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

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Abstract

In recent years, many central banks have set benchmark interest rates to historic lows. In this paper, we provide evidence that individual investors "reach for yield", that is, have a greater appetite for risk taking in such low interest rate environment. We first document this phenomenon in a simple investment experiment, where investment risks and risk premia are held constant. We find significantly higher allocations to risky assets in the low rate condition, among MTurks as well as HBS MBAs. This reaching for yield behavior is unrelated to institutional frictions, and cannot be easily explained by conventional portfolio choice theory. We then propose and provide evidence for two sets of explanations related to people's preferences and psychology. We also present complementary evidence using historical data on individual investors' portfolio allocations and household investment flows.

JEL classification: E03, E43, E44, E52, E58, G02, G11.

Key words: Low interest rate; risk taking; financial stability; individual investment decisions.

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1 Introduction

In the past several years, central banks in major developed countries have set benchmark interest rates to historic lows. While ultra low interest rates aim to spur economic growth, they have raised concerns about unintended consequences. A major concern is "reaching for yield" in financial markets, which refers to the possibility that investors may have a greater appetite for risk taking, all else equal, when interest rates are low.[1] This issue has important implications for understanding the impact of monetary policy on capital markets and financial stability.

Indeed, central bank leaders have frequently discussed reaching for yield in policy remarks. For example, in a 2013 speech, then Chairman of the Federal Reserve Ben Bernanke pointed out: "In light of the current low interest rate environment, we are watching particularly closely for instances of 'reaching for yield' and other forms of excessive risk taking, which may affect asset prices and their relationships with fundamentals (Bernanke, 2013)." Other top central bank officials such as Janet Yellen, Jeremy Stein, Raghu Rajan, etc. (Yellen, 2011; Stein, 2013; Rajan, 2013), as well as a large group of investors, have also publicly discussed their concerns about reaching for yield.

Despite its prominence, reaching for yield has not yet been fully understood; its causes and mechanisms are still under investigation. A common perspective in recent research focuses on how institutional frictions may lead to reaching for yield. Some theories suggest that the nominal interest rate can affect banks' capacity to buy risky assets by changing banks' cost of leverage (Drechsler, Savov, and Schnabl, 2015), while others postulate that financial institutions' risk taking may respond to interest rates due to agency problems (Feroli, Kashyap, Schoenholtz, and Shin, 2014; Morris and Shin, 2015; Acharya and Naqvi, 2015). A number of papers 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, 2015; Di Maggio and Kacperczyk,

[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 to achieve higher yields, 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 constant the risks and excess returns of risky assets.

2016).

Yield seeking behavior, however, does not seem to be confined to institutions. Households and individual investors also appear to reach for yield in personal investment decisions. Some anecdotes suggest that savers have been frustrated with low interest rates in recent years, and often respond by shifting into riskier assets.[2] This observation hints that institutional friction based explanations, while potentially quite important, may not be the entire story.

In this paper, we present evidence that reaching for yield could be partly driven by the way people perceive and evaluate return and risk trade-offs in different interest rate environment. It is significant even when people are investing for themselves, and may arise from preferences and psychology. Our observation points to reaching for yield as a robust phenomenon that is complementary to, yet may exist in the absence of, institutional frictions. Our findings also suggest that investors' propensity to reach for yield likely depends on past economic environment and experiences.

Specifically, we show that individuals demonstrate a stronger preference for risky assets in their investment decisions when the risk-free rate is low. We begin by documenting this phenomenon in a randomized 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 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 level of returns. 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 level of returns under conventional mean variance benchmark.

We find robust evidence—across different settings (hypothetical question as well as incentivized experiment) and among a diverse group of participants (workers on Amazon Mechanical Turk platform as well as Harvard Business School MBA students)—that people in the low interest rate condition (Treatment Group 2) invest significantly more in the risky

[2] "Options for Savers Seeking Better Rates", *New York Times*, July 13, 2012. "Some Investors Can't Wait for the Fed to Raise Rates", *Wall Street Journal*, April 28, 2015. "The High Consequences of Low Interest Rates", *Wall Street Journal*, February 6, 2016.

asset than people in the high interest rate condition (Treatment Group 1). 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 canonical portfolio choice theory, which does not naturally generate this type of behavior under fairly general conditions (specifically, absolute risk aversion is weakly decreasing in wealth).

