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

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Abstract

In recent years, interest rates reached historic lows in many countries. We document that individual investors "reach for yield," that is, have a greater appetite for risk taking when interest rates are low. Using an investment experiment holding fixed risk premia and risks, we show that low interest rates lead to significantly higher allocations to risky assets, among MTurk subjects and HBS MBAs. This behavior cannot be easily explained by conventional portfolio choice theory or by institutional frictions. We then propose and test explanations related to investor psychology. We also present complementary evidence using historical data on household investment decisions.

JEL classification: D03, D14, E03, E44, E52, G02, G11.
Key words: Low interest rates; risk taking; investment experiment; reference dependence; salience.

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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 to stimulate the economy, and function as a new channel by which monetary policy can affect economic activities. It may also pose challenges for financial stability, and call for caution and increased monitoring. Both policy makers and investors have underscored the importance of reaching for yield (Bernanke, 2013; Stein, 2013; Rajan, 2013; Fink, 2016).

What drives reaching for yield? A common perspective in recent research focuses on institutional frictions. Some theories examine agency problems (Feroli, Kashyap, Schoenholtz, and Shin, 2014; Morris and Shin, 2015; Acharya and Naqvi, 2015), and others analyze financial institutions' cost of leverage (Drechsler, Savov, and Schnabl, 2015). A number of studies also provide empirical evidence that banks, money market mutual funds, and corporate bond mutual 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).

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 experiment of investment decision making. 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

[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 about macroeconomic policies and financial stability, "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.

with 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 treatment conditions. The investment decision in each treatment condition represents the simplest mean variance analysis problem, where the solution should not be affected by the risk-free rate under the conventional 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). This finding holds across different settings (hypothetical question as well as incentivized experiment), and among a diverse group of participants (workers on Amazon's Mechanical Turk platform as well as Harvard Business School MBA students). The difference is about 7 to 9 percentage points, on a basis of roughly 60% allocations to the risky asset. Such behavior in individual investment decision making cannot be explained by agency frictions. It is also hard to square with conventional 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. This observation connects to the popular view among investors that 1% interest rates are "too low," in comparison to what they have become used to over past experiences. This intuition can be formalized in the framework of the Prospect Theory (Kahneman and Tversky, 1979). The observation also suggests a novel implication that the degree of reaching for yield when interest rates are low may depend on the previous economic environment.

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 be more salient than 10% average returns relative to 5% risk-free returns. This intuition can be formalized by a version of the Salience Theory of Bordalo, Gennaioli, and Shleifer (2013a), which has been applied in several different settings (Hastings and Shapiro, 2013; Bordalo, Gennaioli, and Shleifer, 2016; Célérier and Vallée, 2016). 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.

We design a set of additional experiments to test these potential explanations, and find support for both categories of mechanisms. In line with predictions of reference dependence, investment history, which may influence investors' reference points, appears to have a significant impact on investment decisions. For instance, participants who first make investment decisions in the high interest rate condition and then make decisions in the low interest rate condition invest substantially more in the risky asset in the low rate condition. In addition, we find that reaching for yield is particularly pronounced when interest rates are low relative to what most participants were accustomed to prior to the Great Recession. In line with predictions of salience and proportional thinking, risk taking decreases and reaching for yield is dampened if investment payoffs are presented using gross returns (e.g. instead of saying 5% returns, we say that one will get 1.05 units for every unit of investment).

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, 2015). 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 to test the underlying mechanisms in detail, and provide more insights on 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 short-term 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, it contributes to the understanding of reaching for yield. We provide new insights on its drivers and novel evidence from individual investment decisions, complementing prior work that studies institutional frictions. The individual-level behavior we document may affect financial markets in several ways. It can influence the investments of households, who are important end investors that decide whether to allocate savings to safe or risky assets. Households' preferences can also shift investment decisions by financial institutions, who often cater to clients' tastes.[2] In addition, the preferences and psychology we document may also affect professional investors. We find that reaching for yield is significant among financially well-educated individuals like HBS MBAs, and it does not appear to diminish with wealth, investment experience, or work experience in finance.

Second, our study contributes to research on portfolio choice decisions. We present evidence of systematic deviations from the classical benchmark, and provide candidate explanations for the observed behavior. These findings add to the growing literature on behavioral frictions in investment decisions (Benartzi and Thaler, 1995; Barberis, Huang, and Santos, 2001; Malmendier and Nagel, 2011; Frydman, Hartzmark, and Solomon, 2016). Relatedly, our findings also suggest the relevance of behavioral frictions for macroeconomic policies and outcomes, which has drawn increasing attention in recent research (Fuster, Laibson, and Mendel, 2010; Gabaix, 2016; Malmendier, Nagel, and Yan, 2016).

Third, our paper relates to a vibrant literature in behavioral and experimental economics on decision under risk and uncertainty. A number of studies use experiments to understand elements that affect risk taking (Holt and Laury, 2002; Gneezy and Potters, 1997; Cohn, Engelmann, Fehr, and Maréchal, 2015). Prior experimental work on choice under uncertainty is primarily based on abstract gambles, and interest rates have not been the focus. However, for most of the monetary risk decisions in practice (e.g. investment decisions of households and corporations), interest rates are essential. Our results suggest that interest rates play an important role in affecting risk taking behavior. In a contemporaneous experiment with hypothetical questions, Ganzach and Wohl (2016) also find increased risk taking when interest rates are low. Our tests provide a large set of evidence across many different settings, and isolate behavior that departs from classical benchmarks. We also connect the empirical evidence to theories in behavioral economics (Kahneman and Tversky, 1979; Malmendier and Nagel, 2011; Bordalo et al., 2013a), design further tests based on theory predictions, and uncover additional findings that shed light on theories and suggest policy implications.

[2]For example, Di Maggio and Kacperczyk (2017) and Choi and Kronlund (2016) show money market mutual funds and corporate bond mutual funds that reach for yield get larger inflows, especially when interest rates are near zero. These flows most likely come from yield seeking end investors. It seems probable that households' yield seeking behavior contributes to reaching for yield by financial institutions.

The remainder of the paper is organized as follows. Section 2 presents results of the benchmark experiment, where participants are randomly assigned to different interest rate conditions and make investment decisions. Section 3 discusses possible explanations for the reaching for yield behavior we observe in the benchmark experiment, and Section 4 tests these potential mechanisms. Section 5 provides suggestive evidence 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 treatment conditions (high vs. low interest rate).

We conduct the benchmark experiment among two groups of participants. The first group consists of workers on Amazon Mechanical Turk (MTurk) that are adults (at least 18 years old) in the US. 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, 2016; DellaVigna and Pope, 2017a,b). The platform 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. 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 pursue finance careers, and some may become key figures 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. The survey form for Experiment B1 is presented in the Survey Appendix.

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 25 to 45 years old, and they have some amount of investment experience. 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 2013 Survey of Consumer Finances shows median household net worth of about $47,000 for people between 35 to 45 and $10,000 for people below 35, and these two age groups represent the majority of our sample).

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. 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 experiments on investment decision-making 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 A2 show the comparison experiments we run to 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 Internet Appendix Table A2, we also verify that behavior is not affected by the delayed bonus. The survey form for Experiment B2 is presented in the Survey Appendix.

Table 1 Panel B shows the demographics of participants in Experiment B2. Experiment B2 has slightly more male participants, and participants are also slightly wealthier. Overall

[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.

the demographics are similar to those in Experiment B1.

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 enrolled MBA students at HBS 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. The payment is processed and issued by the financial offices at Harvard, scheduled for approximately a year after the experiment to adhere to the one year investment horizon. The survey form for Experiment B3 is presented in the Survey Appendix.

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. More than 40% report having some or extensive investment experience, and 40% have worked in finance.

