: Interest Rates and Household Investment Flows

Time series regressions:

$$F_t = \alpha + \beta \Delta r_{f,t-1} + X'_{t-1}\gamma + \epsilon_t$$

where r_f is 3-month Treasury rate. In Panel A, F is monthly flows into equity mutual funds (normalized by net asset value of equity mutual funds, i.e. F is flows as a percentage of net asset value) using data from ICI; X includes controls in Table 7. In Panel B, F is monthly flows into high yield corporate bond mutual funds (normalized by net asset value of high yield corporate bond mutual funds) using data from ICI; X includes past 12-month excess returns of high yield corporate bonds in column (2), past 12-month excess returns and high yield corporate default rates in column (3), and predicted next 12-month high yield corporate bond excess returns (estimated using past 12-month excess returns and corporate default rates) in column (4), as well as the credit spread and real GDP growth in the past four quarters. In Panel C, F is quarterly household sector flows into stocks (including both direct holdings and mutual fund holdings, normalized by household financial assets) using data from Flow of Funds; X includes controls in Table 7 (measured at the end of the previous quarter). In Panel D, F is quarterly household sector flows into interest-bearing safe assets (time and saving deposits, money market mutual funds, commercial papers, normalized by household financial assets, i.e. F is flows as a percentage of household financial wealth) using data from Flow of Funds; X includes controls in Table 7 (measured at the end of the previous quarter). All regressions include four lags of F. Outcome variables are from the beginning of 1985 to the end of 2014, but AAII sentiment is only available starting August 1987. Standard errors are Newey-West, using the automatic bandwidth selection procedure of Newey and West (1994).

Panel A. Equity Mutual Fund Flows (ICI)				
L.D.r_f	-0.42	-0.42	-0.40	-0.44
	[-2.51]	[-2.50]	[-2.39]	[-2.13]
Controls	No	Yes	Yes	Yes
Observations	360	328	328	328
Panel B. High Yield Corp. Bond Mutual Fund Flows (ICI)				
L.D.r_f	-1.01	-0.78	-0.78	-1.17
	[-2.42]	[-1.69]	[-1.70]	[-2.65]
Controls	No	Yes	Yes	Yes
Observations	360	360	360	360
Panel C. Household Flows into Stocks (FoF)				
L.D.r_f	-0.37	-0.47	-0.40	-0.74
	[-2.63]	[-2.89]	[-2.39]	[-3.51]
Controls	No	Yes	Yes	Yes
Observations	120	109	109	109
Panel D. Household Flows into Deposits (FoF)				
L.D.r_f	0.41	0.40	0.38	0.34
	[3.11]	[2.51]	[2.41]	[1.60]
Controls	No	Yes	Yes	Yes
Observations	120	109	109	109

Newey-West t-statistics in brackets

Internet Appendix

A Proofs

A.1 Proof of Proposition 1

Consider first the problem without the constraint $0 \leq \phi \leq 1$. Let $h(\phi) = \mathbb{E}u(w(1+r_p))$. We have $\frac{\partial^2 h(\phi)}{\partial \phi^2} = \mathbb{E}\left[x^2 u''(\tilde{w})\right] < 0$ because u is strictly concave. As a result, $h(\phi)$ is strictly concave and twice differentiable. Define $\phi_1^* = \arg\max_\phi \mathbb{E}u(w(1+r_p)) = \arg\max_\phi h(\phi)$, i.e. the optimal allocation to the risky asset in the unconstrained problem. Because $h(\phi)$ is strictly concave and twice differentiable, ϕ_1^* is fully characterized by the first order condition:

$$\mathbb{E}\left[xu'\left(w(1+r_f)+\phi_1^* wx\right)\right] = 0.$$

Therefore,

$$\frac{\partial \phi_1^*}{\partial r_f} = -\frac{\mathbb{E}\left[xu''\left(w(1+r_f)+\phi_1^* wx\right)\right]}{\mathbb{E}\left[x^2 u''\left(w(1+r_f)+\phi_1^* wx\right)\right]} = -\frac{\mathbb{E}\left[xu''(\tilde{w})\right]}{\mathbb{E}\left[x^2 u''(\tilde{w})\right]} = \frac{\mathbb{E}\left[xu'(\tilde{w})A(\tilde{w})\right]}{\mathbb{E}\left[x^2 u''(\tilde{w})\right]},$$

where $\tilde{w} = (1+r_f)w + \phi_1^* xw$ is the investor's final wealth, and $A(\tilde{w}) = \frac{-u''(\tilde{w})}{u'(\tilde{w})}$ denotes the coefficient of absolute risk aversion.

Since u is strictly concave, $\frac{\mathbb{E}[xu'(\tilde{w})A(\tilde{w})]}{\mathbb{E}[x^2u''(\tilde{w})]}$ has the same sign as $-\mathbb{E}\left[xu'(\tilde{w})A(\tilde{w})\right]$. Note that

$$\begin{aligned}
\mathbb{E}\left[xu'(\tilde{w})A(\tilde{w})\right] &= \int_{x\geq 0} xu'(\tilde{w})A(\tilde{w})\,dx + \int_{x<0} xu'(\tilde{w})A(\tilde{w})\,dx \\
&\leq \int_{x\geq 0} xu'(\tilde{w})A(\tilde{w}(0))\,dx + \int_{x<0} xu'(\tilde{w})A(\tilde{w}(0))\,dx \\
&= A(\tilde{w}(0))\,\mathbb{E}\left[xu'(\tilde{w})\right] = 0
\end{aligned}$$

where $\tilde{w}(0) = w(1+r_f)$ denotes the final wealth level when the realized excess returns is $x = 0$ and we use the fact that $A(\tilde{w})$ is weakly decreasing in $\tilde{w}$. As a result, $\frac{\partial \phi_1^*}{\partial r} \geq 0$, that is, ϕ_1^* is (weakly) increasing in r_f.

We can now consider the constrained problem $\phi^* = \arg\max_{0\leq\phi\leq 1} \mathbb{E}u(w(1+r_p)) = \arg\max_{0\leq\phi\leq 1} h(\phi)$. Because $h(\phi)$ is strictly concave, $h(\phi)$ is increasing in ϕ when $\phi \leq \phi_1^*$ and decreasing in ϕ when $\phi > \phi_1^*$. Thus $\phi^* = \min\{\phi_1^*, 1\}$.[29] It is also (weakly) increasing in r_f.

A.2 Proof of Proposition 2

Let $r_d = r_r - r_f$ denote the difference between the reference point and the risk-free rate. When $r_d = r_r - r_f > 0$, the reference point is larger than the risk-free rate, which falls into

[29]Because $\mathbb{E}x > 0$, by the Arrow-Pratt Theorem $\phi_1^* > 0$.

case 1 of Proposition 2. When $r_d = r_r - r_f < 0$, the reference point is smaller than the risk-free rate, which falls into case 2 of Proposition 2.

We can write function u as

$$u\left(w\left(1+r_p\right)\right) = \begin{cases} w\left(\phi x - r_d\right) & \phi x \geq r_d \\ -\lambda w\left(r_d - \phi x\right) & \phi x < r_d \end{cases}.$$

Note that u is linear in w, so without loss of generality, we can assume $w = 1$. We have

$$\mathbb{E}u\left(1+r_p\right) = \left(\phi \mathbb{E}x - r^d\right) - \int_{-\infty}^{\frac{r_d}{\phi}} \left(\lambda - 1\right)\left(r_d - \phi x\right) f\left(x\right) dx \triangleq h\left(\phi, r_d\right).$$

where f is the probability density function of the distribution of excess returns x, the first term captures expected investment returns in excess of the reference point, and the second term captures the utility loss from loss aversion in the region below the reference point. Take derivatives with respect to ϕ, we have

$$\frac{\partial h\left(\phi, r_d\right)}{\partial \phi} = \mathbb{E}x + \int_{-\infty}^{\frac{r_d}{\phi}} \left(\lambda - 1\right) x f\left(x\right) dx. \tag{A7}$$

Case 1: $\mathbb{E}x < -\int_{-\infty}^{0} \left(\lambda - 1\right) x f\left(x\right) dx$. In this case, there exists unique $\underline{b}, \bar{b} > 0$, such that

$$\mathbb{E}x + \int_{-\infty}^{-\underline{b}} \left(\lambda - 1\right) x f\left(x\right) dx = 0,$$

$$\mathbb{E}x + \int_{-\infty}^{\bar{b}} \left(\lambda - 1\right) x f\left(x\right) dx = 0.$$

When $r_d > 0$,

$$\phi^* = \min\left\{\frac{r_d}{\bar{b}}, 1\right\}. \tag{A8}$$

This is because when $0 \leq \phi < \frac{r_d}{\bar{b}}$, $\frac{\partial h(\phi, r_d)}{\partial \phi} > \mathbb{E}x + \int_{-\infty}^{\bar{b}} \left(\lambda - 1\right) x f\left(x\right) dx = 0$, and when $\phi > \frac{r_d}{\bar{b}}$, $\frac{\partial h(\phi, r_d)}{\partial \phi} < \mathbb{E}x + \int_{-\infty}^{\bar{b}} \left(\lambda - 1\right) x f\left(x\right) dx = 0$.

When $r_d < 0$,

$$\phi^* = \min\left\{-\frac{r_d}{\underline{b}}, 1\right\}. \tag{A9}$$

This is because when $0 \leq \phi < -\frac{r_d}{\underline{b}}$, $\frac{\partial h(\phi, r_d)}{\partial \phi} > \mathbb{E}x + \int_{-\infty}^{-\underline{b}} \left(\lambda - 1\right) x f\left(x\right) dx = 0$, and when $\phi > -\frac{r_d}{\underline{b}}$, $\frac{\partial h(\phi, r_d)}{\partial \phi} < \mathbb{E}x + \int_{-\infty}^{-\underline{b}} \left(\lambda - 1\right) x f\left(x\right) dx = 0$.

Based on Equations (A8) and (A9), we have that the optimal allocation to the risky asset ϕ^* is (weakly) increasing in r_d (and (weakly) decreasing in r_f) if $r_r > r_f$, and (weakly) decreasing in r_d (and (weakly) increasing in r_f) if $r_r < r_f$.

Case 2: $\mathbb{E}x \geq -\int_{-\infty}^{0} \left(\lambda - 1\right) x f\left(x\right) dx$. In this case $\frac{\partial h(\phi, r_d)}{\partial \phi} > 0$, $\phi^* = 1$. That is, the expected returns of the risky asset are so attractive that utility loss due to loss aversion from bad realizations of the risky asset's returns is dominated. Investors prefer to invest all of their wealth in the risky asset. In this case, it is still true that the optimal allocation to the risky asset ϕ^* is weakly decreasing in r_f if $r_r > r_f$, and weakly increasing in r_f if $r_r < r_f$.[30]

A.3 Proof of Corollary 1

Note that the proof of Proposition 2 only depends on $r_d = r_r - r_f$. As a result, this proof follows from the proof of Proposition 2.

A.4 Proof of Proposition 3

Notice that when $r_f > 0$, $\left|\frac{(r_f+\mathbb{E}x)-r_f}{(r_f+\mathbb{E}x)+r_f}\right|$ is decreasing in r_f. As a result, $\delta(r_f+\mathbb{E}x, r_f, Var\left(x\right), 0)$ is decreasing in r_f. Therefore, $\phi_s^* = \min\left\{\frac{\delta\mathbb{E}x}{\gamma Var(x)}, 1\right\}$ is (weakly) decreasing in r_f.

A.5 Influence of Gross Framing

Let ϕ_s^* denote a salient investor's optimal allocation in the risky asset with baseline framing in Experiment T3, according to Equation (5) in the paper. Define $\phi_{s,gross}^*$ as a salient investor's optimal allocation in the risky asset with gross framing in Experiment T3, according to:

$$\phi_{s,gross}^* \triangleq \arg\max_{\phi\in[0,1]} \delta_{gross}\mathbb{E}r_p - \frac{\gamma}{2}Var\left(r_p\right),$$

where $\delta_{gross} = \delta(1 + r_f + \mathbb{E}x, 1 + r_f, Var\left(x\right), 0)$ characterizes the salience of the return dimension relative to the risk dimension with gross framing. Note that the salience function here depends on gross interest rates instead of net interest rates, in contrast to the salience function with baseline framing.

Lemma A1. *For a given distribution of the excess returns x and a given risk-free rate $r_f > 0$, the optimal allocation to the risky asset with baseline framing is always (weakly) larger than that with gross framing, i.e. $\phi_{s,gross}^* \leq \phi_s^*$.*

[30] Note that when $r_d = r_r - r_f = 0$, the loss aversion framework here predicts that the optimal allocation to the risky asset is either 0 (if loss aversion is large enough, that is, $\mathbb{E}x < -\int_{-\infty}^{0}\left(\lambda - 1\right)xf\left(x\right)dx$) or 1 (if loss aversion is not large enough, that is, $\mathbb{E}x > -\int_{-\infty}^{0}\left(\lambda - 1\right)xf\left(x\right)dx$). This prediction is an artifact of the piecewise linear framework we use in Assumption 1 in the main text. To avoid such an extreme prediction, we can study a utility function with both a component featuring diminishing marginal utility over wealth (such as a CARA or CRRA component) and a component featuring gain-loss utility like Assumption 1 (e.g. Kőszegi and Rabin (2006)). In this case, the comparative static of the optimal allocation with respect to the risk-free rate will be influenced by both the force in Proposition 1 (conventional portfolio choice) and the force in Proposition 2 (loss aversion). Accordingly, the comparative static will be a weighted average of these two forces. The analysis in Proposition 2 can be thought of as a version that focuses on studying how loss aversion around the reference point *alone* influences investment decisions' response to the risk-free rate. We use this version to highlight the key mechanism that can drive reaching for yield.