We conjecture two broad categories of mechanisms that contribute to reaching for yield in individual investment decisions. The first category of mechanisms 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 for higher returns. This observation connects to the popular view among investors that 1% interest rates are "too low", in comparison to what people have become used to over past experiences. This intuition 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 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 environment. 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). 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 mechanisms, and find support for both categories of explanations. In line with predictions of reference dependence, investment history, which may influence investors' reference point, 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 below 3%. This cut-off seems consistent with the level of interest rates that most participants are used to prior to recent years. In line with predictions of salience and proportional thinking, risk taking decreases and reaching for yield gets 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).

Experiments are helpful for testing our hypothesis for several reasons. First, they allow us to control for the risks and excess returns of the risky asset, and isolate the impact of changes in the risk-free rate. This overcomes the challenge that people's perception of risks and returns of assets in capital markets is often difficult to measure. For instance, Greenwood and Shleifer (2014) show that subjective beliefs about future stock returns tend to be negatively correlated with model based expected returns. Célérier and Vallée (2016) show that perceptions of risks can be manipulated by product complexity and shrouding. Second, randomized experiments allow us to create large exogenous variations in interest rates in investment decisions, which are otherwise hard to find. Monetary policy shocks, for example, are difficult to identify and mostly very small in magnitude (see Ramey (2015) for a comprehensive summary of the empirical challenges in identifying monetary policy shocks). Finally, experiments help us to test the underlying mechanisms in detail, and provide more insights on what drives the reaching for yield behavior we observe.

Nonetheless, we supplement our experimental results with suggestive evidence from observational data. We draw on 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 valuation ratios, investors' subjective beliefs, and general economic conditions. The magnitude, coincidentally, 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 that they tend to increase when interest rates fall.

Our study contributes to several strands of research. First, it contributes to the understanding of reaching for yield, a central phenomenon that links monetary policy with risk premia, capital market conditions, and financial stability. We provide direct evidence of reaching for yield in investment decisions. Our findings complement the institutional friction based narratives (Hanson and Stein, 2015; Drechsler et al., 2015; Acharya and Naqvi, 2015); it also suggests that reaching for yield may arise even in the absence of institutional friction. The behavior we document in personal investment decisions could have a major impact on the market. Indeed, individuals are the end investors who decide whether to put their savings in safe assets or in risky assets. Households' preferences and behavior affect resources financial institutions have, and institutions often cater to their tastes.[3] In addition, while we focus on household and individual investment decisions, the preferences and psychology we document may also affect professionals. We find that reaching for yield in personal investment decisions is significant among financially well-educated individuals like HBS MBAs, some of whom may become leading figures in financial institutions. We also do not find evidence that reaching for yield in investment decisions diminishes with education, wealth, investment experience, or work experience in finance (if anything slightly the opposite).

Second, our study contributes to research on portfolio choice decisions, which is at the heart of financial economics. 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; Scheinkman and Xiong, 2003; Malmendier and Nagel, 2011; Hartzmark and Shue, 2016; 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; García-Schmidt and Woodford, 2015; Gennaioli, Ma, and Shleifer, 2015a; Gabaix, 2016; Malmendier, Nagel, and Yan, 2016).

Third, our evidence on risk taking and interest rate environment may also have implications for security design and consumer protection, as households' biases could be exploited by institutions and asset managers that highlight returns and shroud risks (Célérier and Vallée, 2016). Shrouding risks will likely aggravate households' risk taking behavior in a low rate environment.

Finally, 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; Thaler, Tversky, Kahneman, and Schwartz, 1997; Cohn, Engelmann, Fehr, and Maréchal, 2015; Kuhnen and Knutson, 2011). 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

[3]For example, Di Maggio and Kacperczyk (2016) and Choi and Kronlund (2015) show that money market mutual funds and corporate fund mutual funds who 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 is an important contributor to reaching for yield by financial institutions.

and corporations), interest rates are essential. We show that interest rates play an important role in affecting risk taking behavior. In an experiment with hypothetical investment questions, Ganzach and Wohl (2016) also find that a low risk-free rate tends to increase the attractiveness of risky assets. Our study provides a large set of evidence across many different settings: hypothetical as well as incentivized experimental treatments, diverse subject pools, and historical data. We perform extensive tests on the influence of the interest rate environment when excess returns of the risky asset are held constant, isolating behavior that departs from predictions of canonical theories. We also connect our empirical findings closely 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 novel findings that shed light on theories and suggest policy implications.