2.2 Results

Table 2 reports results of the benchmark experiment. Table 2 Panel A shows mean allocations to the risky asset in the high and low interest rate conditions for Experiments B1 to B3, the difference in mean allocations between the two conditions, and the t-stat that the difference is significantly different from zero. In all three settings, 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 interest rate condition to 55.32% in the low interest 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 about investing experimental endowment 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.

Figure 1 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 shows the difference between the high and low interest rate conditions controlling for individual characteristics, using the following regression:

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

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 (such as education, risk tolerance, age, and wealth level in the MTurk case, work experience in the MBA case, etc.). The coefficient β is presented together with the associated t-statistics. The coefficient β is about the same as the unconditional mean difference in Panel A, and ranges between 7.1 and 8.5 percentage points.[5]

The increase of mean allocations to the risky asset of around 8 percentage points is sizeable. It is a roughly 15% increase on the base of about 60% allocations to the risky asset. To make the magnitude easier to assess, 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 basis of about 5 percentage point risk premium).

Our results on reaching for yield are very consistent across different settings and subject pools. Some previous studies find the influence of psychological forces in financial decision making diminishes with education and experience (List and Haigh, 2005; Cipriani and Guar-

[5]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 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, Summers, et al., 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.

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

ino, 2009), 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 MTurk participants 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 A1. If anything, participants with more wealth, investment experience, and work experience in finance appear to reach for yield slightly more, but our sample size of 400 generally does not have enough power to detect significant differences in subsample comparisons.

Stake Size in Incentivized Experiments

One constraint of incentivized investment experiments is the stakes are relatively small compared to participants' wealth. Experimental research emphasizes monetary incentives, but researchers have budget limits. With respect to the typical stake size in incentivized experiments, participants should be risk neutral and put everything in investments with the highest average returns. In our data, only about 25% of participants in Experiment B2 (MTurk) and about 30% of participants in Experiment B3 (MBA) invested everything in the risky asset, in line with the majority of previous studies that find participants are typically risk averse with respect to small stakes.

In our setting, we make four observations that could be helpful in light of the concern about modest stake size. First, experimental research has found that risk preferences with respect to small stakes are meaningful and are consistent with participants' risk preferences with respect to larger stakes or in hypothetical decisions (Holt and Laury, 2002). Some studies use experimental stakes to calibrate parameters associated with curvatures in utility functions (Andersen, Harrison, Lau, and Rutström, 2008; Andreoni and Sprenger, 2012; Charness, Gneezy, and Imas, 2013) or test portfolio choice models (Bossaerts et al., 2007), and find informative results. We use stake size that is in line with the literature and with previous work on risk preferences in financial investing (Cohn et al., 2015; Charness and Gneezy, 2010). Second, we find that risk preferences with respect to experimental stakes in our setting do reflect participants' risk preferences in financial investing in general. For example, Table A3 in the Internet Appendix shows that allocations in the experiment are highly correlated with allocations of participants' household financial wealth. Third, the concern about experimental stakes does not apply to the hypothetical questions. We find the same patterns of reaching for yield in hypothetical and incentivized settings, which suggests robustness of the phenomenon. Finally, to the extent that small stakes make participants more risk neutral and decreases variations in investment decisions, it works against us finding significant differences in risk taking across treatment conditions.

In summary, we find that investments in the risky asset increase significantly in the low interest rate condition. Such reaching for yield behavior is remarkably stable across different settings and subject pools. 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 cannot easily explain the reaching for yield behavior we document. We then suggest two categories of possible explanations, reference dependence and salience/proportional thinking, which we will test in Section 4.

3.1 Can Conventional Portfolio Choice Theory Generate Reaching For Yield?

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 denote $1 + r_p = 1 + r_f + \phi x$ returns on the portfolio as a whole. 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.[7]

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).[8] 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.*

The intuition for this result is that, for a given distribution of x, when r_f increases the investor effectively becomes wealthier. If the 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.[9]

Proposition 1 assumes weakly decreasing absolute risk aversion, a property shared by

[7] 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.

[8] The approximation is exact with constant absolute risk aversion (i.e. $\frac{-u''(w)}{u'(w)}$ is constant) and x having a normal distribution. Note that the approximation is not exact with constant relative risk aversion and x having a log normal distribution. This is because while x has a log normal distribution, the portfolio returns $1 + r_p = 1 + r + \phi x$ are not necessarily log normally distributed.

[9] 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).

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 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 sum, the conventional portfolio choice framework does not seem to naturally generate predictions in line with the reaching for yield phenomenon we find in Section 2.

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 formalize this intuition is through a framework of loss aversion around reference points (Benartzi and Thaler, 1995; He and Zhou, 2011), an important component of the Prospect Theory (Kahneman and Tversky, 1979; Barberis et al., 2001). In the following, we first use this type of framework to analyze the investment decision problem, and show how it can generate predictions of reaching for yield. We then discuss how reference points are formed in our setting, as well as alternative ways of modeling reference dependent investment decisions. Finally we discuss additional empirical predictions and novel implications.

We use the same set-up as before, 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 of the Prospect Theory (Kahneman and Tversky, 1979), without adding additional features 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 later. 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.

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

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 behind the result is that when interest rates are below the reference point and drop further, investing in the risk-free asset will make the investor bear the entire increase in the first-order loss (i.e. utility loss from loss aversion). The risky asset, in contrast, provides at least some chance to avoid the increase of 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 evidence we document 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^* will be (weakly) increasing in r_f. 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. Accordingly, the incentive to invest in the risky asset will increase with interest rates. In other words, the investor would "reach against yield" in this case with $r_f > r_r$.

Proposition 2 focuses on how investment decisions change as we shift the risk-free rate r_f while fixing the reference point r_r. Reference dependence also generates predictions about how decisions are affected by the reference point r_r for a given level of interest rate r_f.

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 of Corollary 1 is similar to that of Proposition 2. For example, when the risk-free rate is below the reference point, 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. As a result, higher reference points are associated with stronger incentives to invest in the risky asset.

Reference Point Formation

One 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 behavior. We provide formal proofs and more discussions in the Internet Appendix.

In the framework of 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 will be higher than the status quo reference level $r_f \geq r_r = 0$. This falls into the second case of Proposition 2, and does not explain the reaching for yield behavior in our benchmark experiment.[10]

In later work, Barberis et al. (2001) propose reference points which are equal to the risk-free rate ($r_r = r_f$), and Kőszegi and Rabin (2006) propose reference points that are rational expectations of asset returns in the investor's investment choice set. In both cases, when the risk-free rate changes while the distribution of excess returns is 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 are essentially unchanged. As a result, the optimal allocation to the risky asset stays the same, and investment decisions should not be different across the treatment conditions in our benchmark experiment.[11]

[10] That said, we are not suggesting 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.

[11] 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).

Another line of work suggests that people's past experiences have a significant impact on preferences and behavior (Kahneman and Miller, 1986; Malmendier and Nagel, 2011; Bordalo, Gennaioli, Shleifer, 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 drops below the level they are used to, people experience discomfort and become more willing to invest in the risky asset.[12] This falls in the first case of Proposition 2, which predicts reaching for yield behavior. Given the economic environment in the decades prior to the Great Recession, reference points from past experiences appear in line with the investors' view that 1% or 0% interest rates are "too low."[13]

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 used to live in an environment of modest interest rates. It might also be different when rates decline sharply as opposed to gradually.

Functional Forms for Modeling Reference Dependence

The functional form we use to model reference dependence in the above follows the traditional Prospect Theory formulation. Our emphasis is that *reference dependence* can generate reaching for yield behavior, but we do not stick to a particular functional form of modeling reference dependence in investment decisions. We provide two additional formulations of reference dependence in Internet Appendix Sections A1.4 and A1.5.

First, we present a model of reference dependence where investors experience discomfort/loss aversion when the expected returns of the portfolio are below the reference point. (In contrast, in the traditional Prospect Theory formulation discussed above, investors suffer

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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.

[12]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.