Proof. Notice that when $r_f > 0$, $\left|\frac{(r_f+\mathbb{E}x)-r_f}{(r_f+\mathbb{E}x)+r_f}\right| > \left|\frac{(1+r_f+\mathbb{E}x)-(1+r_f)}{(1+r_f+\mathbb{E}x)+(1+r_f)}\right|$. As a result, $\delta = \delta(r_f + \mathbb{E}x, r_f, Var\left(x\right), 0) > \delta(1 + r_f + \mathbb{E}x, 1 + r_f, Var\left(x\right), 0) = \delta_{gross}$. Therefore, $\phi_s^* = \min\left\{\frac{\delta\mathbb{E}x}{\gamma Var(x)}, 1\right\} \geq \min\left\{\frac{\delta_{gross}\mathbb{E}x}{\gamma Var(x)}, 1\right\} = \phi_{s,gross}^*$. $\square$

B Additional Discussions

B.1 Dynamic Portfolio Choice

In Section 3.1 we follow the experiment in Section 2 and study a static portfolio choice problem. In this section, we discuss the impact of interest rates on portfolio allocations in other environments, such as dynamic portfolio choice with life cycle motives or hedging motives. While they do not map directly into the setting of our simple experiments, we explain the forces in these environments and predictions that are different from our results.

Life Cycle Portfolio Choice

A number of recent studies analyze dynamic portfolio choice with life-cycle motives (Cocco, Gomes, and Maenhout, 2005; Wachter and Yogo, 2010). The key insight of life cycle models is the role of future labor income. To the extent that labor income risks and stock market risks are not very correlated, future labor income can effectively constitute holdings of safe assets.

One way interest rates may play a role in life cycle models is by affecting the present value of future labor income. When interest rates are higher, an investor may have less discounted future labor income (thus effectively less safe asset), and invest less in risky asset.

However, for this mechanism to be powerful, the change in interest rates needs to be fairly persistent. Moreover, given that older people have much less future labor income, this force would become minimal. In our data, the reaching for yield behavior we document does not diminish among the elderly. For example, as shown in Appendix C.2, the majority of participants in the Dutch sample are 60 years old or above. Reaching for yield is highly significant in that sample. For instance, for the baseline interest rate conditions (1% vs. 5% interest rates), the difference in mean allocations is 10.2 percentage points in the Dutch data, slightly higher than that the baseline samples in the US (7 to 9 percentage points as shown in Table 2, where the participants are primarily under 40).

In sum, life cycle motives are important in many applications and may also help understand the impact of interest rates. However, our results in this simple experiment do not seem to be driven by life cycle motives.

Dynamic Hedging

In dynamic portfolio choice problems, one may also consider hedging motives. For dynamic hedging to generate reaching for yield behavior, it needs to be that the risky asset has better hedging properties when interest rates are low. In our experiment, it does not seem obvious why people assigned to low interest rate conditions would think the risky asset has better hedging properties. The risky asset payoffs are also uncorrelated with people's background risks.

B.2 Diminishing Sensitivity

Below we provide a discussion about how the diminishing sensitivity component of the Prospect Theory (Kahneman and Tversky, 1979; Tversky and Kahneman, 1992) may affect reaching for yield. Diminishing sensitivity refers to the idea that the investor's utility is concave above the reference point (i.e. marginal utility gain becomes smaller when the gain is larger) and convex below the reference point (i.e. marginal utility loss becomes smaller when the loss is larger).

We show that the theoretical prediction of whether diminishing sensitivity contributes to reaching for yield is ambiguous. Consider for instance the case where the reference point is above the risk-free rate. Diminishing sensitivity above the reference point unambiguously contributes to reaching for yield: if the portfolio returns are above the reference point, as the risk-free rate falls, the same excess returns on the risky asset generate a *higher* marginal utility gain. Diminishing sensitivity below the reference point, however, may either contribute to or work against reaching for yield: if the portfolio returns are below the reference point but the risky asset has positive excess returns, then as the risk-free rate falls, the same excess returns on the risky asset generate a *lower* marginal utility gain. This force works against reaching for yield. If the portfolio returns are below the reference point and the risky asset has negative excess returns, then diminishing sensitivity again unambiguously contributes to reaching for yield (as the risk-free rate falls, the same excess returns on the risky asset generate a *lower* marginal utility loss). We then evaluate the case with diminishing sensitivity numerically, based on standard parameter values (Tversky and Kahneman, 1992; Barberis et al., 2006) together with investment payoffs in our experiment. We find that diminishing sensitivity generally contributes to reaching for yield, but the magnitude is relatively small.

We analyze a set-up that includes both loss aversion around the reference point as in Section 3.2 and diminishing sensitivity. The investor's optimization problem is the same as Equation (2) in the main text, except the utility function u features both loss aversion around the reference point and diminishing sensitivity, specified as follows:

Assumption A3.

$$u\left(1+r_p\right) = \begin{cases} \frac{1}{\alpha}\left[\left(\left(r_p - r_r\right)+1\right)^{\alpha} - 1\right] & r_p \geq r_r \\ -\frac{\lambda}{\beta}\left[\left(-\left(r_p - r_r\right)+1\right)^{\beta} - 1\right] & r_p < r_r \end{cases} \tag{A10}$$

where r_r is the reference return, $0 < \alpha \leq 1$ reflects the degree of diminishing sensitivity above the reference point, $0 < \beta \leq 1$ reflects the degree of diminishing sensitivity below the reference point, and $\lambda \geq 1$ reflects the degree of loss aversion below the reference point. Lower α and β correspond to a higher degree of diminishing sensitivity.

Here we specify the gain loss utility as a function of investment returns instead of the wealth level. Effectively, we analyze the case where the gain loss utility scales linearly with initial wealth, as opposed to having additional curvature driven by initial wealth.[31] The curvature of utility driven by initial wealth can be separately captured by a CRRA component, as discussed in footnote 30 of Section A.2. In addition, our specification avoids the property in the Tversky and Kahneman (1992) specification that marginal utility at the reference point is infinity,[32] which complicates the analysis and is also somewhat counterfactual. Instead, Equation (A10) normalizes the curvature of the utility function just above the reference point to 1 and the curvature of the utility function just below the reference point to λ, consistent with the utility function in Assumption 1.

We now analyze how the optimal allocation to the risky asset ϕ^* moves with the risk-free rate r_f (reference point r_r) under Assumption A3. We begin with a decomposition that illustrates how different channels influence the comparative statics of the optimal allocation ϕ^* with respect to the risk-free rate r_f and the reference point r_r. As in the proof of Proposition 2, let $r_d = r_r - r_f$ denote the difference between the reference point and the risk-free rate. We can rewrite the utility function u as

$$u\left(1+r_p\right) = \begin{cases} \frac{1}{\alpha}\left[\left(\left(\phi x - r_d\right)+1\right)^{\alpha}-1\right] & \phi x \geq r_d \\ -\frac{\lambda}{\beta}\left[\left(\left(r_d - \phi x\right)+1\right)^{\beta}-1\right] & \phi x < r_d \end{cases}. \tag{A11}$$

Let

$$\begin{aligned} h\left(\phi, r_d\right) \triangleq \mathbb{E}\left[u\left(1+r_p\right)\right] = & \int_{\frac{r_d}{\phi}}^{+\infty} \frac{1}{\alpha}\left[\left(\left(\phi x - r_d\right)+1\right)^{\alpha}-1\right] f\left(x\right) dx \\ & -\frac{\lambda}{\beta}\int_{-\infty}^{\frac{r_d}{\phi}} \left[\left(1+\left(r_d-\phi x\right)\right)^{\beta}-1\right] f\left(x\right) dx \end{aligned}$$

where f is the probability density function of the distribution of the excess returns x.[33] The first term captures the utility gain when investment returns are above the reference point, and the second term captures the utility loss when investment returns are below the reference point. By Topkin's Theorem, to study how $\arg\max_{0\leq\phi\leq1} h\left(\phi, r_d\right)$ moves with respect to r_d, we only need to study the sign of $\frac{\partial^2}{\partial\phi\partial r_d} h\left(\phi, r_d\right)$, that is, how the marginal gain of investing in the risky asset changes with respect to r_d.

$$\frac{\partial}{\partial\phi} h\left(\phi, r_d\right) = \int_{\frac{r_d}{\phi}}^{+\infty} x\left(\left(\phi x - r_d\right)+1\right)^{\alpha-1} f\left(x\right) dx + \lambda\int_{-\infty}^{\frac{r_d}{\phi}} x\left(1+\left(r_d-\phi x\right)\right)^{\beta-1} f\left(x\right) dx,$$

[31] This can be extended to the case where the utility function is homothetic with respect to initial wealth.

[32] The specification following Tversky and Kahneman (1992) would be

$$u\left(\left(1+r_p\right)\right) = \begin{cases} \frac{1}{\alpha}\left(\left(r_p - r_r\right)\right)^{\alpha} & r_p \geq r_r \\ -\frac{\lambda}{\beta}\left(-\left(r_p - r_r\right)\right)^{\beta} & r_p < r_r \end{cases}.$$

[33] In this proof, for technical simplicity, we assume that the pdf f has full support on the real line.

$$\frac{\partial^2}{\partial\phi\partial r_d}h\left(\phi,r_d\right)=(1-\alpha)\int_{\frac{r_d}{\phi}}^{+\infty}x\left(\left(\phi x-r_d\right)+1\right)^{\alpha-2}f\left(x\right)dx$$
$$-\lambda(1-\beta)\int_{-\infty}^{\frac{r_d}{\phi}}x\left(1+\left(r_d-\phi x\right)\right)^{\beta-2}f\left(x\right)dx+(\lambda-1)\frac{r_d}{\phi^2}f\left(\frac{r_d}{\phi}\right). \tag{A12}$$

Let us consider two cases.

Case 1: $r_d > 0$, i.e. the reference point is higher than the risk-free rate.

The first term in (A12), $(1-\alpha)\int_{\frac{r_d}{\phi}}^{+\infty}x\left(\left(\phi x-r_d\right)+1\right)^{\alpha-2}f\left(x\right)dx \geq 0$, since $\alpha \leq 1$. When the realized portfolio returns are above the reference point, the marginal gain of investing in the risky asset is higher as the risk-free rate decreases (the reference point increases), due to diminishing sensitivity. This force contributes to reaching for yield.

The second term in (A12), $-\lambda(1-\beta)\int_{-\infty}^{\frac{r_d}{\phi}}x\left(1+\left(r_d-\phi x\right)\right)^{\beta-2}f\left(x\right)dx$, can be further decomposed into

$$-\lambda(1-\beta)\int_{-\infty}^{\frac{r_d}{\phi}}x\left(1+\left(r_d-\phi x\right)\right)^{\beta-2}f\left(x\right)dx=-\lambda(1-\beta)\int_{0}^{\frac{r_d}{\phi}}x\left(1+\left(r_d-\phi x\right)\right)^{\beta-2}f\left(x\right)dx$$
$$-\lambda(1-\beta)\int_{-\infty}^{0}x\left(1+\left(r_d-\phi x\right)\right)^{\beta-2}f\left(x\right)dx. \tag{A13}$$

The first term in (A13), $-\lambda(1-\beta)\int_{0}^{\frac{r_d}{\phi}}x\left(1+\left(r_d-\phi x\right)\right)^{\beta-2}f\left(x\right)dx \leq 0$, since $\beta \leq 1$. This term reflects the situation where the portfolio returns are below the reference point but the excess returns of the risky asset are positive. In this region, the marginal gain of investing in the risky asset is lower as the risk-free rate decreases (the reference point increases), due to diminishing sensitivity. This force works against reaching for yield.

The second term in (A13), $-\lambda(1-\beta)\int_{-\infty}^{0}x\left(1+\left(r_d-\phi x\right)\right)^{\beta-2}f\left(x\right)dx \geq 0$, since $\beta \leq 1$. This reflects the situation where the portfolio returns are below the reference point and the excess returns of the risky asset are negative. In this case, the marginal loss of investing in the risky asset is lower as the risk-free rate decreases (the reference point increases), due to diminishing sensitivity. This force contributes to reaching for yield.

The third term in (A12), $(\lambda-1)\frac{r_d}{\phi^2}f\left(\frac{r_d}{\phi}\right) \geq 0$, since $\lambda \geq 1$. This is exactly the term that reflects how loss aversion around the reference point affects reaching for yield, as in Proposition 2 in the main text. When $r_d > 0$, this force contributes to reaching for yield.

Case 2: $r_d < 0$. i.e. the reference point is lower than the risk-free rate.

The first term in (A12), $(1-\alpha)\int_{\frac{r_d}{\phi}}^{+\infty}x\left(\left(\phi x-r_d\right)+1\right)^{\alpha-2}f\left(x\right)dx$, can be further decomposed into

$$(1-\alpha)\int_{\frac{r_d}{\phi}}^{+\infty} x\left((\phi x-r_d)+1\right)^{\alpha-2} f(x)\,dx = (1-\alpha)\int_{0}^{+\infty} x\left((\phi x-r_d)+1\right)^{\alpha-2} f(x)\,dx$$
$$+(1-\alpha)\int_{\frac{r_d}{\phi}}^{0} x\left((\phi x-r_d)+1\right)^{\alpha-2} f(x)\,dx \tag{A14}$$

The first term in (A14), $(1-\alpha)\int_0^{+\infty} x\left((\phi x-r_d)+1\right)^{\alpha-2} f(x)\,dx \geq 0$, since $\alpha \leq 1$. This reflects the situation where the portfolio returns are above the reference point, and the excess returns of the risky asset are positive. In this case, the marginal gain of investing in the risky asset is higher as the risk-free rate decreases (the reference point increases), due to diminishing sensitivity. This force contributes to reaching for yield.

The second term in (A14), $(1-\alpha)\int_{\frac{r_d}{\phi}}^{0} x\left((\phi x-r_d)+1\right)^{\alpha-2} f(x)\,dx \leq 0$ since $\alpha \leq 1$. This reflects the situation where the portfolio returns are above the reference point, but the excess returns of the risky asset are negative. In this case, the marginal loss of investing in the risky asset is higher as the risk-free rate decreases (the reference point increases), due to diminishing sensitivity. This force works against reaching for yield.

The second term in (A12), $-\lambda(1-\beta)\int_{-\infty}^{\frac{r_d}{\phi}} x\left(1+(r_d-\phi x)\right)^{\beta-2} f(x)\,dx \geq 0$ since $\beta \leq 1$. When the realized portfolio returns are below the reference point, the marginal loss of investing in the risky asset is lower as the risk-free rate decreases (the reference point increases), due to diminishing sensitivity. This force contributes to reaching for yield.