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 of reaching for yield in personal investment decisions in observational data. 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 very 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 return is 18%, which is 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 payment structure, experimental setting, 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. In the hypothetical experiment, participants consider making investment decisions in a hypothetical setting. In the incentivized experiments, participants consider allocating experimental endowment to different investments, and may receive bonus payment proportional to their investment outcomes.

We conduct the benchmark experiment with two main groups of participants. The first group is workers on Amazon Mechanical Turks who are adults (18 years old or above) from across the US.[4] MTurk has become a popular platform for experimental studies and is increasingly used in economics research (e.g. Kuziemko, Norton, Saez, and Stantcheva (2015); Ambuehl, Niederle, and Roth (2015); D'Acunto (2015); Cavallo, Cruces, and Perez-Truglia (2016)). It offers a large and diverse subject pool compared to lab experiments, requires relatively low costs, takes a very short amount of time, and provides response quality similar to that of lab experiments (Casler, Bickel, and Hackett, 2013). These features are helpful for our study, especially given that our subsequent experiments testing potential mechanisms require a very large number of participants. For our experiments on MTurk, the participation payment and the stake size (in the incentivized case) are high relative to the average pay rate on MTurk, to make sure that we provide significant incentives for our participants.

We also conduct the benchmark experiment with Harvard Business School MBA students. HBS MBA students are a unique pool of individuals 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. Therefore, experiments

[4] We restrict to US workers by setting the eligibility of our MTurk work request to workers who are based in the US, and by subsequently verifying their IP addresses.

with HBS MBA students will help us understand the extent to which the reaching for yield behavior exists among this important group of financial decision makers. For our experiments with HBS MBAs, the payment and stake size 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 hypothetical questions about investing total savings of \$100,000 between the risk-free asset and the risky asset. The investment horizon is one year. Participants are recruited on MTurk in June 2016. They receive a fixed participation payment of \$1. Survey form for Experiment B1 is presented in the Survey Appendix.

Table 1 Panel A presents summary statistics of participant demographics in Experiment B1. Roughly a half of the participants are male. About 75% 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% participants have financial wealth (excluding housing) above \$10,000, with about ten to fifteen percent in debt and another five to ten percent having financial wealth more than \$200,000, which is largely in line with the US general population (2013 Survey of Consumer Finance finds median household net worth to be 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 experimental endowment of 100,000 Francs to the risk-free asset and the risky asset. The investment horizon is one year. Participants are recruited on MTurk in February 2016. They receive participation payment of \$0.7, and 10% randomly chosen participants receive bonus payment proportional to their investment outcome, with every 8,950 Francs converted to one dollar (so the bonus payment is on the scale of \$12).[5] Given the one year investment horizon, the bonus payment is de-

[5] We use 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

livered a year after participation. We also perform extensive tests showing that our results are robust to payment structure and investment horizon. 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 the demographics are quite similar to those in Experiment B1.

Experiment B3: HBS MBA, Incentivized

In Experiment B3, participants consider allocating 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 current HBS MBAs in April 2016. They receive a $12 dining hall lunch voucher in appreciation for their participation, and 10% randomly chosen participants receive bonus payment proportional to their investment outcome, with every 4,950 Francs converted to one dollar (so the bonus payment is on the scale of $210). Given the one year investment horizon, the bonus payment is delivered a year after participation. Survey form for Experiment B3 is presented in the Survey Appendix.

Table 1 Panel C shows that about 60% of the 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 work experience in finance.

2.2 Results

Table 3 reports results of the benchmark experiment. Table 3 Panel A shows mean allocations to the risky asset in high and low interest rate conditions for Experiments B1 to B3, the difference in mean allocations between high and low rate 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%).[6] Figure 1 plots the

to make the investment problem easier to think about.