[13]In our incentivized experiments, like in the classic Prospect Theory experiments (Kahneman and Tversky, 1979) and many other ones, framing (which concerns the set of payoffs an investor considers together) affects the application of mechanisms. If investors fully mingle the experimental payoffs with other risks in their lives, they should invest everything in the risky asset, which is not what we observe in the data. 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, and helps to explain common phenomena that are otherwise puzzling. 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 mechanisms studied in this section.

from loss aversion for each state where the realized returns are below the reference point.) This alternative formulation predicts reaching for yield when interest rates are low, but does not predict reaching against yield when interest rates are high.

Second, we also consider the traditional Prospect Theory formulation with diminishing sensitivity. We show that the theoretical prediction of whether diminishing sensitivity contributes to reaching for yield is ambiguous (the Internet Appendix gives a detailed explanation). We provide a few special conditions under which diminishing sensitivity yields unambiguous predictions. We then evaluate the general case 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 in our setting, but the magnitude of the effect is relatively small. Overall, it seems hard for diminishing sensitivity *alone* to account for the evidence in Section 2 without the loss aversion component discussed above.

Nominal Illusion

One may wonder whether a form of "nominal illusion" can explain the behavior we document in Section 2. "Nominal illusion" *alone*—that is, investors may confuse real and nominal returns (Modigliani and Cohn, 1979; Campbell and Vuolteenaho, 2004; Cohen, Polk, and Vuolteenaho, 2005)—does not generate predictions of reaching for yield. Specifically, the excess returns and risks of the risky asset are not affected by whether people think about the investment payoffs in our setting in nominal terms or in real terms. Accordingly, predictions by conventional portfolio choice analysis do not change.[14] Nonetheless, nominal illusion may interact with reference dependence: investors' reference points could be more about nominal returns, so low nominal interest rates may affect behavior differently than low real interest rates.

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 salient compared to 1% risk-free returns than 10% average returns compared to 5% risk-free returns. This

[14] Similarly, the optimal allocation based on conventional portfolio choice analysis would not change for any given inflation expectation. Thus deviations from rational inflation expectations alone cannot explain the reaching for yield behavior.

intuition can be formalized by a version of the Salience Theory of Bordalo et al. (2013a). 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 (2015)).

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 its risks. The relative weight between these two dimensions, however, depends not only 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 risk premium defined as the *difference* between the average returns on the risky asset and the risk-free rate. 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. (2013a), 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.[15] We adopt a specification of δ following Bordalo et al. (2013a).

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

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

[15]In our context, the Salience Theory and proportional thinking are broadly the same. In the Internet Appendix Section A2.3, we discuss a subtle difference between the way "salience" is defined in Bordalo et al. (2013a) and proportional thinking, which is not important in our application. We also explain the relationship between our framework and other models related to salience/proportional thinking such as Bordalo, Gennaioli, and Shleifer (2012), Bordalo, Gennaioli, and Shleifer (2013b), and Bushong et al. (2015).

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

This definition is a generalization of the original formulation in Bordalo et al. (2013a), which is also applied in Bordalo et al. (2016).[16] In this framework, δ depends on both the ratio of the average returns between the two assets and the ratio of their variance: the first part in the parenthesis can be rewritten as $\left|\frac{(r_f+\mathbb{E}x)/r_f-1}{(r_f+\mathbb{E}x)/r_f+1}\right|$, which is increasing in the ratio of the average returns $(r_f + \mathbb{E}x)/r_f$; analogously, δ is decreasing in the ratio of the assets' variance. In our setting, the focus is how changes in the average returns of the assets affect investment decisions, and we keep the risk properties of the two assets fixed (so the second term in the parenthesis is always one, as the variance of the risky asset is held fixed and the variance of the safe asset is zero).

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. We will present detailed tests of salience and proportional thinking in Section 4.

4 Testing Mechanisms

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

4.1 Experiment T1 (Mapping Gradient)

In this experiment, we test investment allocations using a larger set of investment payoffs. Specifically, we keep the excess returns of the risky asset fixed, and vary the risk-free rate

[16] 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 will not change the salience of the return dimension relative to the risk dimension. We generalize Bordalo et al. (2013a) 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 when f takes an extreme form such that $f(t) = \begin{cases} \beta & t > 0 \\ \frac{1}{\beta} & t < 0 \end{cases}$, where $\beta > 1$. In addition, the decision problem in Bordalo et al. (2013a) and Bordalo et al. (2016) is a discrete choice problem. We generalize it to settings where the decision is continuous, which applies to the portfolio choice problem here. See Internet Appendix Section A2.3 for more discussions.

from -1% to up to 15%. The excess returns are the same as those in the benchmark experiment, and the average excess returns is 5%. For example, in the condition with the lowest interest rate, participants consider investing between a safe asset with -1% returns and a risky asset with 4% average returns; in the condition with the highest interest rate, participants consider investing between a safe asset with 15% returns and a risky asset with 20% average returns; there are several other conditions in between. We randomly assign participants to one of these conditions.

Through this experiment, we would like to examine two main questions. The first question is whether there is non-linearity in how investment decisions respond to interest rates; in particular, whether reaching for yield is most significant when interest rates are below a certain range. Both reference dependence and salience/proportional thinking predict such non-linearity. For example, in the model of reference point and loss aversion specified in Section 3.2, allocations to the risky asset would increase as interest rates fall when interest rates are below the reference point. In the model of salience/proportional thinking discussed 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 r_f. On the other hand, conventional portfolio choice theory with increasing absolute risk aversion, for instance, does not predict strong non-linearity. The non-linearity in risk taking may also have policy implications. The second question is whether we observe "reaching against yield" (i.e. less allocations to the risky asset as the risk-free rate increases) when interest rates are sufficiently high, as predicted by the traditional Prospect Theory formulation discussed in Section 3.2 Proposition 2.

We conduct Experiment T1 in June 2016. Participants are recruited on MTurk, and randomly assigned to one of the interest rate conditions. As in the benchmark experiments, each 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 A6 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.[17]

Table 3 presents the results of Experiment T1. We see that the mean allocation to the risky asset is about 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 to the risky asset change more slowly. The mean allocation to the risky asset is 57% when the risk-free rate moves to 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%. The mean allocations across different interest rate conditions are also plotted in Figure 2.

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.[18] 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.[19] On the other hand, conventional portfolio choice theory with increasing absolute risk aversion does not square with the strong non-linearity we find in the data.

In addition, while we see clear patterns of reaching for yield (i.e. allocations to the risky asset increase as interest rates decline) when interest rates get into the low range, we do not observe reaching against yield when the risk-free rate approaches the high end. Section 3.2 Proposition 2 shows that the baseline Prospect Theory formulation predicts reaching against yield when the risk-free rate is higher than the reference point, which we do not find. One possibility is that reaching against yield is modest in magnitude, and

[17]For incentivized experiments in this section, participants receive their bonus payments shortly after participation. Delaying the bonus by one year requires us to collect contact information of our MTurk participants, in case they no longer work on MTurk in one year's time. In Section 2 and Internet Appendix Table A2, we have tested that the results are robust to the timing of payment. Therefore, for the additional experiments in this section, we pay the bonus within a week after the experiment to simplify the logistics.

[18]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. 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 F-stat 7.40.

[19]While intuitively it may seem that negative interest rates are quite "salient," existing models do not yet provide a clear way to deal with negative quantities. The salience function we use in Assumption 2 can work with r_f that is modestly negative, as long as $(r_f + \mathbb{E}x) + r_f > 0$, which is satisfied when the risk-free rate r_f is -1% and the average excess returns $\mathbb{E}x$ is 5%. But more generally, how to generalize models of salience/proportional thinking to negative quantities is still an open question in the literature.