The third term in (A12), $(\lambda-1)\frac{r_d}{\phi^2} f\left(\frac{r_d}{\phi}\right) \leq 0$ since $\lambda \geq 1$. Again, this is exactly the term that reflects how loss aversion around the reference point affects reaching for yield, as in Proposition 2 in the main text. When $r_d < 0$, this force works against reaching for yield.

The proposition below summarizes predictions in two special cases:

Proposition A4. *Under Assumption A3, for a given distribution of the excess returns x, if*

$$\text{(i) } r_f < r_r \text{ and } \beta = 1, \qquad \text{or} \qquad \text{(ii) } r_f > r_r \text{ and } \alpha = 1,\ \lambda = 1,$$

the optimal allocation to the risky asset ϕ^* is (weakly) decreasing in r_f and (weakly) increasing in r_r in the following sense: suppose

$$r_d < r_d', \quad \phi^* \in \arg\max_{0\leq\phi\leq 1} h(\phi, r_d), \quad \text{and} \quad \phi^{*\prime} \in \arg\max_{0\leq\phi\leq 1} h(\phi, r_d'),$$

then we have $\phi^{*\prime} \geq \phi^*$.[34]

Proof. Consider the case that either

$$\text{(i) } r_f < r_r,\ \alpha < 1, \text{ and } \beta = 1, \qquad \text{or} \qquad \text{(ii) } r_f > r_r,\ \alpha = 1,\ \beta < 1,\ \lambda = 1$$

(otherwise we can directly apply Propostion 2 in the main text). From the decomposition in (A12) and Topkin's Theorem, we know that either

[34] $\arg\max_{0\leq\phi\leq 1} h(\phi, r_d)$ could be a set due to the convex part of the utility function under diminishing sensitivity.

$$\phi^* \le \phi^{*'},$$

which proves the Proposition, or

$$\phi^* > \phi^{*'} \quad \text{and} \quad \left\{\phi^*, \phi^{*'}\right\} \subseteq \arg\max_{0\le\phi\le1} h\left(\phi, r_d\right) \cap \arg\max_{0\le\phi\le1} h\left(\phi, r_d'\right).$$

However, if either

$$\text{(i) } r_f < r_r,\ \alpha < 1, \text{ and } \beta = 1, \quad \text{or} \quad \text{(ii) } r_f > r_r,\ \alpha = 1,\ \beta < 1,\ \lambda = 1,$$

we have $\frac{\partial^2}{\partial\phi\partial r_d} h\left(\phi, r_d\right) > 0$ according to the decomposition in (A12). As a result, it is impossible that

$$h\left(\phi^*, r_d\right) = h\left(\phi^{*'}, r_d\right) \quad \text{and} \quad h\left(\phi^*, r_d'\right) = h\left(\phi^{*'}, r_d'\right).$$

The proposition is thus proved. □

The first part of Proposition A4 shows that if the reference point is above the interest rate and we shut down diminishing sensitivity in the loss region, the framework introduced in Assumption A3 unambiguously contributes to reaching for yield. The second part of Proposition A4 shows that if the reference point is below the interest rate and we shut down diminishing sensitivity in the gain region as well as loss aversion, the framework introduced in Assumption A3 also unambiguously contributes to reaching for yield.

Unfortunately, without these further restrictions, analytically it is not clear whether diminishing sensitivity contributes to or works against the reaching for yield behavior documented in Section 2, as discussed above. Therefore, we perform a numerical exercise to evaluate the relative importance of the different terms in Equation (A12) in our setting.

We use the canonical Prospect Theory parameter values (Tversky and Kahneman, 1992; Barberis et al., 2006) to specify the degree of diminishing sensitivity. Specifically, we set $\alpha = \beta = 0.88$ and $\lambda = 2.25$. We start by examining how the diminishing sensitivity component in Assumption A3 influences the response of investment decisions to a small perturbation of the risk-free rate in the low interest rate condition in the benchmark experiment in Section 2 of the main text. In other words, we evaluate the influence of the first two terms in Equation (A12). We assume the mean excess returns $\mathbb{E}x = 5\%$, the volatility of the excess returns $\sqrt{Var\left(x\right)} = 18\%$, and the risk-free rate $r_f = 1\%$, as in our benchmark experiment in Section 2. We use $\phi = 60\%$, roughly matching the level of allocations to the risky assets in the low interest rate condition in the experiment. In Figure A6, we plot the first two terms in Equation (A12) as a function of the reference point r_r, ranging from -10% to 10%. We find that the terms are both positive, that is, diminishing sensitivity above and below the reference point both contribute to reaching for yield for all levels of the reference point.

We also find the loss aversion component in Assumption A3 influences the optimal allocation more than the diminishing sensitivity component. In Figure A7, we consider the same exercise and same parameter values as those in Figure A6. Here we plot the effect of diminishing sensitivity (the sum of the first two terms in Equation (A12)) and the effect of loss aversion (the last term in Equation (A12)), as a function of the reference point r_r. Figure A7 suggests that the loss aversion component has a much larger influence than the diminishing sensitivity component. The comparative static of how allocations to the risky asset move with the risk-free rate is dominated by the loss aversion component. In addition, if we shut down the loss aversion component (i.e. setting $\lambda = 1$ in Assumption A3) and keep the other parameter values the same as in Figures A6 and A7, investors would invest 100% in risky assets.

Figure A6: Impact of Diminishing Sensitivity in Equation (A12), $r_f = 1\%$

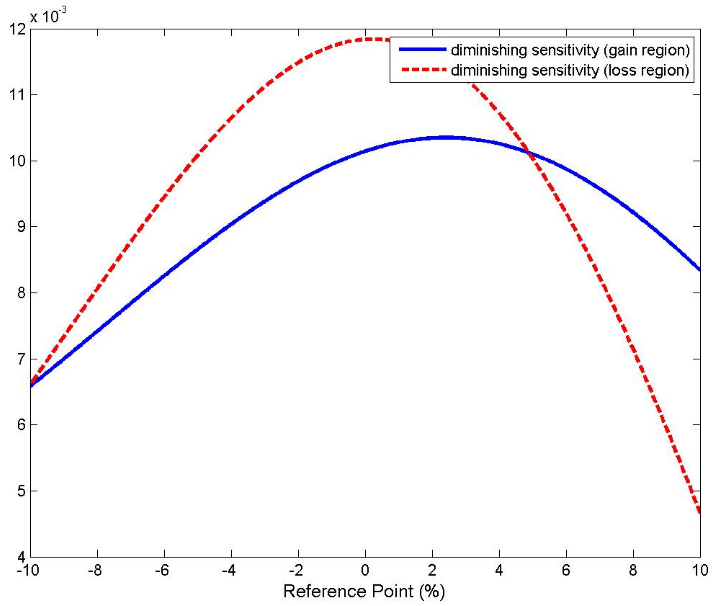
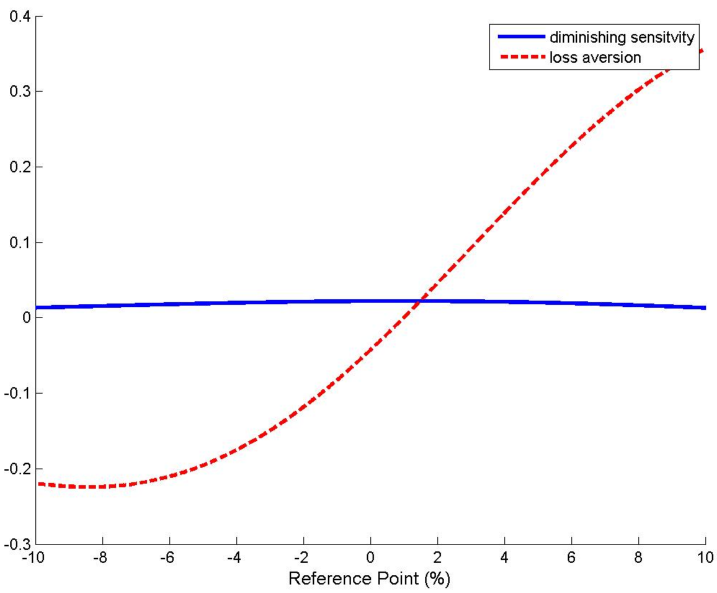


Figure A7: Impact of Diminishing Sensitivity and Loss Aversion in Equation (A12), $r_f = 1\%$



Taken together, diminishing sensitivity may contribute to reaching for yield in our setting, but diminishing sensitivity *alone* may not fully explain the reaching for yield behavior documented in Section 2.

B.3 Reference Point in Expected Returns

Here we provide an alternative formulation of reference dependence. In this formulation, investors experience discomfort when the expected returns of the portfolio are below the reference point. In contrast, in the conventional Prospect Theory formulation discussed in Section 3.2, investors suffer from loss aversion in each state where the realized return is below the reference point. This alternative formulation of reference dependent loss aversion would modify Proposition 2, keeping predictions of reaching for yield, and eliminating predictions of reaching against yield when interest rates are sufficiently high.

Specifically, the investor trades off the expected returns and the variance of the portfolio, like in the mean variance case. The difference with traditional mean variance analysis is here the investor has a reference point about expected returns, and experience discomfort when the expected returns of his portfolio are below the reference point:

$$\phi^*_{mv,r} \triangleq \arg\max_{0\le\phi\le1} v\left(\mathbb{E}r_p, r_r\right) - \frac{\gamma}{2}Var\left(r_p\right), \tag{A15}$$

where

$$v\left(\mathbb{E}r_p, r_r\right) = \begin{cases} \mathbb{E}r_p - r_r & \mathbb{E}r_p \ge r_r \\ -\lambda\left(r_r - \mathbb{E}r_p\right) & \mathbb{E}r_p < r_r \end{cases},$$

r_r is the reference point and $\lambda > 1$ captures the degree of loss aversion.

Proposition A5. *For a given distribution of the excess returns x, the optimal allocation to the risky asset, $\phi^*_{mv,r}$ is (weakly) decreasing in r_f.*

Proof. Let $h\left(\phi\right) = v\left(\mathbb{E}r_p, r_r\right) - \frac{\gamma}{2}Var\left(r_p\right).$ We have

$$\frac{\partial h\left(\phi\right)}{\partial\phi} = \begin{cases} \mathbb{E}x - \gamma\phi Var\left(x\right) & \mathbb{E}r_p > r_r \\ \lambda\mathbb{E}x - \gamma\phi Var\left(x\right) & \mathbb{E}r_p < r_r \end{cases}.$$

As a result,

$$\phi^*_{mv,r} = \begin{cases} \frac{\mathbb{E}x}{\gamma Var(x)} & \frac{(\mathbb{E}x)^2}{\gamma Var(x)} + r_f > r_r \\ \frac{r_r - r_f}{\mathbb{E}x} & \frac{\lambda(\mathbb{E}x)^2}{\gamma Var(x)} + r_f \ge r_r \ge \frac{(\mathbb{E}x)^2}{\gamma Var(x)} + r_f \\ \frac{\lambda\mathbb{E}x}{\gamma Var(x)} & \frac{\lambda(\mathbb{E}x)^2}{\gamma Var(x)} + r_f < r_r \end{cases}.$$

$\phi^*_{mv,r}$ is (weakly) decreasing in r_f. □

B.4 Reference Point Formation

In the following, we discuss in detail the leading theories of reference point formation. We explain why investors' past interest rate experiences appear to be the main contributor to the type of reference dependence that generates reaching for yield under the framework of Section 3.2 and Assumption 1.

1. The reference point is the status quo wealth level (Kahneman and Tversky, 1979), or $r_r = 0$. This captures the notion that people experience "loss" when their final wealth falls below their original wealth level. It turns out that loss aversion around zero *alone* cannot explain the reaching for yield behavior documented in Section 2. This is because when $r_r = 0$, the reference point is below a positive risk-free rate, which falls into the second case of Proposition 2. As a result, loss aversion around zero *alone* can only generate "reaching against yield" in the setting of the benchmark experiment, contrary to the empirical evidence. That said, we are not suggesting that loss aversion at zero does not matter. It is perhaps important for many behavior (e.g. aversion to small risks), but it does not appear to be the key driver of reaching for yield, if not partially offsetting it.

2. The reference point is the risk-free rate (Barberis et al., 2001), or $r_r = r_f$. This suggests that people are disappointed when their final wealth is below the wealth level they would have if they had invested everything in the risk-free assets. This set-up, however, also would not be able to generate reaching for yield behavior.

   Lemma A2. *Under Assumption 1, if $r_r = r_f$, for a given distribution of the excess returns x, the optimal allocation to the risky asset ϕ^* is independent of r_f.*

   Proof. Note that

$$u\left(w\left(1+r_p\right)\right) = \begin{cases} w\left(r_p - r_r\right) = w\phi x & x \geq 0 \\ -\lambda w\left(r_r - r_p\right) = \lambda w \phi x & x < 0 \end{cases}$$

   is independent of r_f. As a result $\phi^* = \arg\max_{\phi\in[0,1]} \mathbb{E}u\left(w\left(1+r_p\right)\right)$ is independent or the risk-free rate r_f. □

   The intuition behind Lemma A2 is that as the risk-free rate r_f changes, returns on the safe asset, returns on the risky asset, and the reference point move in parallel. Accordingly, the trade-offs in the investment decision are essentially unchanged. As a result, the optimal allocation to the risky asset ϕ^* is independent of r_f.

3. The reference point is rational expectations of asset returns in the investment choice set (Kőszegi and Rabin, 2006). In our setting, there are two ways to formalize this type of reference points.

   a). The reference point is given by a weighted average of the risk-free rate and the expected returns of the risky asset. That is, $r_r = (1-\omega)\, r_f + \omega\left(r_f + \mathbb{E}x\right)$, where ω is an *exogenous* weight. This leads to:

   Lemma A3. *Under Assumption 1, if $r_r = (1-\omega)\, r_f + \omega\left(r_f + \mathbb{E}x\right)$, for a given distribution of the excess returns x, the optimal allocation to the risky asset ϕ^* is independent of the risk-free rate r_f.*

Proof. Note that

$$u\left(w\left(1+r_p\right)\right)=\begin{cases} w\left(r_p-r_r\right)=w\left(\phi x-\omega\mathbb{E}x\right) & \phi x\geq\omega\mathbb{E}x \\ -\lambda w\left(r_r-r_p\right)=\lambda w\left(\phi x-\omega\mathbb{E}x\right) & \phi x<\omega\mathbb{E}x \end{cases}$$

is independent of r_f. As a result $\phi^*=\arg\max_{\phi\in[0,1]}\mathbb{E}u\left(w\left(1+r_p\right)\right)$ is independent or r_f. □

The intuition of Lemma A3 is similar to that of Lemma A2: when the risk-free rate r_f changes, returns on the safe asset, returns on the risky asset, and the reference point move in parallel.

b). The reference point is the expected returns of the *optimal* portfolio. That is, $r_r=(1-\phi^*)r_f+\phi^*(r_f+\mathbb{E}x)$, where ϕ^* is the *endogenous* optimal allocation defined in Equation (2). At the same time, the investor's utility in turn depends on r_r (based on Assumption 1). This follows the concept of the personal equilibrium in Kőszegi and Rabin (2006). In other words, the investor's reference point is determined by the optimal allocation, while the optimal allocation in turn depends on the reference point.