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 it is specific to the functional form used in the baseline Prospect Theory formulation. As mentioned in Section 3.2, an alternative formulation of reference dependence predicts reaching for yield when interest rates are low, but no reaching against yield when interest rates are high. We present this alternative formulation in Section A1.5 of the Internet Appendix.[20]

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 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) first make investment decisions in the low rate condition, and then make decisions in the high rate condition. Group 1 mimics the situation in which 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

[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, how the reference point influences the optimal allocation's response to interest rates is sensitive to the functional form. 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.

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. Table A7 in the Internet Appendix shows the demographics of participants in Experiment T2.

Table 4 presents results of Experiment T2 and demonstrates several findings. First, there is evidence of 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 than the group facing the high rate condition (Group 1). This is analogous to the benchmark experiment.

Second and importantly, we see that 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 appear consistent with predictions of reference dependence laid out in Corollary 1 and the idea that reference points are history-dependent. Correspondingly, the reaching for yield behavior (i.e. higher allocations to the risky asset in the low rate condition compared to the high rate condition within group) is also particularly pronounced among participants in Group 1.

The finding suggests potential path dependence of reaching for yield. Experiences of

[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.

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 shows the importance of past experiences in economic decision making (Malmendier and Nagel, 2011, 2016; Bordalo et al., 2017).

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. Specifically, participants in Group 2 (who consider the low rate condition first) have similar allocations to the risky asset in the high rate condition as participants in Group 1 (who consider the high rate condition directly). According to Corollary 1 of Section 3.2, 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, which we do not observe in the data. Since Corollary 1 follows from Proposition 2, this prediction is essentially the same as the reaching against yield prediction we discussed in Experiment T1, and therefore shares the same explanations for the lack of evidence in our data. One possibility is our sample size of 200 does not have enough power to detect this type of behavior. Another possibility is this prediction is not very robust, and it depends on the functional form of the traditional Prospect Theory specification. As discussed in Sections 3.2 and 4.1, an alternative formulation of reference dependence features loss aversion when the average returns of the portfolio are below the reference point. This formulation predicts that risk taking is sensitive to the reference point when interest rates are low, but not when interest rates are relatively high. In this case, the experience of the low rate condition will not affect investment decisions in the high rate condition.[22]

In the Internet Appendix Section A2.2, we present alternative designs to test history

[22]Can salience/proportional thinking explain the results of the history dependence experiments? In Assumption 2 of Section 3.3, the salience function we introduce is static, and the optimal allocation ϕ_s^* defined in Equation (5) is independent of investment history. Recent work such as Bordalo et al. (2017) explores combining history-dependent reference points with salience. In this case, a higher reference point (e.g. due to past experiences) will make the low interest rates on the safe asset appear more pronounced. However, it will also make the returns on the risky asset appear less attractive. These two forces push in different directions and which one is stronger depends on the functional form, which the literature does not yet provide guidance. Conceptually, this approach is broadly in line with the idea of history-dependent reference points that we emphasize in Section 3.2. As we mention in Section 3.2, the key of our observation is history-dependent reference points, and there can be multiple ways to model it in investment decisions (e.g. combining history-dependent reference points with different forms of loss aversion, or potentially with some form of salience or other models).

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. The excess returns of the risky assets are always held fixed (same as all of our other experiments, with 5% average excess returns). 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.

4.3 Experiment T3 (Salience and Proportional Thinking)

In Experiment T3, we test the extent to which salience and proportional thinking affect investment decisions. In particular, we study whether results vary when we present investment payoffs using net returns (Baseline Framing) versus gross returns (Gross Framing), as explained in detail below.

Baseline Framing: 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. The returns are presented as net returns (e.g. 1%, 5% etc.), which is most common in financial markets. In addition, for the risky investment, we approximate a normal distribution with nine truncated outcomes, and further explain the distribution of the risky asset using a plot and corresponding examples. In the plot and the examples, we describe the probability that one will get a certain number of Francs if one invests 100 or 1000 Francs. The investment 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 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.
> ...

Gross Framing: In the gross framing experiments, instead of using the commonly used net returns, we describe the investments' payoffs using gross returns. In other words, instead of 5%, we say for every Franc invested one would get 1.05 Francs. We keep everything else the same. In particular, when we explain the distribution of the risky asset through examples, we again say that, with a certain probability, one will get a certain number of Francs if one invests 100 (respectively 1,000) Francs. The investment 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. In particular, 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). For similar reasons, salience and proportional thinking could also 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.[23] In addition, the results also help to further differentiate our findings from conventional portfolio choice theory with increasing absolute risk aversion, which does not predict variations based on framing.

[23]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 (or 1000) 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 A5.

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. Table A8 in the Internet Appendix shows the demographics of participants in Experiment T3.

Table 5 presents 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, particularly when interest rates are low. This result is consistent with predictions of salience and proportional thinking. Moreover, the degree of reaching for yield is dampened with gross framing.[24]

4.4 Discussion

Taken together, results in Experiments T1 to T3 suggest that both reference dependence and salience/proportional thinking appear to contribute to reaching for yield. The findings are also hard to be explained by conventional portfolio choice theory with increasing absolute risk aversion.

Specifically, we find significant non-linearity in how risk taking responds to changes in interest rates, and reaching for yield is particularly pronounced when interest rates are low. The non-linearity is consistent with reference dependence based on past experiences, and also broadly consistent with salience and proportional thinking. In addition, in line with predictions of reference dependence, we find the degree of risk taking is significantly affected by perturbations that may influence participants' reference points. In line with predictions of salience and proportional thinking, we find that allocations to the risky asset decrease and reaching for yield is dampened when investment payoffs are described in gross returns. In the experiments, we ask participants to explain their investment decisions. The

[24] 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.

explanations also show that both categories of mechanisms contribute to the reaching for yield behavior.

5 Suggestive Evidence from Observational Data

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

We start by documenting the basic patterns using OLS regressions of household investment allocations on the risk-free rate. Section A4 of the Internet Appendix provides a summary of variable definitions and data sources. Table 6 presents summary statistics of the main variables used in this section's analysis.

There are two important empirical challenges in the analysis using observational data. First, to mimic the comparative statics in the experiment, 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 expected excess returns. Moreover, recent research documents that households do not appear to have rational expectations about stock returns. Instead, subjective expectations of future stock returns tend to be negatively correlated with expected returns based on rational expectations models (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 endogenous and correlated with other drivers of household investment decisions, which may create omitted variable biases. One type of omitted variable problem arises if interest rates are correlated with investors' expectations of excess returns, and if expectations of excess returns are imperfectly measured. Since interest rates tend to be low in economic downturns, the bias may magnify our results if investors have rational expectations (given that rational expected returns tend to be high in recessions), and dampen our results if investors do not have rational expectations and are more pessimistic in recessions. Another type of omitted variable problem arises if interest rates are correlated with investors' risk aversion. If investors have higher risk aversion in recessions, the bias will again dampen our results. We include controls of economic conditions (e.g. GDP growth) in the regressions. In the data, these controls strengthen our results.[25]

We first look at data on 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 stock mutual funds), bonds (direct holdings and bond 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). A nice feature of this data is that it documents portfolio allocations, which correspond directly to quantities in our experiment. We primarily focus on allocations to stocks (risky asset) and "cash" (safe asset), since the AAII question about allocations to bonds does not distinguish between risky bonds (e.g. high yield) and relatively safe bonds (e.g. investment grade, municipal, agency); we will examine high yield bonds later using high yield bond fund flow data. The AAII series starts in November 1987 and we use data till the end of 2014. In addition, AAII's monthly member survey also asks about views of the stock market (bullish, neutral, bearish), which we use as a proxy for subjective perceptions of future stock market performance. Greenwood and Shleifer (2014) show the AAII investor sentiment measure is highly correlated with subjective expectations of future stock returns from several other sources, and highly correlated with investor behavior such as equity mutual fund flows.