Lemma A4. *Under Assumption 1, if $r_r=\left(1-\phi^*\right)r_f+\phi^*\left(r_f+\mathbb{E}x\right)$, for a given distribution of the excess returns x, the optimal allocation to the risky asset ϕ^* is independent of the risk-free rate r_f.*

Proof. Note that

$$u\left(w\left(1+r_p\right)\right)=\begin{cases} w\left(r_p-r_r\right)=w\left(\phi x-\phi^*\mathbb{E}x\right) & \phi x\geq\phi^*\mathbb{E}x \\ -\lambda w\left(r_r-r_p\right)=\lambda w\left(\phi x-\phi^*\mathbb{E}x\right) & \phi x<\phi^*\mathbb{E}x \end{cases} \tag{A16}$$

where ϕ^* solves

$$\phi^*=\arg\max_{\phi\in[0,1]}\mathbb{E}u\left(w\left(1+r_p\right)\right). \tag{A17}$$

Because u in Equation (A16) is independent of r_f, the ϕ^* jointly determined by Equations (A16) and (A17) is independent of r_f. □

The intuition here is similar to the intuition of Lemma A2 and Lemma A3: when the risk-free rate r_f changes, returns on the safe asset, returns on the risky asset, and the reference point move in parallel. This leaves the investment decision unchanged.

4. The reference point is influenced by individuals' past experiences (Kahneman and Miller, 1986; Simonsohn and Loewenstein, 2006; Malmendier and Nagel, 2011; Bordalo et al., 2017). In our setting, one intuition is that people adapt to or anchor on some level of investment returns based on past experiences. When the risk-free rate falls

below the level they are used to, people experience discomfort and become more willing to invest in risky assets. Formally, the reference point is given by a weighted average of the risk-free rate and realized returns of risky assets in the past. That is, $r_r = (1-\omega)\, r_{f,past} + \omega\, (r_{f,past} + x_{past})$, where ω can be either an exogenous weight or a weight that depends on investors' past portfolio choices.[35] Note that ω, $r_{f,past}$, and x_{past} are all predetermined. As a result, this case can be analyzed with Proposition 2. Given the economic environment in the decades prior to the Great Recession, reference points from past experiences appear in line with the popular view among investors that 1% or 0% interest rates are "too low," which predicts reaching for yield behavior.

B.5 Additional Experiments on History Dependence

As mentioned in Section 4.2 of the main text, there are alternative research designs to test the history dependence of reaching for yield. Below we present a design where all participants face the same interest rate environment in the final round, but prior to that, one group starts with an environment with higher interest rates, while another group starts with an environment with lower interest rates.[36] We show results from two settings that follow this design.[37]

The first setting is a hypothetical experiment with three rounds of investment decisions: participants in Group 1 first consider a very high interest rate environment (15% safe returns and 20% average risky returns), then consider a high interest rate environment (13% safe returns and 18% average risky returns), and finally consider a medium interest rate environment (3% safe returns and 8% average risky returns); participants in Group 2 first consider a very low interest rate environment (0% safe returns and 5% average risky returns), then consider a low interest rate environment (1% safe returns and 6% average risky returns), and finally consider a medium interest rate environment (3% safe returns and 8% average risky returns). Our discussant Cary Frydman conducted this experiment on MTurk in November 2016 using our experimental protocol. There are 200 participants in Group 1 and 200 participants in Group 2.

[35] Past returns are calculated as a weighted average of returns over a given horizon; the length of the horizon does not change the mechanism about how past reference point can contribute to the reaching for yield behavior.

[36] One possible concern with the design of Experiment T2 in Section 4.2 is that we find substantially higher risk taking in the low interest rate condition if participants first consider the high interest rate condition, but this could be driven by an order issue: for some reasons, participants take more risks in the second round of investment decision in general. We do not find evidence for this concern in the data. Results in Section 4.2 in the main text and in this section show that risk taking does not increase in general after the first round. It only increases if interest rates fall significantly. The alternative design also verifies that the concern does not affect our results.

[37] In the alternative design, since all participants end in a "medium" interest rate environment, the range of interest rates in the initial round may need to be wider. If we stay within the baseline range of interest rates (e.g. between 1% and 5%), the power could be lower for a given sample size, since the change from the high rate condition in the first round to the medium rate condition in the second round needs to be smaller in order to have everything stay within the range.

The second setting is an incentivized experiment with two rounds of investment decisions: participants in Group 1 first consider a high interest rate environment (5% safe returns and 10% average risky returns), and then consider a medium interest rate environment (2% safe returns and 7% average risky returns); participants in Group 2 first consider a low interest rate environment (1% safe returns and 6% average risky returns), and then consider a medium interest rate environment (2% safe returns and 7% average risky returns). We performed this experiment on MTurk in December 2016. There are again 200 participants in Group 1 and 200 participants in Group 2. We do not perform a hypothetical experiment with the same investment pay-offs, since by this time our previous experiments have used more than 6,000 MTurk workers and our additional experiments are experiencing capacity constraints and lower data quality (Stewart, Ungemach, Harris, Bartels, Newell, Paolacci, and Chandler, 2015).

Table A12 presents the results. In both settings, participants in Group 1 invest more aggressively in the final round than participants in Group 2. The results are consistent with history-based reference dependence discussed in Section 3.2.[38]

B.6 Salience and Related Models

In this section, we elaborate several issues about salience and related models.

Salience of Attributes vs. Salience of States

First, we discuss the relationship between the salience theory applied in Section 3.3 (which follows Bordalo et al. (2013b, 2016) and adapts this framework to portfolio allocations), and several related ways of modeling salience. Specifically, we discuss the relationship between our formulation and Bordalo et al. (2012) and Bordalo et al. (2013a), which use a different formulation of the salience theory in the context of choice under risk.

The key difference between these two seemingly similar approaches is the following. In the first approach (Bordalo et al., 2013b, 2016), the investor's optimization problem represents the optimal portfolio problem based on the portfolio's average returns and variance (like in the case of conventional mean variance analysis), and he overweights the dimension (average returns or variance) that is salient. In the second approach (Bordalo et al., 2012, 2013a), the investor considers the pay-off of an asset *state by state*, and overweights the states in which the pay-offs of different assets differ by more (these are salient states).

It seems plausible that the first approach is a better approximation of investor behavior, as investors do not necessarily have a clear mental representation of all possible economic states when making investment decisions. In fact, the second approach generates predictions of reaching against yield, which is contrary to the findings we document in Section 2. The intuition is that people focus on downside risks more than upside risks. As interest rates fall, holding the distribution of the excess returns fixed, there is a downward shift in the

[38]In addition, we also see verification of the baseline reaching for yield phenomenon: participants allocate less to the risky asset when interest rates are high, both within and across treatment groups.

returns of all assets in all states, which makes the downside risk more salient.[39] Our findings provide some evidence for the way salience operates in the context of investment decisions and choice under risk, and may help to guide related models.

Discrete vs. Continuous Choices

Second, we note that in the models of Bordalo et al. (2013b) and Bordalo et al. (2016), the decision problem is a discrete choice problem. In the portfolio choice problem we consider in Section 3.3, however, the decision is continuous. Our set-up makes the following departure from Bordalo et al. (2013b) to streamline the investor's decision problem. In Bordalo et al. (2013b), the salience of an attribute is choice-specific. Accordingly, the relative salience of the return dimension will be different for different portfolios. In other words, a strict adherence to such a choice-specific salience function requires the relative salience of the return dimension in Equation (5), δ, to be a function of the asset allocation in the portfolio, ϕ. When the choice variable is continuous, this approach could become quite cumbersome. Instead, in our formulation (Assumption 2) δ is a function of the properties of assets in the underlying choice set, independent of portfolio allocation ϕ. We use this formulation as a parsimonious way to capture the idea that when interest rates are low and the ratio of the expected returns of the two assets is high, the expected return dimension becomes more salient. Fernandes (2016) also shows that the salience function should depend on the properties of the available assets and be independent of the portfolio allocation.

"Salience" and Proportional Thinking

Third, we discuss the subtle difference between the notion of salience defined in Bordalo et al. (2013b) and the intuition of proportional thinking in our setting. Bordalo et al. (2013b) emphasize that choices have different attributes/dimensions (return vs. risk, price vs. quality); one dimension could be more salient than another (depending on which dimension has larger proportional difference) and decision makers pay more attention to the salient dimension. Specifically, the *expected return dimension* of the *portfolio*, $\mathbb{E}r_p$, is more salient when interest rates are lower, because low interest rates make the proportional difference in the expected return dimension larger. The intuition of proportional thinking, in its simplest form, does not depend on the relative importance of the two dimensions in a decision-maker's mind. Rather, investors' evaluation of the attractiveness of the risky asset is influenced by the ratio of average returns: investors perceive the risky asset to be better when the ratio is high. 6% average (risky) returns jump out as a more preferable alternative compared to 1% safe returns; 10% average (risky) returns appear as a less preferable alternative compared to 5% safe returns. When the intuition is framed this way, it is not that the dimension of the average portfolio returns is more salient, but that the risky asset's pay-offs are more salient/attractive.

In application, this distinction seems quite subtle and not very important. Because the

[39]For example, in Equation (3) of Bordalo et al. (2013a), a decrease in the risk-free rate tends to make the state in which the risky asset performs poorly more salient.

relative importance of the return dimension according to the salience function a la Bordalo et al. (2013b) is essentially driven by the ratio of the average returns (and the ratio of the risks, which are kept fixed in our experiments), the investor's optimal portfolio choice problem is essentially the same with both interpretations. Equation (5) in the main text nests both interpretations. δ in Equation (5) can be interpreted both as the salience of the return dimension (relative to the risk dimension), and as a way to effectively link the attractiveness of the risky asset to the ratio of average returns. In the main text, we use the most straightforward explanations to explain the intuition behind investor behavior, and do not draw distinctions between the notion of salience and proportional thinking.

"Relative Thinking" (Bushong et al., 2016) and "Focusing" (Kőszegi and Szeidl, 2013)

Finally, we discuss models of "relative thinking" (Bushong et al., 2016) and "focusing" (Kőszegi and Szeidl, 2013). Both models study how the range/variability of each dimension of choices affects people's perception and decision-making.

Bushong et al. (2016) study the idea that a given absolute difference appears small when outcomes in that dimension exhibit greater variability in the choice set. For instance, an example in Bushong et al. (2016) is that "in searching for flights, spending extra for convenience feels bigger when the range of flight prices is \$250 to \$450 than when the range is \$200 to \$800." On the other hand, Kőszegi and Szeidl (2013) study the idea that people pay more attention to attributes that have greater variability. For instance, an example in Kőszegi and Szeidl (2013) is that students' perceived happiness across different (randomly assigned) dorms "depends greatly on features (e.g. location) that vary a lot between dorms, not on features (e.g. social life) that vary little between dorms—whereas actual happiness does not show the same pattern." In some ways, Bushong et al. (2016) and Kőszegi and Szeidl (2013) are the opposite of each other: Kőszegi and Szeidl (2013) predict over-weighting attributes that have more variability/wider range, while Bushong et al. (2016) suggest that wider range can lead to under-weighting. Bushong et al. (2016) provide a more detailed discussion about the relationship and differences between the two models (specifically, Kőszegi and Szeidl (2013) may be most relevant when there are many dimensions, while Bushong et al. (2016) apply when there are two or three dimensions).

In our setting, in each interest rate condition, the range of the assets' payoffs is held fixed, given that the excess returns of the risky asset are always the same. The variability of returns and the variability of risks are identical in each condition. Thus these range-based theories do not directly explain the differences in investment decisions across the interest rate conditions that we find.

B.7 Inflation

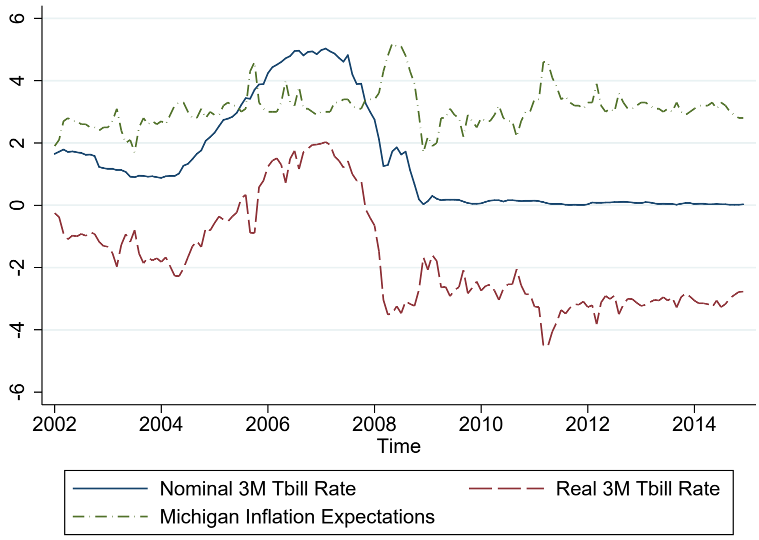
In this section, we discuss the role of inflation for understanding reaching for yield behavior.

First, in our randomized experiments, we study how investment allocations change with respect to interest rates, holding constant inflation.[40] Participants in all treatment conditions face the same inflation environment; different treatment conditions lead to differences in both nominal and real returns. In this setting, the predictions for reaching for yield follow exactly from Section 3.