Table 7 presents time series regressions of the mean portfolio share in stocks (Panel A) or "cash" (Panel B) on short-term interest rates measured using three-month Treasury bill rates. We control for model-based measures of expected excess returns, AAII investor sentiment, VIX^2 (the square of VIX, which measures expected variance of the S&P 500 index), as well as commonly used proxies for general economic conditions: past year real GDP growth, and the credit spread (Gilchrist and Zakrajšek, 2012). In column (2), we use the Campbell-Shiller price-earnings ratio (P/E10), a standard statistical predictor of future stock returns. One caveat is that price-earnings ratios (or other valuation ratios like dividend yield, etc.) are in theory related to expected returns (Campbell and Shiller, 1988;

[25]Another empirical strategy is using monetary policy shocks to instrument for changes in the risk-free rate. In our sample period, among the well known monetary policy shocks, only the shocks used by 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 obtain results with similar coefficients but less power using this shock. In addition, to the extent that monetary policy shocks can affect stock market conditions and excess returns, they are not perfect instruments unless we can find precise measures of expectations of excess stock returns.

Campbell, 1991), not expected *excess* returns, which may affect our results.[26] To check robustness, in column (3) we instead control for the surplus consumption ratio (*Surp*) of Campbell and Cochrane (1999), which is theoretically linked to expected excess returns and empirically shown as a strong predictor (Campbell and Cochrane, 1999; Cochrane, 2011); in column (4) we control for predicted next twelve-month excess stock returns (estimated using past twelve-month stock returns and surplus consumption). We lag all of 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).

Table 7 shows that lower interest rates are associated with higher allocations to stocks and lower allocations to "cash." In terms of magnitude, 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 four percentage points difference in the level of interest rates, which is associated with a roughly eight percentage points change in the mean allocation to the risky asset. Interestingly, the magnitude of investment allocations' response to interest rates seems similar in the experiment and in the observational data. In Table A9 of the Internet Appendix, we present regressions using changes in allocations and changes in interest rates, which show similar results. We also find that the results are weaker using real interest rates instead of nominal interest rates, suggesting that nominal interest rates may play a more important role.

We perform similar analyses using data on household investment flows into various types of assets. Table 8 presents the results using monthly equity mutual fund flows (Panel A) and monthly high yield corporate bond fund flows (Panel B) from the Investment Company Institute (ICI), as well as Flow of Funds quarterly household sector flows into stocks (Panel C) and interest-bearing safe assets (Panel D). Because flows are analogous to changes in allocations, we use changes in interest rates on the right hand side. Control variables are the

[26]For a given market risk premium, an increase in the risk-free rate can mechanically increase the expected return/discount rate. If we control for model-based expected returns, as opposed to expected *excess* returns, the coefficient on the risk-free rate could be biased, and the direction depends on how household investment allocations respond to model-based expected excess returns. If allocations to stocks are positively correlated with model-based expected excess returns, then the magnitude of the coefficient on the risk-free rate could be inflated (bias for us). If allocations to stock are negatively correlated with model-based expected excess, then the magnitude of the coefficient on the risk-free rate could be dampened (bias against us). The latter case appears to hold in the data: households invest more aggressively in stocks when valuations are high and model-based expected excess returns are low, consistent with findings in Greenwood and Shleifer (2014).

same as before, and all right hand side variables are lagged by one period. Across different data sources, decreases in interest rates are consistently associated with flows into risky assets and out of safe interest-bearing assets.

We also use standard structural VAR (sVAR) to study the impulse response of investment decisions to innovations in interest rates, presented in the Internet Appendix Figure A3 and Figure A4. 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 A10, 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. The net inflows are equal to net issuance by accounting identity. Table A10 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 following a fall in interest rates. 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 A5 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, followed by lower excess returns in the long term, consistent with prior findings by Bernanke and Kuttner (2005). Taken together, the results appear consistent with increased household demand for equities when interest rates fall, which generates a positive price impact in the near term (as inflows persist for a while). The rest of the world accommodates a portion of the inflows. Higher overall demand for equities also induces more issuance by firms. After equity prices and valuations go up, there are eventually lower excess returns going forward.

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 present evidence of reaching for yield in individual investment decisions. We document that people demonstrate a greater appetite for risk taking when interest rates are low. Using a simple investment experiment, 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. We propose two categories of explanations, reference dependence and salience/proportional thinking, and provide evidence that both appear to contribute to the reaching for yield behavior we document. 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 have adopted extraordinary policies to stimulate the economy. A large volume of research studies how these policies affect borrowers (Di Maggio, Kermani, and Ramcharan, 2015; Auclert, 2016; Greenwald, 2016). There has been less focus on responses by savers. Our evidence suggests there is also much to be understood about savers' behavior. Indeed, many savers appear to have a deeply ingrained notion that saving is the preservation of wealth, and wealth should grow at a "decent" rate. This mindset could lead to saver behavior that is at odds with predictions of canonical models when interest rates are low or negative, as our evidence suggests. Savers' tendencies to take more risks in a low interest environment can also influence financial institutions' actions: institutions may invest in riskier assets to cater to clients' preferences, or they may design securities that highlight returns and shroud risks to further exploit these preferences (Célérier and Vallée, 2016).

Finally, while we have emphasized monetary policy, low interest rates likely arise from a confluence of factors. Our evidence could be relevant not only to monetary policy, but also to forces contributing to secular declines in interest rates, such as low productivity growth (Gordon, 2015), weak aggregate demand (Summers, 2015), shortage of assets (Caballero, Farhi, and Gourinchas, 2008), or financial innovation (Iachan, Nenov, and Simsek, 2016). The impact of the interest rate environment on investor behavior could have important implications for the link between key macroeconomic issues and capital market dynamics and financial stability.

References

Abbink, Klaus, and Bettina Rockenbach, 2006, Option pricing by students and professional traders: A behavioural investigation, *Managerial and Decision Economics* 27, 497–510.

Acharya, Viral, and Hassan Naqvi, 2015, On reaching for yield and the coexistence of bubbles and negative bubbles, Working paper.

Ambuehl, Sandro, Muriel Niederle, and Alvin Roth, 2015, More money, more problems? Can high pay be coercive and repugnant?, *American Economic Review* 105, 357–360.

Amromin, Gene, and Steven A Sharpe, 2013, From the horse's mouth: Economic conditions and investor expectations of risk and return, *Management Science* 60, 845–866.

Andersen, Steffen, Glenn W Harrison, Morten I Lau, and E Elisabet Rutström, 2008, Eliciting risk and time preferences, *Econometrica* 76, 583–618.

Andreoni, James, and Charles Sprenger, 2012, Estimating time preferences from convex budgets, *American Economic Review* 102, 3333–56.

Auclert, Adrien, 2016, Monetary policy and the redistribution channel, Working paper.

Barberis, Nicholas, Ming Huang, and Tano Santos, 2001, Prospect theory and asset prices, *Quarterly Journal of Economics* 116, 1–53.

Barberis, Nicholas, Ming Huang, and Richard H Thaler, 2006, Individual preferences, monetary gambles, and stock market participation: A case for narrow framing, *American economic review* 96, 1069–1090.

Becker, Bo, and Victoria Ivashina, 2015, Reaching for yield in the bond market, *Journal of Finance* 70, 1863–1902.

Benartzi, Shlomo, and Richard H Thaler, 1995, Myopic loss aversion and the equity premium puzzle, *Quarterly Journal of Economics* 110, 73–92.

Bernanke, Ben S, 2013, Monitoring the financial system, Speech at the 49th Annual Conference on Bank Structure and Competition, Federal Reserve Bank of Chicago.

Bernanke, Ben S, and Kenneth N Kuttner, 2005, What explains the stock market's reaction to federal reserve policy?, *Journal of Finance* 60, 1221–1257.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2012, Salience theory of choice under risk, *Quarterly Journal of Economics* 127, 1243–1285.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2013a, Sailence and consumer choice., *Journal of Political Economy* 121, 803–843.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2013b, Salience and asset prices, *American Economic Review* 103, 623–628.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer, 2016, Competition for attention, *Review of Economic Studies* 83, 481–513.