In recent years in the US, inflation and inflation expectations have stayed relatively stable, and both nominal and real interest rates declined as shown in Figure A8 below. This maps closely into the setting above.

Figure A8: Nominal and Real Interest Rates in the US

The solid blue line shows the nominal 3-month Treasury bill rate. The red dashed line shows the real 3-month Treasury bill rate (nominal rate minus expected inflation). The green dash-dot line shows inflation expectations from the Michigan survey.



Then, we discuss two main questions related to inflation outside of our experiments. We explain how to understand these situations in the conventional portfolio choice framework in Section 3.1, the reference dependence mechanism in Section 3.2, and the salience/proportional thinking framework in Section 3.3. The results from observational data in Section 5 may shed some light on these questions.

1. For given nominal interest rates (nominal returns), does it matter whether they come from inflation expectations or real interest rates (real returns)?

   For example, consider 5% interest rates and 10% average returns on the risky asset. Does it matter if this is coming from, for instance, a) 5% and 10% real returns respectively and 0% expected inflation vs. b) 1% and 6% real returns respectively and 4% expected inflation?[41]

[40] In the demographics section, we also ask participants their inflation expectations, which are very similar across different treatment conditions, at about 3%.

[41] An equivalent question is: For fixed nominal interest rates (nominal returns), does it matter whether an investor has higher inflation expectations? For example, consider 5% interest rates and 10% average returns on the risky asset. Does it matter if one particular investor has 0% inflation expectation or 4% inflation expectation?

2. For fixed real interest rates (real returns), do inflation expectations matter?

   For example, consider 1% real interest rates and 6% average real returns on the risky asset. Does it matter if a) inflation expectation is 0% (and the nominal interest rates and nominal returns are 1% and 6% respectively) versus b) 4% (and the nominal interest rates and nominal returns are 5% and 10% respectively)?

Conventional Portfolio Choice (Section 3.1)

Consider the textbook mean-variance analysis: the allocations depend on the Sharpe ratio of the risky asset, pinned down by the excess returns. Holding fixed the excess returns of the risky asset, inflation does not make a difference in the two questions above, where the Sharpe ratio of the risky asset is always the same in all the scenarios.

In the more general case without mean-variance approximations, higher real interest rates generate a higher-order wealth effects, which can lead to higher allocations in the risky asset (with decreasing absolute risk aversion). Thus for Question 1, if the higher interest rates (higher returns) are coming from higher real interest rates as in scenario a), there would be *reaching against yield* effect; if the higher interest rates (higher returns) are coming from higher expected inflation as in scenario b), then things are the same in real terms and portfolio allocations are the same. For Questions 2, scenarios a) and b) would be the same.

Reference Dependence (Section 3.2)

Here we consider the region where reference dependence predicts reaching for yield (i.e. interest rates lower than reference point).

For Question 1:

- If reference points are about nominal returns, then scenarios a) and b) are the same, given that nominal returns are the same in both scenarios.
- If reference points are about real returns, then scenarios a) and b) are different. Holding nominal returns the same, when the real returns are higher (scenario a) allocations to the risky asset would be lower.

For Question 2:

- If reference points are about nominal returns, then scenarios a) and b) are different. Holding real returns the same, when the nominal returns are higher (scenario b) allocations to the risky asset would be lower.
- If reference points are about real returns, then scenarios a) and b) are the same.

Salience and Proportional Thinking (Section 3.3)

For Question 1:

- If salience/proportional thinking is based on nominal returns, then scenarios a) and b) are the same.

- If salience/proportional thinking is based on real returns, then scenarios a) and b) are different. Holding nominal returns the same, when the real returns are higher (scenario a) allocations to the risky asset would be lower.

For Question 2:

- If salience/proportional thinking is based on nominal returns, then scenarios a) and b) are different. Holding real returns the same, when the nominal returns are higher (scenario b) allocations to the risky asset would be lower.

- If salience/proportional thinking is based on real returns, then scenarios a) and b) are the same.

Based on the observational data in Section 5, we find that changes in nominal interest rates appear to have a stronger impact on investment allocations than changes in real interest rates, which suggests that reference dependence or salience/proportional thinking could be more about nominal returns in the US data.

Finally, another question is: all else equal, does past inflation play a role?

For example, consider 5% interest rates and 10% average returns on the risky asset. Does it matter if a) past inflation was 5% versus b) 2%?

Here scenarios a) and b) do not make a difference for conventional portfolio choice and salience/proportional thinking. For history-dependent reference points:

- If reference points are about nominal returns, then scenarios a) and b) can be different. Higher past inflation may lead to higher reference point.

- If reference points are about real returns, then scenarios a) and b) are the same.

C Additional Tables and Figures

C.1 Additional Experimental Results

Table A9: Subsample Results in Benchmark Experiments

This table shows the regression coefficient β in

$$Y_i = \alpha + \beta Low_i + X_i'\gamma + \epsilon_i$$

for subsamples in the benchmark experiments, where Y_i is the allocation to the risky asset, and Low_i is an indicator variable that takes value one if the participant is in the low interest rate condition. The regression is estimated for each subsample; β, the associated t-statistics, and the number of participants in the subsample are reported. Controls are the same as in Table 2 in the paper, except that variables are dropped from the controls when they are used to split the sample. We did not include wealth in the MBA survey because it could be a sensitive question.

Panel A. Experiment B1: MTurk, Hypothetical

	Wealth			Investment Experience		Education	
	Below 10K	10K to 100K	100K+	Some or Extensive	No or Limited	College or above	High School
β	3.43	8.40	12.90	12.54	5.27	5.79	13.48
$[t]$	[0.79]	[1.92]	[1.87]	[2.47]	[1.53]	[1.80]	[2.23]
N	161	170	69	134	266	298	102

Panel B. Experiment B2: MTurk, Incentivized

	Wealth			Investment Experience		Education	
	Below 10K	10K to 100K	100K+	Some or Extensive	No or Limited	College or above	High School
β	5.55	7.55	13.90	5.78	8.66	8.89	3.66
$[t]$	[1.22]	[2.04]	[2.47]	[1.36]	[2.70]	[3.11]	[0.65]
N	133	175	92	146	254	310	90

Panel C. Experiment B3: MBA, Incentivized

	Investment Experience		Worked in Finance	
	Some or Extensive	No or Limited	Yes	No
β	10.56	7.31	10.02	7.66
$[t]$	[2.57]	[1.96]	[2.47]	[2.06]
N	178	222	170	230

Table A10: Robustness Checks of Benchmark Experiments

This table presents results in the benchmark incentivized experiment with different payment methods. This set of experiments are conducted on MTurk together and participants are randomly assigned to different payment methods and different interest rate conditions. In all cases, participants consider allocating experimental endowment of 100,000 Francs to the risk-free asset and the risky asset. "Proportional" refers to the setting where all participants receive a bonus payment proportional to their investment outcomes, with every 89,500 Francs converted to one dollar (so the bonus payment is on the scale of $1.2). "Randomized" refers to the setting where 10% randomly chosen participants receive a bonus payment proportional to their investment outcomes, with every 8,950 Francs converted to one dollar (so the bonus payment is on the scale of $12). In the "immediate" payment conditions, the bonus payment is delivered within one week of the experiment. In the "one year" payment conditions, the bonus payment is delivered one year after the experiment. Panel A shows mean allocations to the risky asset in the high and low interest rate conditions, the difference in mean allocations across the two conditions, and the t-statistics associated with the test that the difference is different from zero. The final column also shows the p-value from the Mann-Whitney-Wilcoxon test, against the null that allocations in the high and low interest rate conditions are the same. Panel B presents the mean difference in allocations controlling for individual characteristics, both through OLS and through propensity score matching (ATE). The individual characteristics include dummies for gender, education level, age group, risk tolerance, investment experience, and wealth level.

Panel A. Mean Allocations to Risky Asset (%)

	High: 5—10	Low: 1—6	**Dif** (Raw)	[t]	U test (p)
Proportional, immediate	59.20	66.68	7.48	[2.64]	(0.00)
Proportional, one year	60.63	67.79	7.16	[2.43]	(0.01)
Randomized, immediate	58.07	66.80	8.73	[3.13]	(0.00)
Randomized, one year	58.58	66.64	8.06	[3.06]	(0.00)

Panel B. Differences Controlling for Individual Characteristics

Payment scheme	**Dif** (OLS)	[t]	**Dif** (Match)	[t]
Proportional, immediate	6.75	[2.43]	7.94	[2.79]
Proportional, one year	7.27	[2.56]	6.22	[1.99]
Randomized, immediate	8.40	[3.12]	9.00	[3.18]
Randomized, one year	8.14	[3.23]	8.66	[2.81]

Table A11: Experimental Decisions and Household Portfolio Allocations

Cross-sectional regression:

$$y_i = \alpha + \beta x_i + \epsilon_t$$

where y_i is the allocation to the risky asset in the incentivized experimental decision, and x_i is the fraction of the participant's household financial wealth in bank deposits (the stock market), as reported by the participant. Columns (1) and (2) present results in the sample of Experiment B2 (MTurk, Incentivized), and columns (3) and (4) present results in the sample of Experiment B3 (MBA, Incentivized).

	% in Risky (Experimental Decision)			
	MTurk		MBA	
% Asset in bank deposits	-0.12		-0.13	
	[-3.02]		[-3.29]	
% Asset in stocks		0.12		0.10
		[2.69]		[2.52]

Robust t-statistics in brackets

Table A12: Additional Results on History Dependence

This table presents results of additional experiments on history dependence. Panel A shows results from a hypothetical experiment: half of the participants are randomly assigned to Group 1, where they first consider a very high interest rate environment (15% safe returns and 20% average risky returns), then consider a high interest rate environment (13% safe returns and 18% average risky returns), and finally consider a medium interest rate environment (3% safe returns and 8% average risky returns); the other half of the participants are assigned to Group 2, where they first consider a very low interest rate environment (0% safe returns and 5% average risky returns), then consider a low interest rate environment (1% safe returns and 6% average risky returns), and finally consider a medium interest rate environment (3% safe returns and 8% average risky returns). Panel B shows results from a hypothetical experiment: half of the participants are randomly assigned to Group 1, where they first consider a high interest rate environment (5% safe returns and 10% average risky returns), and then consider a medium interest rate environment (2% safe returns and 7% average risky returns); the other half of the participants are assigned to Group 2, where they first consider a low interest rate environment (1% safe returns and 6% average risky returns), and then consider a medium interest rate environment (2% safe returns and 7% average risky returns).

Panel A. Setting 1 (Hypothetical Experiment)

G1	Very High: 15—20	High: 13—18	Medium: 3—8
Mean Alloc. to Risky	37.74	38.43	60.29
G2	Very Low: 0—5	Low: 1—6	Medium: 3—8
Mean Alloc. to Risky	61.57	57.41	49.80
G1 (Med) - G2 (Med)	Difference	[t]	
	10.49	[3.35]	

Panel B. Setting 2 (Incentivized Experiment)

G1	High: 5—10	Medium: 2—7
Mean Alloc. to Risky	59.73	66.68
G2	Low: 1—6	Medium: 2—7
Mean Alloc. to Risky	64.68	62.14
G1 (Med) - G2 (Med)	Difference	[t]
	4.54	[1.66]

Table A13: Baseline and Net Framing

This table examines the robustness of reaching for yield with net framing. Panel A shows mean allocations to the risky asset in the high and low interest rate conditions, the difference in mean allocations between the two conditions, and the t-statistics associated with the test that the difference is different from zero. Panel B presents the coefficient and t-statistics on the dummy of low returns condition, controlling for individual characteristics. The individual characteristics include dummies for gender, education level, age group, risk aversion, and household financial wealth.

Panel A. Mean Allocations to Risky Asset (%)

	High: 5—10	Low: 1—6	Difference	[t]	U test (p)
Baseline	57.13	64.51	7.38	[2.69]	(0.00)
Net	51.46	58.55	7.08	[2.53]	(0.01)

Panel B. Differences Controlling for Individual Characteristics

	Dif (OLS)	[t]	Dif (Match)	[t]
Baseline	5.90	[2.62]	6.76	[2.47]
Net	6.35	[2.22]	5.71	[1.98]

Discussion of Table A13: In our data, the degree of reaching for yield is about the same with baseline framing and with net framing. The level of allocations to the risky asset is lower with net framing. This could be because net framing makes losing money more salient and decreases the general risk taking propensity.

Table A14: Demographic Information of Experiment T1 (Mapping Gradient) Sample

This table presents the demographics of Experiment T1. The first row denotes the risk-free rate in different conditions; the mean excess returns of the risky asset is 5% in all conditions. The statistics are the same as those in Table 1.

	Condition: $r_f =$	-1%		0%		1%		3%		5%		10%		15%	
		N	%	N	%	N	%	N	%	N	%	N	%	N	%
Gender	Male	99	49.5	84	42.0	89	45.6	97	48.5	92	46.0	95	47.7	101	50.5
	Female	101	50.5	116	58.0	106	54.4	103	51.5	108	54.0	104	52.3	99	49.5
Education	Graduate school	32	16.0	37	18.5	30	15.4	37	18.5	34	17.0	36	18.1	32	16.0
	College	111	55.5	118	59.0	119	61.0	119	59.5	111	55.5	114	57.3	121	60.5
	High school	50	25.0	40	20.0	43	22.1	41	20.5	52	26.0	42	21.1	45	22.5
Age	Below 30	85	42.5	82	41.0	87	44.6	80	40.0	96	48.0	85	42.7	98	49.0
	30—40	59	29.5	69	34.5	66	33.9	64	32.0	51	25.5	53	26.6	57	28.5
	40—50	25	12.5	26	13.0	25	12.8	36	18.0	27	13.5	34	17.1	26	13.0
	Above 50	31	15.5	23	11.5	17	8.7	20	10.0	26	13.0	27	13.6	19	9.5
Risk tolerance	Low	115	57.5	91	45.5	98	50.3	89	44.5	101	50.5	109	54.8	97	48.5
	Medium	49	24.5	76	38.0	58	29.7	71	35.5	67	33.5	61	30.7	64	32.0
	High	36	18.0	33	16.5	39	20.0	40	20.0	32	16.0	29	14.6	39	19.5
Fin. wealth (ex. housing)	200K+	17	8.5	19	9.5	17	8.7	17	8.5	16	8.0	24	12.1	18	9.0
	50K–200K	43	21.5	52	26.0	45	23.1	59	29.5	35	17.5	50	25.1	40	20.0
	10K–50K	59	29.5	56	28.0	68	34.9	55	27.5	49	24.5	47	23.6	59	29.5
	0–10K	51	25.5	40	20.0	43	22.1	48	24.0	69	34.5	52	26.1	54	27.0
	In debt	30	15.0	33	16.5	22	11.3	21	10.5	31	15.5	26	13.1	30	15.0
Investing experience	Extensive	11	5.5	6	3.0	6	3.1	9	4.5	4	2.0	9	4.5	9	4.5
	Some	52	26.0	66	33.0	48	24.6	62	31.0	61	30.5	72	36.2	48	24.0
	Limited	84	42.0	92	46.0	90	46.2	82	41.0	85	42.5	83	41.7	86	43.0
	No	53	26.5	36	18.0	51	26.2	47	23.5	50	25.0	35	17.6	57	28.5
Total		200		200		195		200		200		199		200	

Table A15: Demographic Information of Experiment T2 (History Dependence) Sample

This table presents the demographics of Experiment T2. Participants in Group 1 first make investment decisions in the high interest rate condition (5% risk-free rate and 10% average returns on the risky asset), and then make decisions in the low interest rate condition (1% risk-free rate and 6% average returns on the risky asset). Participants in Group 2 first make investment decisions in the low rate condition, and then make decisions in the high rate condition. The statistics are the same as those in Table 1.

Panel A. Hypothetical

		Group 1		Group 2	
		N	%	*N*	%
Gender	Male	105	51.7	95	48.2
	Female	98	48.3	102	51.8
Education	Graduate school	31	15.4	40	20.5
	College	114	56.7	107	54.9
	High school	56	27.9	48	24.6
Age	Below 30	85	41.9	77	39.1
	30—40	54	26.6	51	25.9
	40—50	18	8.9	27	13.7
	Above 50	46	22.7	42	21.3
Risk tolerance	Low	106	52.2	121	61.4
	Medium	68	33.5	50	25.4
	High	29	14.3	26	13.2
Fin. wealth (ex. housing)	200K+	16	7.9	17	8.6
	50K–200K	31	15.3	74	37.6
	10K–50K	66	32.5	46	23.4
	0–10K	51	25.1	36	18.3
	In debt	39	19.2	24	12.2
Investing experience	Extensive	8	3.9	4	3.6
	Some	52	25.6	52	26.4
	Limited	77	37.9	73	37.1
	No	66	32.5	65	33.0
Total		203		197	

Panel B. Incentivized

		Group 1		Group 2	
		N	%	*N*	%
Gender	Male	107	53.5	89	45.6
	Female	93	46.5	106	54.4
Education	Graduate school	30	15.0	34	17.4
	College	102	51.0	108	55.4
	High school	61	30.5	50	25.6
Age	Below 30	95	47.5	79	40.5
	30—40	60	30.0	69	35.4
	40—50	27	13.5	26	13.3
	Above 50	18	9.0	21	10.8
Risk tolerance	Low	106	53.0	112	57.4
	Medium	54	27.0	52	26.7
	High	40	20.0	31	15.9
Fin. wealth (ex. housing)	200K+	12	6.0	14	7.2
	50K–200K	61	30.5	54	27.7
	10K–50K	45	22.5	52	26.7
	0–10K	45	22.5	42	21.5
	In debt	37	18.5	33	16.9
Investing experience	Extensive	9	4.5	2	1.0
	Some	44	22.0	61	31.3
	Limited	91	45.5	76	39.0
	No	56	28.0	56	28.7
Total		200		195	

Table A16: Demographic Information of Experiment T3 (Salience and Proportional Thinking) Sample

This table presents the demographics of Experiment T3. In the Low condition, the risk-free rate is 1%; in the High condition, the risk-free rate is 5%. The mean excess returns of the risky asset is 5% in both conditions. The statistics are the same as those in Table 1.

		Baseline				Gross				Net			
		Low		High		Low		High		Low		High	
		N	%	N	%	N	%	N	%	N	%	N	%
Gender	Male	89	45.6	92	46.0	88	43.6	94	47.5	85	42.1	84	43.5
	Female	106	54.4	108	54.0	114	56.4	104	52.5	117	57.9	109	56.5
Education	Graduate school	30	15.4	34	17.0	40	19.8	28	14.1	31	15.3	33	17.1
	College	119	61.0	111	55.5	115	56.9	122	61.6	114	56.4	112	58.0
	High school	43	22.1	52	26.0	43	21.3	45	22.7	54	26.7	42	21.8
Age	Below 30	87	44.6	96	48.0	93	46.0	89	45.0	72	35.6	92	47.7
	30—40	66	33.9	51	25.5	52	25.7	62	31.3	69	34.2	61	31.6
	40—50	25	12.8	27	13.5	28	13.9	27	13.6	30	14.9	22	11.4
	Above 50	17	8.7	26	13.0	29	14.4	20	10.1	31	15.4	18	9.3
Risk tolerance	Low	98	50.3	101	50.5	98	48.5	100	50.5	109	54.0	112	58.0
	Medium	58	29.7	67	33.5	75	37.1	58	29.3	56	27.7	47	24.4
	High	39	20.0	32	16.0	29	14.4	40	20.2	37	18.3	34	17.6
Fin. wealth (ex. housing)	200K+	17	8.7	16	8.0	26	12.9	16	8.1	15	7.4	17	8.8
	50K–200K	45	23.1	35	17.5	53	26.2	46	23.2	57	28.2	36	18.7
	10K–50K	68	34.9	49	24.5	55	27.2	56	28.3	50	24.8	53	27.5
	0–10K	43	22.1	69	34.5	46	22.8	52	26.3	47	23.3	57	29.5
	In debt	22	11.3	31	15.5	22	10.9	28	14.1	33	16.3	30	15.5
Investing experience	Extensive	6	3.1	4	2.0	5	2.5	4	2.0	6	3.0	8	4.1
	Some	48	24.6	61	30.5	79	39.1	83	41.9	53	26.2	55	28.5
	Limited	90	46.2	85	42.5	77	38.1	57	28.8	95	47.0	73	37.8
	No	51	26.2	50	25.0	41	20.3	54	27.3	48	23.8	57	29.5
Total		195		200		202		198		202		193	

C.2 Dutch Replication

The findings in the US are replicated in the Netherlands by the Dutch Authority for the Financial Markets (AFM) in August 2017. The AFM identified "search for yield" as one of the top 10 risks in its 2017 supervisory agenda. The regulators want to better understand how risk appetite may shift in low and negative interest rate environments. For more information about the Dutch AFM, see the joint VOX post with Wilte Zijlstra who led the AFM replication (https://voxeu.org/article/new-take-low-interest-rates-and-risk-taking).

The AFM conducted the experiment among 901 Dutch households, drawn from an online AFM consumer panel. Participants are randomly assigned into conditions with interest rates from -1% to 10% (holding fixed the excess returns of the risky asset and 5% risk premium as in Section 2 and Section 4). The Dutch experiments used the hypothetical version of our protocol, translated into Dutch. Respondents do not receive financial payments, but do have high response rates (>50%).

Table A17 shows the overall demographics of the Dutch sample. The AFM consumer panel tilts toward the elderly, and 58% are 60 years old or above. Participants are predominantly male. They are well-educated and financially well-off, and most have some investment experience.

Figure A9 and Table A18 show the results in the Dutch sample (red diamonds). There is again significant reaching for yield and substantial non-linearity. The reaching for yield effect seems slightly higher in the Dutch sample: for example, the difference in mean allocations between the 1% interest rate condition and the 5% interest rate condition is 10.16 percentage points in the Dutch sample, compared to around 8 percentage points in the US sample shown in Table 2.

Table A17: Demographics of the Dutch Sample

This table presents the demographics of the Dutch AFM sample. The experiment was run in August 2017 by the AFM.

		N	%
Gender	Male	754	83.7
	Female	147	16.3
Education	High	530	66.4
	Medium	212	26.6
	Low	56	7.0
Age	Below 40	44	4.9
	40-50	132	14.7
	50-60	202	22.4
	60-70	339	37.6
	Above 70	184	20.4
Risk Tolerance	High	303	33.6
	Middle	233	25.9
	Low	365	40.5
Financial wealth (ex. housing, €)	150K+	218	27.3
	50K-150K	161	20.2
	10K-50K	170	21.3
	<10K	123	15.4
	N/A	126	15.8
Investing experience	Extensive	194	21.5
	Some	264	29.3
	Limited	207	23.0
	No	236	26.2
Total		901	

Figure A9: Mean Allocations Across Interest Rate Conditions: Dutch Sample

Mean allocations to the risky asset across various interest rate conditions in the Dutch sample. Each condition has around 150 participants. The x-axis shows the risk-free rate in each condition. The mean excess returns on the risky asset is 5% in all conditions. The y-axis is the mean allocation to the risky asset. The vertical bar shows the 95% confidence interval for the mean allocation.

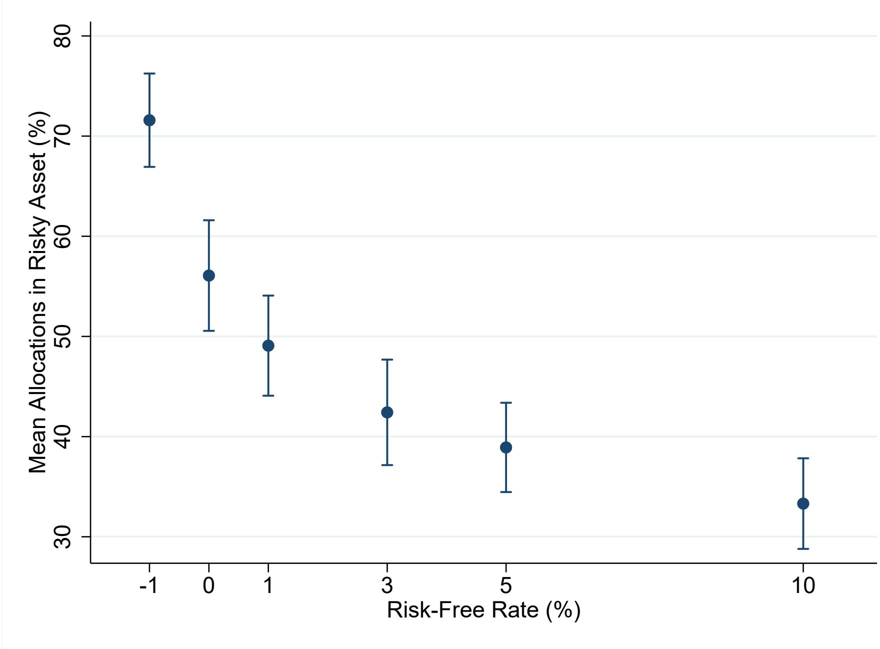


Table A18: Mean Allocations Across Interest Rate Conditions: Dutch Sample

Mean allocations to the risky asset across various interest rate conditions in the Dutch sample. Each condition has around 150 participants. Each column presents results for one condition. The first two rows show the properties of the investments in a given condition: the first row is the returns on the safe asset; the second row is the mean returns on the risky asset. The excess returns of the risky asset are the same in all conditions. The third row shows mean allocations to the risky asset in each condition, and the fourth row shows the 95% confidence interval.

Risk-Free Rate	-1%	0%	1%
Mean Returns of Risky Asset	4%	5%	6%
Mean Allocations to Risky Asset (%)	71.59	56.08	49.08
95% CI	(66.93, 76.25)	(50.56, 61.60)	(44.08, 54.08)

Risk-Free Rate	3%	5%	10%
Mean Returns of Risky Asset	8%	10%	15%
Mean Allocations to Risky Asset (%)	42.42	38.92	33.31
95% CI	(37.15, 47.69)	(34.46, 43.38)	(28.79, 37.84)

C.3 Additional Results in Observational Data

C.3.1 Interest Rates and Household Investment Allocations

Table A19: Interest Rates and AAII Portfolio Allocations: Specification in Changes

Monthly time series regressions:

$$\Delta Y_t = \alpha + \beta \Delta r_{f,t-1} + X'_{t-1}\gamma + \epsilon_t$$

where r_f is 3-month Treasury rate; X includes P/E10 in column (2), the surplus consumption ratio in column (3), and predicted next 12-month excess stock returns in column (4) (estimated using the surplus consumption ratio and past 12-month excess stock returns), as well as AAII stock market sentiment, VIX^2, real GDP growth in the past four quarters, and the credit spread. Y is mean allocations to stocks in Panel A and mean allocations to "cash" in Panel B. All regressions include four lags of the outcome variable. Monthly from November 1987 to December 2014. Standard errors are Newey-West, using the automatic bandwidth selection procedure of Newey and West (1994).

Panel A. Interest Rates and Mean Allocations to Stocks

	Change in Mean Allocations to Stocks			
	(1)	(2)	(3)	(4)
L.D.r_f	-1.48	-1.36	-1.32	-1.87
	[-1.74]	[-1.46]	[-1.43]	[-1.92]
Controls	No	Yes	Yes	Yes
Observations	320	320	320	320

Newey-West t-statistics in brackets

Panel B. Interest Rates and Mean Allocations to "Cash"

	Change in Mean Allocations to "Cash"			
	(1)	(2)	(3)	(4)
L.D.r_f	1.64	1.48	1.43	1.66
	[2.12]	[1.72]	[1.38]	[1.73]
Controls	No	Yes	Yes	Yes
Observations	320	320	320	320

Newey-West t-statistics in brackets

Table A20: Interest Rates and Investment Allocations: Results with Monetary Policy Shocks

Time series regressions:

$$\Delta Y_t = \alpha + \beta r_{s,t} + X'_{t-1}\gamma + \epsilon_t$$

where r_s is a measure of monetary policy shock, following Romer and Romer (2004) and Gertler and Karadi (2015) (current month Fed Funds futures). In Panels A to D, the regressions are monthly, and the outcome variables are respectively changes in mean allocations to stocks and cash from AAII, and flows into equity and high yield corporate bond mutual funds (normalized by net asset value) respectively. In Panels E and F, the regressions are quarterly, and the outcome variables are respectively household sector flows into stocks and interest-bearing safe assets (normalized by household financial assets). The outcome variables are the same as those in Table A19 and Table 8, and the same controls X are used in each case. The Romer-Romer shocks end in December 2007; the Gertler-Karadi shocks end in June 2012. Standard errors are Newey-West, using the automatic bandwidth selection procedure of Newey and West (1994).