Bordalo, Pedro, Nicola Gennaioli, Andrei Shleifer, et al., 2017, Memory, attention and choice, Working paper.

Bossaerts, Peter, Charles Plott, and William R Zame, 2007, Prices and portfolio choices in financial markets: Theory, econometrics, experiments, *Econometrica* 75, 993–1038.

Bushong, Benjamin, Matthew Rabin, and Joshua Schwartzstein, 2015, A model of relative thinking, Working paper.

Caballero, Ricardo J, Emmanuel Farhi, and Pierre-Olivier Gourinchas, 2008, An equilibrium model of "Global Imbalances" and low interest rates, *American Economic Review* 98, 358–393.

Camerer, Colin F, 1987, Do biases in probability judgment matter in markets? Experimental evidence, *American Economic Review* 77, 981–997.

Campbell, John Y, 1991, A variance decomposition for stock returns, *Economic Journal* 101, 157–179.

Campbell, John Y, and John H Cochrane, 1999, By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107.

Campbell, John Y, and N Gregory Mankiw, 1989, Consumption, income and interest rates: Reinterpreting the time series evidence, in *NBER Macroeconomics Annual 1989, Volume 4*, 185–246.

Campbell, John Y, and Robert J Shiller, 1988, The dividend-price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, 195–228.

Campbell, John Y, and Tuomo Vuolteenaho, 2004, Inflation illusion and stock prices, *American Economic Review* 94, 19–23.

Casler, Krista, Lydia Bickel, and Elizabeth Hackett, 2013, Separate but equal? A comparison of participants and data gathered via Amazon's MTurk, social media, and face-to-face behavioral testing, *Computers in Human Behavior* 29, 2156–2160.

Cavallo, Alberto, Guillermo Cruces, and Ricardo Perez-Truglia, 2016, Inflation expectations, learning, and supermarket prices: Evidence from survey experiments, *American Economic Journal: Macroeconomics* forthcoming.

Célérier, Claire, and Boris Vallée, 2016, Catering to investors through security design: Headline rate and complexity, *Quarterly Journal of Economics* forthcoming.

Charness, Gary, and Uri Gneezy, 2010, Portfolio choice and risk attitudes: An experiment, *Economic Inquiry* 48, 133–146.

Charness, Gary, Uri Gneezy, and Alex Imas, 2013, Experimental methods: Eliciting risk preferences, *Journal of Economic Behavior & Organization* 87, 43–51.

Chodorow-Reich, Gabriel, 2014, Effects of unconventional monetary policy on financial institutions., *Brookings Papers on Economic Activity* .

Choi, Jaewon, and Mathias Kronlund, 2016, Reaching for yield by corporate bond mutual funds, Working paper.

Cipriani, Marco, and Antonio Guarino, 2009, Herd behavior in financial markets: an experiment with financial market professionals, *Journal of the European Economic Association* 7, 206–233.

Cochrane, John H, 2011, Presidential address: Discount rates, *Journal of Finance* 66, 1047–1108.

Cohen, Randolph B, Christopher Polk, and Tuomo Vuolteenaho, 2005, Money illusion in the stock market: The Modigliani-Cohn hypothesis, *Quarterly Journal of Economics* 120, 639–668.

Cohn, Alain, Jan Engelmann, Ernst Fehr, and Michel André Maréchal, 2015, Evidence for countercyclical risk aversion: An experiment with financial professionals, *American Economic Review* 105, 860–885.

Cunningham, Thomas, 2013, Comparisons and choice, Working paper.

D'Acunto, Francesco, 2015, Identity, overconfidence, and investment decisions, Working paper.

DellaVigna, Stefano, and Devin Pope, 2017a, Predicting experimental results: Who knows what?, *Journal of Political Economy* forthcoming.

DellaVigna, Stefano, and Devin Pope, 2017b, What motivates effort? Evidence and expert forecasts, *Review of Economic Studies* forthcoming.

Di Maggio, Marco, and Marcin T Kacperczyk, 2017, The unintended consequences of the zero lower bound policy, *Journal of Financial Economics* 123, 59–80.

Di Maggio, Marco, Amir Kermani, and Rodney Ramcharan, 2015, Monetary policy pass-through: Household consumption and voluntary deleveraging, Working paper.

Drechsler, Itamar, Alexi Savov, and Philipp Schnabl, 2015, A model of monetary policy and risk premia, *Journal of Finance* forthcoming.

Feroli, Michael, Anil K Kashyap, Kermit L Schoenholtz, and Hyun Song Shin, 2014, Market tantrums and monetary policy, Working paper.

Fink, Larry, 2016, Chairman's letter, *Blackrock 2015 Annual Report*.

Frydman, Cary, Samuel M Hartzmark, and David Solomon, 2016, Rolling mental accounts, Working paper.

Frydman, Cary, and Milica Mormann, 2016, The role of salience and attention in choice under risk: An experimental investigation, Working paper.

Fuster, Andreas, David Laibson, and Brock Mendel, 2010, Natural expectations and macroeconomic fluctuations, *Journal of Economic Perspectives* 24, 67–84.

Gabaix, Xavier, 2016, A behavioral New Keynesian model, Working paper.

Ganzach, Yoav, and Avi Wohl, 2016, The effect of the risk free rate on the attractiveness of risky assets, Working paper.

Gertler, Mark, and Peter Karadi, 2015, Monetary policy surprises, credit costs, and economic activity, *American Economic Journal: Macroeconomics* 7, 44–76.

Gilchrist, Simon, and Egon Zakrajšek, 2012, Credit spreads and business cycle fluctuations, *American Economic Review* 102, 1692–1720.

Gneezy, Uri, and Jan Potters, 1997, An experiment on risk taking and evaluation periods, *Quarterly Journal of Economics* 631–645.

Gordon, Robert J, 2015, Secular stagnation: A supply-side view, *American Economic Review* 105, 54–59.

Greenwald, Daniel L, 2016, The mortgage credit channel of macroeconomic transmission, Working paper.

Greenwood, Robin, and Andrei Shleifer, 2014, Expectations of returns and expected returns, *Review of Financial Studies* 27, 714–746.

Haigh, Michael S, and John A List, 2005, Do professional traders exhibit myopic loss aversion? An experimental analysis, *Journal of Finance* 60, 523–534.

Hall, Robert E, 1988, Intertemporal substitution in consumption, *Journal of Political Economy* 339–357.

Hanson, Samuel G, and Jeremy C Stein, 2015, Monetary policy and long-term real rates, *Journal of Financial Economics* 115, 429–448.

Hastings, Justine S, and Jesse M Shapiro, 2013, Fungibility and consumer choice: Evidence from commodity price shocks, *Quarterly Journal of Economics* 128, 1449–1498.

He, Xue Dong, and Xun Yu Zhou, 2011, Portfolio choice under cumulative prospect theory: An analytical treatment, *Management Science* 57, 315–331.

Holt, Charles A, and Susan K Laury, 2002, Risk aversion and incentive effects, *American Economic Review* 92, 1644–1655.

Iachan, Felipe S, Plamen T Nenov, and Alp Simsek, 2016, The choice channel of financial innovation, Technical report.

Jiménez, Gabriel, Steven Ongena, José-Luis Peydró, and Jesús Saurina, 2014, Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking?, *Econometrica* 82, 463–505.

Kahneman, Daniel, and Dale T Miller, 1986, Norm theory: Comparing reality to its alternatives, *Psychological Review* 93, 136.

Kahneman, Daniel, and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 263–291.

Kőszegi, Botond, and Matthew Rabin, 2006, A model of reference-dependent preferences, *Quarterly Journal of Economics* 1133–1165.