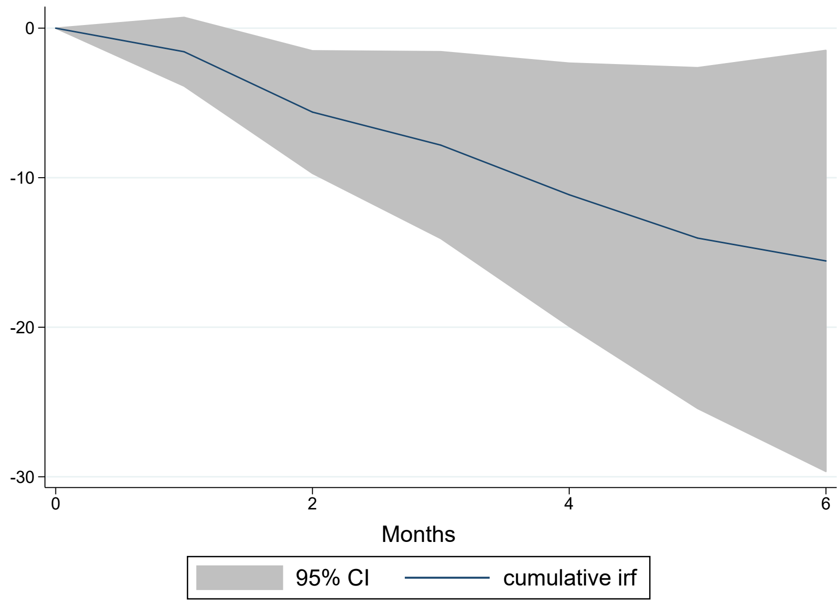
Panel A. Change in Mean Allocations to Stocks (AAII)								
Romer-Romer	-3.89	-4.48	-4.24	-5.05				
	[-2.82]	[-2.89]	[-2.77]	[-3.12]				
Gertler-Karadi					-3.52	-2.73	-2.87	-3.66
					[-1.06]	[-0.80]	[-0.83]	[-1.03]
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	235	235	235	235	284	284	284	284
Panel B. Change in Mean Allocations to "Cash" (AAII)								
Romer-Romer	2.89	3.26	3.11	3.64				
	[2.30]	[2.34]	[2.22]	[2.52]				
Gertler-Karadi					1.40	0.80	0.87	1.35
					[0.45]	[0.25]	[0.27]	[0.40]
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	235	235	235	235	284	284	284	284
Panel C. Equity Mutual Fund Flows (ICI)								
Romer-Romer	-0.05	-0.13	-0.25	-0.56				
	[-0.22]	[-0.56]	[-1.18]	[-1.60]				
Gertler-Karadi					-1.29	-1.30	-1.32	-1.52
					[-2.71]	[-2.80]	[-2.75]	[-2.97]
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	276	244	244	244	284	284	284	284
Panel D. High Yield Corp. Bond Mutual Fund Flows (ICI)								
Romer-Romer	-1.40	-1.22	-1.19	-1.34				
	[-2.25]	[-1.90]	[-1.83]	[-1.44]				
Gertler-Karadi					-2.61	-2.40	-2.58	-2.53
					[-1.51]	[-1.40]	[-1.51]	[-1.52]
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	276	276	276	276	284	284	284	284
Panel E. Household Flows into Stocks (FoF)								
Romer-Romer	-0.23	-0.32	-0.02	-0.61				
	[-0.84]	[-1.07]	[-0.09]	[-1.23]				
Gertler-Karadi					-0.79	-1.16	-0.95	-1.77
					[-1.11]	[-1.80]	[-1.44]	[-2.35]
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	92	81	81	81	120	109	109	109
Panel F. Household Flows into Deposits (FoF)								
Romer-Romer	0.03	0.08	-0.07	0.49				
	[0.09]	[0.25]	[-0.23]	[0.90]				
Gertler-Karadi					0.12	0.08	0.06	-0.15
					[0.17]	[0.12]	[0.09]	[-0.20]
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	92	81	81	81	120	109	109	109

Newey-West t-statistics in brackets

Figure A10: Interest Rates and AAII Portfolio Allocations: sVAR Impulse Response

Impulse response plots of American Association of Individual Investors (AAII) member portfolio allocations to innovations in interest rates. Variables include (in VAR ordering sequence): monthly inflation and industrial production (standard inputs in macro VARs and slowest moving), allocations (stocks in Panel A and "cash" in Panel B), AAII Sentiment (% Bullish - % Bearish), VIX^2, P/E10, and the 3-month Treasury rate. We order the risk-free rate at the end to be conservative in our identification of interest rate innovations (results are similar if we drop some variables or use alternative orderings). Eight lags are used. Monthly from November 1987 to December 2014.

Panel A. Mean Allocations to Stocks



Panel B. Mean Allocations to "Cash"

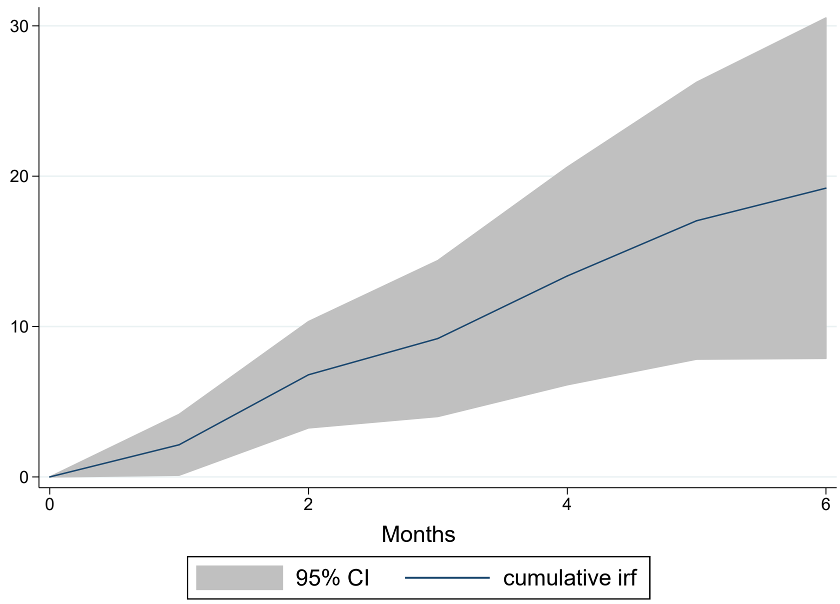
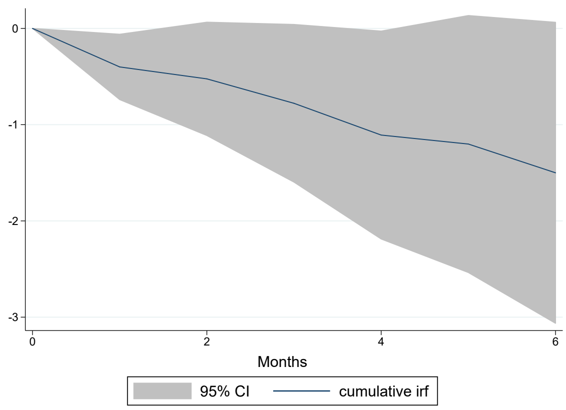
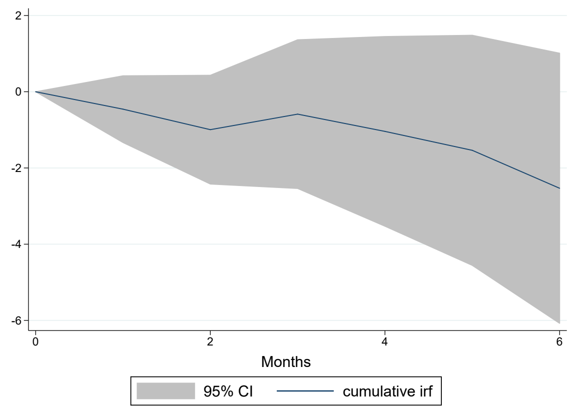


Figure A11: Interest Rates and Household Investment Flows: sVAR Impulse Response

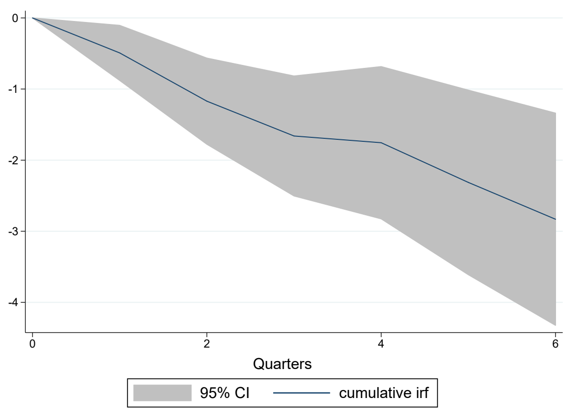
Impulse response plots of household investment flows to innovations in interest rates. Plot (a) shows monthly sVAR results of equity mutual fund flows (normalized by equity mutual fund net asset value) using data from the Investment Company Institute (ICI). Plot (b) shows monthly sVAR results of high yield corporate bond mutual fund flows (normalized by high yield corporate bond mutual fund net asset value) using data from ICI. Plot (c) shows quarterly household sector flows into stocks (including direct holdings and mutual fund holdings, normalized by household sector financial assets) using data from Flow of Funds. Panel (d) shows quarterly household sector flows into interest-bearing safe assets (including time and saving deposits, money market mutual fund, and commercial paper, normalized by household sector financial assets) using data from Flow of Funds. Variables include (in VAR ordering sequence): inflation rate, industrial production growth, allocations (stocks in Panel A and "cash" in Panel B), AAII Sentiment (% Bullish - % Bearish), P/E10, VIX^2, and the 3-month Treasury rate; AAII sentiment, P/E10, and VIX^2 are not included in plot (b). Eight lags are used.



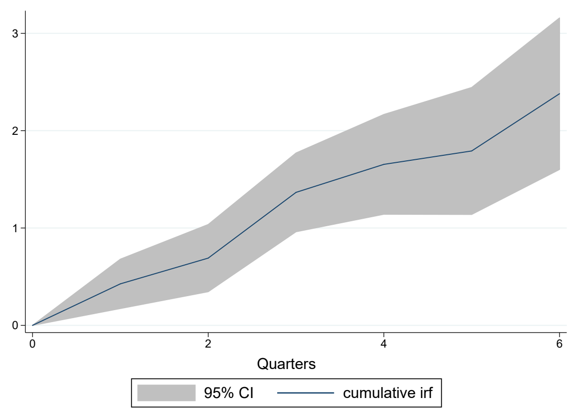
(a) Equity Mutual Fund Flows (ICI)



(b) High Yield Mutual Fund Flows (ICI)



(c) Household Flows into Stocks (FoF)



(d) Household Flows into Deposits (FoF)

Figure A12: Impulse Response of Excess Stock Returns to Interest Rate Innovations

Impulse response plots of monthly excess stock returns to innovations in interest rates. Variables include (in VAR ordering sequence): inflation rate, industrial production growth, monthly stock returns, and the 3-month Treasury rate. Eight lags are used. Monthly from January 1985 to December 2014.

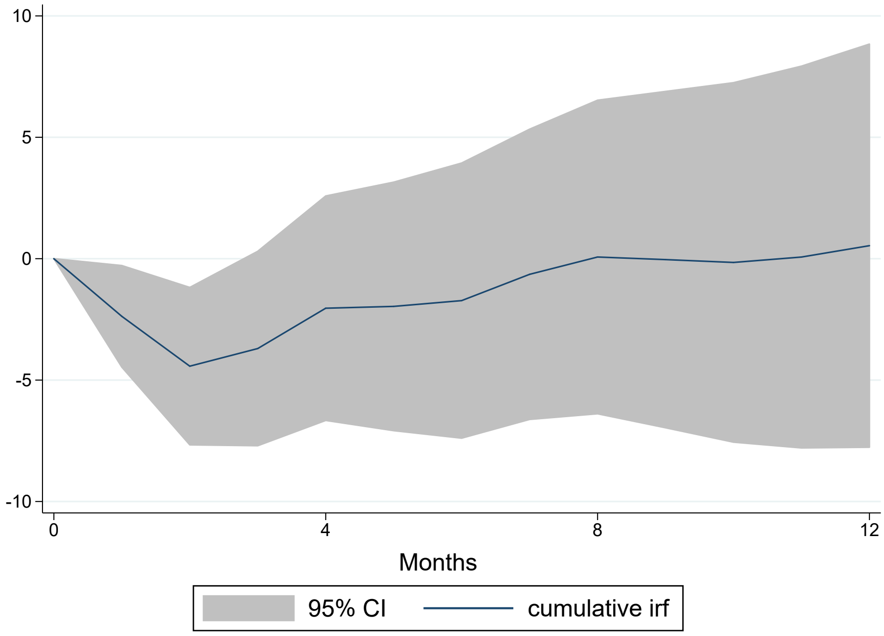


Table A21: Flows and Issuance by Sector

Time series regressions:

$$F_t = \alpha + \beta \Delta r_{f,t-1} + X'_{t-1}\gamma + \epsilon_t$$

where r_f is 3-month Treasury rate; F is quarterly net flows into corporate equities (normalized by US GDP) in columns (1) to (3), and quarterly net equity issuance of equities (normalized by US GDP) in columns (5) to (7); X includes controls in Table 7: Spec 1 has the same controls as Table 7 column (2), Spec 2 has the same controls as Table 7 column (3), and Spec 3 has the same controls as Table 7 column (4). All regressions include four lags of F. Outcome variables are from the beginning of 1985 to the end of 2014, but AAII sentiment is only available starting August 1987. Standard errors are Newey-West, using the automatic bandwidth selection procedure of Newey and West (1994). Regression coefficient β and the associated t-statistics are reported. Data on flows and issuance are from Flow of Funds, and they are in net terms. Flows from all sectors sum up to issuance by all sectors. On the flow side, all sectors include households, domestic financial sector, rest of the world, as well as a few other components such as government and non-financial corporations' holdings of mutual fund shares.

	Net Flows into Stocks				Net Issuance of Stocks		
	Household	Financials	RoW	All Sectors	Non-Fin.	Financials	RoW
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No Control	-0.68	-0.02	0.06	-0.79	-0.45	-0.41	0.03
	[-1.86]	[-0.07]	[0.51]	[-3.46]	[-2.31]	[-2.49]	[0.21]
w/ Control, Spec 1	-0.72	-0.28	0.09	-1.27	-0.63	-0.54	-0.05
	[-1.69]	[-0.91]	[0.57]	[-4.51]	[-2.41]	[-2.14]	[-0.29]
w/ Control, Spec 2	-0.61	-0.34	0.04	-1.24	-0.55	-0.53	-0.12
	[-1.33]	[-1.05]	[0.25]	[-4.39]	[-2.12]	[-2.09]	[-0.68]
w/ Control, Spec 3	-1.13	0.08	0.19	-1.30	-0.40	-0.47	-0.33
	[-1.67]	[0.17]	[0.77]	[-3.97]	[-1.13]	[-1.56]	[-1.72]

C.3.2 History-Dependent Reference Points: Results from the SCF

In the following, we present suggestive evidence of history-dependent reference points using data from the Survey of Consumer Finances (SCF). We follow the empirical strategy of Malmendier and Nagel (2011), and exploit differences in different individuals' lifetime interest rate experiences. We show that, at a given point in time, individuals who experienced high past interest rates appear less satisfied with safe assets and display a higher propensity of risk taking.

Figure A13 follows Figure 1 in Malmendier and Nagel (2011), and plots the differences in mean allocations to stocks (as well as deposits) between old and young against the differences in experienced past interest rates. It shows that in periods where old individuals' experienced interest rates are significantly higher than young individuals, old individuals' propensity to invest in stocks is also much higher.

Table A22 presents regressions following Malmendier and Nagel (2011):

$$Y_{it} = \alpha + \eta_t + \beta \bar{r}_{f,it} + \gamma \bar{r}_{x,it} + \xi' X_{it} + \epsilon_{it} \tag{A18}$$

where Y_{it} captures investment decisions of household i in year t. $\bar{r}_{f,it}$ is the main independent variable of interest, which measures average experienced past interest rates. We control for $\bar{r}_{x,it}$, which is average excess stock returns in household i's previous lifetime experiences as of year t; it proxies for beliefs or preferences related to stocks due to prior experiences, as documented by Malmendier and Nagel (2011). $\bar{r}_{f,it}$ and $\bar{r}_{x,it}$ are calculated using the experience function in Malmendier and Nagel (2011), which is (exponentially-decaying) weighted averages of past experiences; we use the default decay parameter $\lambda = 1.5$ from Malmendier and Nagel (2011). We also control for a set of demographic characteristics, including dummies for education, race, marital status, employment status, income deciles, wealth (log financial assets). As in Malmendier and Nagel (2011), we include time and cohort (age) dummies. This identifies experience effects from cross-sectional heterogeneity among individuals at a given point in time, and separates experience effects from cohort effects.

Table A22 shows that, at a given point in time, individuals that experienced high interest rates in the past invest less in deposits and have a higher propensity of risk taking. For a one percentage point increase in average experienced past interest rates, portfolio shares in stocks (deposits) on average increase (decrease) by about 1.5 percentage points. The changes in portfolio shares are more pronounced among stock market participants. This pattern is consistent with the idea that these individuals are accustomed to higher levels of interest rates and are less satisfied with the current interest rates. Thus they invest less in deposits and are more likely to invest in risky assets.

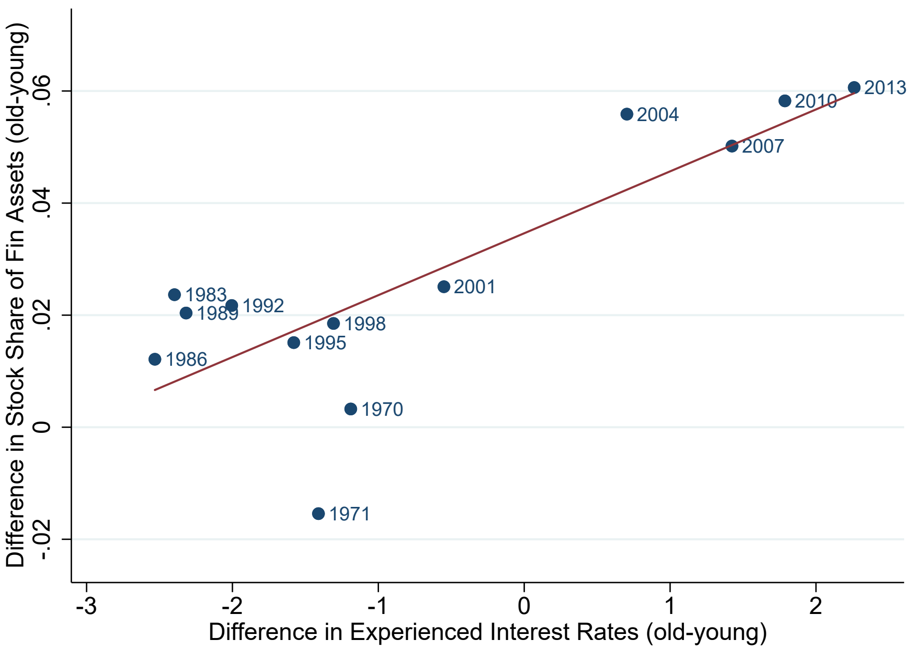
There are, however, several caveats in this analysis using observational data. First, the SCF does not have data on beliefs about the risky asset's returns and risks. Thus it is challenging to adequately control for potential heterogeneity in beliefs. For instance, to the extent that interest rates tend to be higher in booms and lower in recessions, individuals who experienced higher past interest rates may have more experiences of booms and are thus more optimistic. Second, in the past half a century, interest rates experienced a secular decline, so the gap in interest rate experiences is correlated with the age gap: as can be seen in Figure A13, both differences in old and young individuals' experienced interest rates and differences their investment shares in stocks secularly increase. Thus it may be hard to rule out influences from systematic demographic shifts. Finally, the reference points in the reference dependence model of Section 3.2 could be influenced by experiences of both past interest rates and past stock returns. Accordingly, in the SCF data it could be hard to tease apart experience effects that work through history-dependent reference points from experience effects that work through beliefs and other channels.

In sum, there are multiple challenges in observational data that can make it harder to cleanly isolate the underlying mechanisms. Nonetheless, the patterns in the observational data appear in line with our findings in the transparent randomized experiments. We hold the evidence of Figure A13 and Table A22 as suggestive of history-dependent reference points.

Figure A13: Differences in Mean Investment Shares between Old and Young

Differences in mean investment shares between old (household age > 60) and young (household age < 40). In Panel A, the y-axis is the difference in mean shares of stocks (directly held and through mutual funds) in financial assets between these two groups. In Panel B, the y-axis is the difference in mean shares of deposits (including checking, saving, CD, money market deposits) in financial assets between these two groups. The x-axis is the average short-term interest rates in the past 40 years minus the average in the past 20 years. Because SCF data is not very clear about investment of IRA and other retirement saving accounts before 2004, here we do not include retirement assets in financial assets.

Panel A. Differences in Mean Shares in Stocks



Panel B. Differences in Mean Shares in Deposits

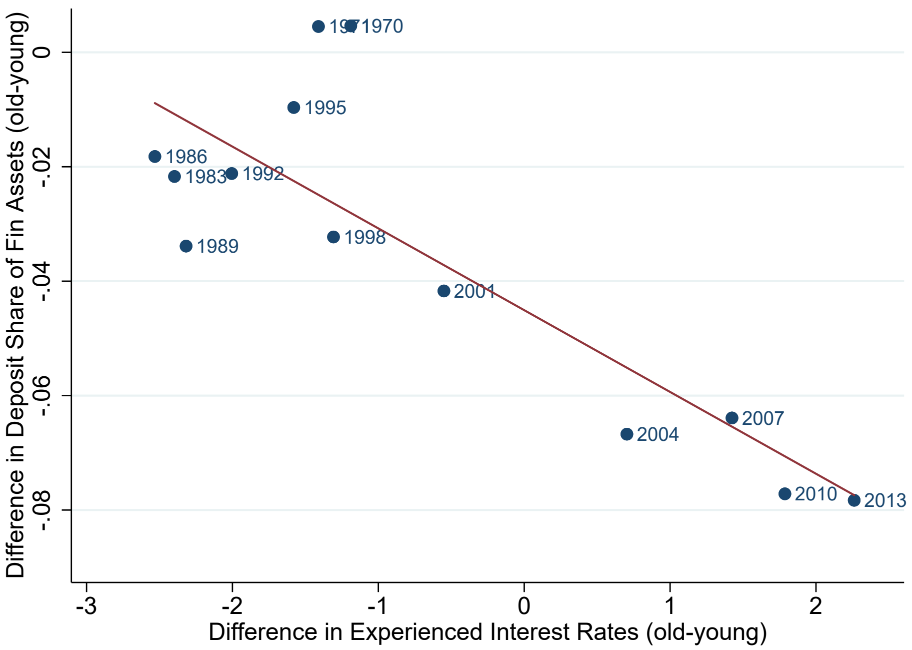


Table A22: Investment Decisions and Interest Rate Experiences

Panel regressions using Survey of Consumer Finance data:

$$Y_{it} = \alpha + \eta_t + \beta \bar{r}_{f,it} + \gamma \bar{r}_{x,it} + \xi' X_{it} + \epsilon_{it}$$

In column (1), the outcome variable is a categorical question about risk tolerance (1. not willing to take any financial risks; 2. take average financial risks expecting to earn average returns; 3. take above average financial risks expecting to earn above average returns; 4. take substantial financial risks expecting to earn substantial returns). The regression is estimated using ordered probit. In column (2), the outcome variable is a dummy variable that takes value one if household i holds a positive amount of stocks at time t. In column (3), the outcome variable is the share of household i's financial assets in stocks at time t. In column (4), the outcome variable is the share of household i's financial assets in deposits at time t. The main dependent variable $\bar{r}_{f,it}$ measures average experienced past interest rates. We also include $\bar{r}_{x,it}$, which is average experienced past excess stock returns. $\bar{r}_{f,it}$ and $\bar{r}_{x,it}$ are calculated using the experience function in Malmendier and Nagel (2011), with default $\lambda = 1.5$. Controls include dummies for education, age, race, marital status, employment status, income deciles, and wealth (log financial assets). Because SCF data is not very clear about investment of IRA and other retirement saving accounts before 2004, here we do not include retirement assets in financial assets. Standard errors are corrected for multiple imputation.

Outcome	Risk Tolerance Ordered Probit (1)	Holds Stocks OLS (2)	% in Stocks OLS (3)	% in Deposits OLS (4)
Experienced interest rates	0.05	0.03	1.58	-1.91
	[3.94]	[6.78]	[6.40]	[-5.81]
Experienced excess stock returns	0.03	0.01	0.36	-0.13
	[3.10]	[4.44]	[2.36]	[-0.74]
High School	0.12	0.02	0.12	-0.56
	[6.47]	[4.15]	[0.34]	[-1.40]
College	0.36	0.13	4.00	-4.52
	[18.13]	[18.90]	[9.72]	[-9.35]
Log financial assets	0.10	0.08	4.68	-6.01
	[28.61]	[53.35]	[28.62]	[-28.80]
Age Dummies	Y	Y	Y	Y
Time Dummies	Y	Y	Y	Y
Other Controls	Y	Y	Y	Y
Obs	41,260	43,947	43,941	43,932
R^2		0.335	0.252	0.286

t-statistics in brackets, corrected for multiple imputation

D Data

D.1 List of Experiments

	Population	Setting	Test	N	Time
1	Mturk	Hypothetical	Benchmark	400	Jun-16
2	Mturk	Incentivized	Benchmark	400	Feb-16
3	Mturk	Incentivized	Robustness checks (payment methods)	1,200	Feb-16
4	HBS MBA	Incentivized	Benchmark	400	Apr-16
5	Mturk	Incentivized	Experiment T1: gradient & non-linearity	1,400	Jun-16
6	Mturk	Incentivized	Experiment T3: gross framing	400	Jun-16
7	Mturk	Incentivized	Experiment T3: net framing robustness	400	Jun-16
8	Mturk	Hypothetical	Experiment T2: history dependence	400	Aug-15
9	Mturk	Incentivized	Experiment T2: history dependence	400	Jun-16
10	Mturk	Hypothetical	Experiment T2: history dependence additional design (run by Cary Frydman)	400	Nov-16
11	Mturk	Incentivized	Experiment T2: history dependence additional design	400	Dec-16
12	Mturk	Incentivized	Robustness (binary distribution)	400	Jun-16
13	Dutch households	Hypothetical	Experiment T1 (run by Dutch AFM)	901	Aug-17
Total				7,501	

D.2 Sources and Variable Definitions for Observational Data

Variable	Construction	Source
Portfolio share in stocks and "cash"	Stocks include both direct holdings and stock mutual funds; "cash" refers to savings accounts, CDs, money market funds, etc.	American Association of Individual Investors
Flows into equity and high yield corporate bond mutual funds		Investment Company Institute
Net asset value of equity and high yield corporate bond mutual funds		Investment Company Institute
Household sector flows into stocks	FA153064105.Q+FA153064205.Q	Flow of Funds
Household sector flows into interest-bearing safe assets	FA153030005.Q+FA153034005.Q+FA163069103.Q	Flow of Funds
Household sector total financial wealth	FL154090005.Q	Flow of Funds
Stock market sentiment	% Bullish - % Bearish	American Association of Individual Investors
P/E10		Robert Shiller's website
Surplus consumption	Follows Campbell and Cochrane (1999)	
Real GDP		Federal Reserve Economic Data (FRED)
VIX		CBOE
Credit spread	Baa bond yield - 10-year Treasury yield	FRED
High yield corporate bond excess returns	High yield corporate bond returns - risk-free returns	Bank of America Merrill Lynch
High yield corporate bond default rate		Moody's
Inflation rate	CPI for all urban consumers	FRED
Industrial production		FRED