Kőszegi, Botond, and Adam Szeidl, 2013, A model of focusing in economic choice, *Quarterly Journal of Economics* 128, 53–104.

Kuziemko, Ilyana, Michael I Norton, Emmanuel Saez, and Stefanie Stantcheva, 2015, How elastic are preferences for redistribution? Evidence from randomized survey experiments, *American Economic Review* 105, 1478–1508.

Lei, Vivian, Charles N Noussair, and Charles R Plott, 2001, Nonspeculative bubbles in experimental asset markets: Lack of common knowledge of rationality vs. actual irrationality, *Econometrica* 69, 831–859.

List, John A, and Michael S Haigh, 2005, A simple test of expected utility theory using professional traders, *Proceedings of the National Academy of Sciences* 102, 945–948.

Maddaloni, Angela, and José-Luis Peydró, 2011, Bank risk-taking, securitization, supervision, and low interest rates: Evidence from the euro-area and the us lending standards, *Review of Financial Studies* 24, 2121–2165.

Malmendier, Ulrike, and Stefan Nagel, 2011, Depression babies: Do macroeconomic experiences affect risk taking?, *Quarterly Journal of Economics* 126, 373–416.

Malmendier, Ulrike, and Stefan Nagel, 2016, Learning from inflation experiences, *Quarterly Journal of Economics* 131, 53–87.

Malmendier, Ulrike, Stefan Nagel, and Zhen Yan, 2016, The making of hawks and doves: Inflation experiences and voting on the FOMC, Working paper.

Mankiw, N Gregory, Julio J Rotemberg, Lawrence H Summers, et al., 1985, Intertemporal substitution in macroeconomics, *Quarterly Journal of Economics* 100, 225–251.

Markowitz, Harry, 1952, Portfolio selection, *Journal of Finance* 7, 77–91.

Modigliani, Franco, and Richard A Cohn, 1979, Inflation, rational valuation and the market, *Financial Analysts Journal* 35, 24–44.

Morris, Stephen, and Hyun Song Shin, 2015, Risk-taking channel of monetary policy: A global game approach, Working paper.

Newey, Whitney K, and Kenneth D West, 1994, Automatic lag selection in covariance matrix estimation, *Review of Economic Studies* 61, 631–653.

Rajan, Raghuram, 2013, A step in the dark: Unconventional monetary policy after the crisis, Andrew Crockett Memorial Lecture, Bank for International Settlements.

Ramey, Valerie A, 2015, Macroeconomic shocks and their propagation, *Handbook of Macroeconomics* forthcoming.

Ryan, Camille L, and Kurt Bauman, 2015, Educational attainment in the United States: 2015, US Census Bureau.

Sharpe, William F, 1964, Capital asset prices: A theory of market equilibrium under conditions of risk, *Journal of Finance* 19, 425–442.

Smith, Alec, Terry Lohrenz, Justin King, P Read Montague, and Colin F Camerer, 2014, Irrational exuberance and neural crash warning signals during endogenous experimental market bubbles, *Proceedings of the National Academy of Sciences* 111, 10503–10508.

Stein, Jeremy, 2013, Remarks at the restoring household financial stability after the great recession research symposium, Federal Reserve Bank of St. Louis.

Summers, Lawrence H, 2015, Demand side secular stagnation, *American Economic Review* 105, 60–65.

Tversky, Amos, and Daniel Kahneman, 1981, The framing of decisions and the psychology of choice, *Science* 211, 453–458.

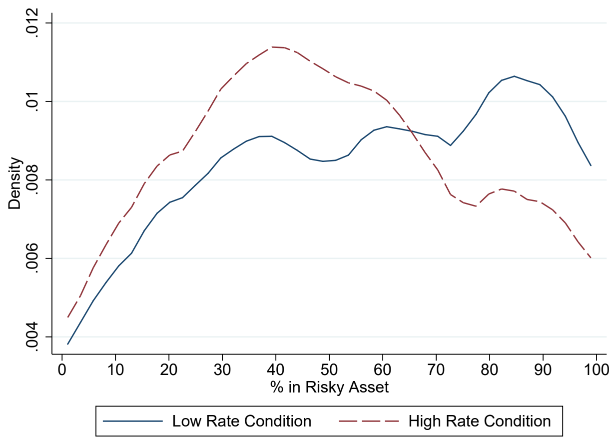
Tversky, Amos, and Daniel Kahneman, 1992, Advances in prospect theory: Cumulative representation of uncertainty, *Journal of Risk and Uncertainty* 5, 297–323.

A Figures

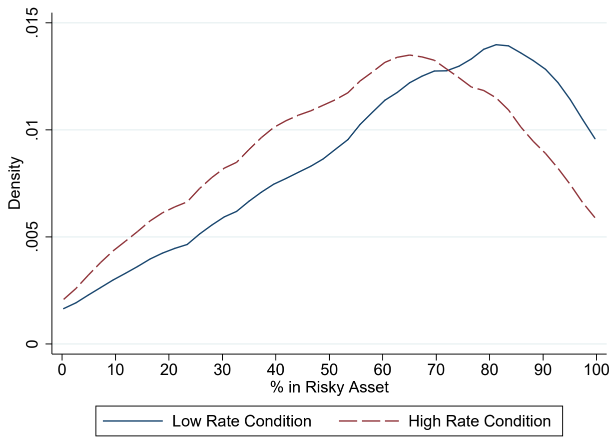
Figure 1: Distribution of Allocations to the Risky Asset in Benchmark Experiments

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: MBA, Incentivized

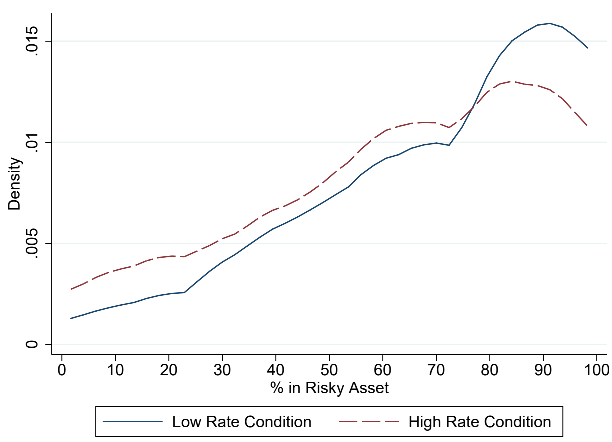
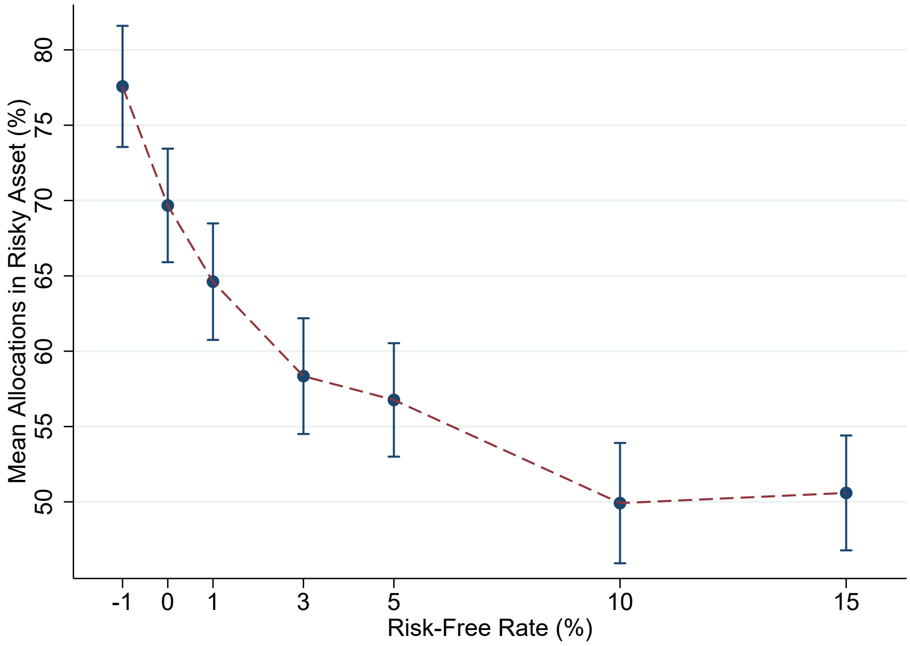


Figure 2: Mean Allocations Across Interest Rate Conditions in Experiment T1

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 vertical bar shows the 95% confidence interval for the mean allocation.



B Tables

Table 1: Summary Statistics of Benchmark Experiment Samples

This table presents the demographics of benchmark experiment samples. Panels A, B, C tabulate information 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.

Panel A. Experiment B1: MTurk, Hypothetical

		Low		High	
		N	%	*N*	%
Gender	Male	82	40.0	102	52.3
	Female	123	60.0	93	47.7
Education	Graduate school	38	18.5	30	15.4
	College	112	54.6	118	60.5
	High school	53	25.9	45	23.1
Age	Below 25	59	28.8	51	26.2
	25–45	116	56.6	120	61.5
	45–65	29	14.1	24	12.3
	Above 65	1	0.5	0	0.0
Investing exper.	Extensive experience	7	3.4	6	3.1
	Some experience	61	29.8	60	30.8
	Limited experience	88	42.9	75	38.5
	No experience	49	23.9	54	27.7
Fin. wealth (ex. housing)	In debt	23	11.2	28	14.4
	0–10K	59	28.8	51	26.2
	10K–50K	57	27.8	43	22.1
	50K–200K	56	27.3	56	28.7
	200K+	10	4.9	17	8.7
Total		205		195	

Panel B. Experiment B2: MTurk, Incentivized

		Low		High	
		N	%	*N*	%
Gender	Male	116	56.6	111	56.9
	Female	89	43.4	84	43.1
Education	Graduate school	30	14.6	33	16.9
	College	122	59.5	125	64.1
	High school	52	25.4	35	17.9
Age	Below 25	51	24.9	39	20.0
	25–45	123	60.0	127	65.1
	45–65	30	14.6	27	13.8
	Above 65	1	0.5	2	1.0
Investing exper.	Extensive experience	6	2.9	6	3.1
	Some experience	68	33.2	66	33.8
	Limited experience	83	40.5	75	38.5
	No experience	48	23.4	48	24.6
Fin. wealth (ex. housing)	In debt	31	15.1	25	12.8
	0–10K	42	20.5	35	17.9
	10K–50K	60	29.3	58	29.7
	50K–200K	47	22.9	55	28.2
	200K+	25	12.2	22	11.3
Total		205		195	

Panel C. Experiment B3: MBA, Incentivized

		Low		High	
		N	%	*N*	%
Gender	Male	117	58.2	129	64.8
	Female	84	41.8	70	35.2
Past 15 yrs of life	US	140	69.7	133	66.8
	Abroad	61	30.3	66	33.2
Primary educational field	Humanities	26	12.9	23	11.6
	Social Science	64	31.8	43	21.6
	Science and Engineering	80	39.8	95	47.7
	Other	31	15.4	38	19.1
Investment exper.	Extensive/professional	22	10.9	25	12.6
	Some experience	71	35.3	60	30.2
	Limited experience	70	34.8	69	34.7
	No experience	38	18.9	45	22.6
Worked in finance	Yes	84	41.8	86	43.2
	No	117	58.2	113	56.8
		201		199	

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

This table presents results of the benchmark experiments. 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 rate condition, controlling for individual characteristics. The individual characteristics include dummies for gender, education level, age group, risk aversion level, and wealth level in the MTurk experiments, and dummies for gender, primary education background (humanities, social sciences, natural sciences, other), risk aversion level, having work experience in finance, and being an international student in the MBA experiment.

Panel A. Mean Allocations to Risky Asset (%)

	High: 5—10	Low: 1—6	Difference	t-stat
B1: MTurk, Hypothetical	48.15	55.32	7.17	2.52
B2: MTurk, Incentivized	58.58	66.64	8.06	3.06
B3: MBA, Incentivized	66.79	75.61	8.83	3.13

Panel B. Differences Controlling for Individual Characteristics

	Coef.	t-stat
B1: MTurk, Hypothetical	7.10	2.47
B2: MTurk, Incentivized	8.19	3.25
B3: MBA, Incentivized	8.53	3.15

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. In this experiment, 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.

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-stat 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-stat 3.14

(b) Incentivized

Table 5: Baseline and Gross Framing

This table presents results of Experiment T3. 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. It also compares allocations with baseline framing to allocations with gross framing. Panel B presents the coefficient and t-statistics on the dummy of low interest rate condition, controlling for individual characteristics. The individual characteristics include dummies for gender, education level, age group, risk aversion level, and wealth level.

Panel A. Mean Allocations to Risky Asset (%)

	High: 5—10	Low: 1—6	Difference	t-stat
Baseline	57.13	64.51	7.38	2.69
Gross	52.65	54.44	1.79	0.65
Baseline - Gross	4.47	10.06	5.59	
t-stat	1.61	3.72	1.44	

Panel B. Differences Controlling for Individual Characteristics

	Coef.	t-stat
Baseline	7.18	2.72
Gross	2.40	0.89

Table 6: Summary Statistics of Observational Data

Summary statistics for observational data. Mean, median, standard deviation, quartiles, and data time period are presented. Variables include: allocations to stocks and bonds using data from the American Association of Individual Investors (AAII); equity (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 fund, 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 rate - 10-year Treasury rate).

	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	1987M12	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	1985M2	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 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. 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	-0.3784	-1.4652	-1.9244	-1.9980
	[-0.51]	[-4.49]	[-2.46]	[-2.57]
L.P/E10		0.8433		
		[9.16]		
L.$Surp$			6.7891	
			[0.40]	
L.$E[rx^{12}_{stk}]$				-0.1221
				[-0.60]
L.AAII Sentiment		0.0371	0.1705	0.1620
		[1.66]	[4.01]	[3.67]
L.VIX^2		-6.3403	-14.4527	-5.7282
		[-0.78]	[-0.96]	[-0.27]
L.Past 12M GDP Growth		0.3412	2.1078	2.1727
		[0.85]	[2.61]	[2.77]
L.Credit Spread		-3.8702	-2.6354	-3.3687
		[-4.02]	[-1.34]	[-1.46]
Constant	61.4669	52.5819	66.0072	68.8711
	[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	0.6226	1.5067	1.1859	1.2752
	[1.21]	[3.85]	[2.26]	[1.99]
L.P/E10		-0.4727		
		[-4.22]		
L.$Surp$			20.5606	
			[1.78]	
L.$E[rx^{12}_{stk}]$				-0.2074
				[-1.27]
L.AAII Sentiment		-0.0239	-0.1259	-0.1303
		[-1.00]	[-4.29]	[-3.41]
L.VIX^2		9.6947	11.0089	27.0219
		[1.10]	[1.06]	[1.52]
L.Past 12M GDP Growth		-0.0051	-1.3331	-1.0977
		[-0.01]	[-2.45]	[-1.63]
L.Credit Spread		3.8334	2.8172	1.6920
		[3.56]	[2.11]	[0.86]
Constant	21.8509	21.3176	15.1410	19.5041
	[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 short-term 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	-0.4188	-0.4205	-0.4030	-0.4387
	[-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	-1.0098	-0.7764	-0.7818	-1.1745
	[-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	-0.3663	-0.4678	-0.4042	-0.7435
	[-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	0.4141	0.3953	0.3812	0.3432
	[3.11]	[2.51]	[2.41]	[1.60]
Controls	No	Yes	Yes	Yes
Observations	120	109	109	109

Newey-West t-statistics in brackets