[6]The *level* of mean allocation in the three settings is somewhat different. It is highest in the MBA incentivized experiment, somewhat lower in in the MTurk incentivized experiment, and lowest in the MTurk

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 a downward shift in allocations from the low rate condition to the high rate condition.

Table 3 Panel B shows the difference across treatment 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 educational background, 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.[7]

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 $\gamma = 3$,[8] 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).

It is interesting to note that our results on reaching for yield are highly consistent across different settings and subject pools. Some previous studies find that the influence of psychological forces in financial decision making diminishes with education and experience (List and Haigh, 2005; Cipriani and Guarino, 2009), while others do not find such an effect or

hypothetical experiment. This pattern is intuitive as MBAs tend to be more risk tolerant than MTurk workers, and participants tend to be more risk tolerant investing experimental endowment than investing a significant amount of personal savings. However, these differences in risk tolerance do not seem to affect our results on reaching for yield.

[7]In the experiment, participants make decisions about investing a fixed amount of money. In practice, interest rates may also affect the consumption/saving decision and therefore the amount of money people decide to invest in the first place. Prior empirical studies, however, often do not find significant responses of consumption and saving 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.

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

find the opposite (Haigh and List, 2005; Abbink and Rockenbach, 2006; Cohn et al., 2015). In our data, HBS MBAs and MTurk workers 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 Supplementary Appendix Table A1. If anything, participants with more wealth, more investment experience, and past 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. In Table A2, we also provide evidence that results in the incentivized experiments are robust to different payment methods and payment horizons.

One potential concern with our incentivized experiments is the stakes are relatively small compared to participants' net worth. While experimental economics emphasizes providing monetary incentives to elicit more reliable responses, this design certainly comes with limitations given researchers' budget constraints. With respect to the typical stake size in incentivized experiments, participants should be risk neutral and put everything in investments with highest average returns. In our data, however, only about 25% participants in Experiment B2 (MTurk) and about 30% 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, research in experimental economics 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 research uses small experimental stakes to calibrate parameters associated with curvatures in utility functions and find informative results (Andersen, Harrison, Lau, and Rutström, 2008; Andreoni and Sprenger, 2012; Charness, Gneezy, and Imas, 2013). Prior work also uses small experimental stakes to estimate and test formal models of portfolio choice (Bossaerts et al., 2007). We use stake size that is in line with the literature and with previous work on risk preferences in financial decisions that has found compelling results (Cohn et al., 2015; Charness and Gneezy, 2010). Second, we find that risk preferences with respect to experimental stakes in our setting are very informative about participants' risk preferences in financial decision making in general. For example, Table A3 in the Supplementary Appendix shows that allocations in the experiment are highly correlated with allocations of participants' household financial wealth. Third, the concern about small 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 will likely work against us finding significant differences in risk taking across treatment conditions.

In summary, we find that propensity to invest in the risky asset increases significantly in the low interest rate condition. This result holds across different experimental settings and subject pools. In the next section, we discuss potential explanations of this behavior. We first show that conventional portfolio choice theories cannot easily generate this prediction. We then outline two categories of potential explanations building on insights from behavioral economics and behavioral finance.

3 Potential Mechanisms

In this section, we discuss potential explanations of the results we document in Section 2. We begin by showing that conventional portfolio choice theories cannot easily generate predictions of reaching for yield. 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 maps into the 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 most 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 expected returns and the variance of the portfolio:

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

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

Proposition 1. *For a given distribution of the excess returns x, the optimal allocation to the risky asset, $\phi_{mv}^{*} = \min\left(\frac{\mathbb{E}x}{\gamma Var(x)}, 1\right)$, of an investor following mean variance analysis does not change with the risk-free rate r_f.*

In other words, if we fix the distribution of the excess returns x, changing r_f creates parallel shifts of the returns of both assets; this does not change the risk-return trade-off between them in mean variance analysis.

The optimal mean variance portfolio allocation ϕ_{mv}^{*} defined in Equation (3) is only an approximation to the optimal allocation to the risky asset ϕ^{*} defined in Equation (2) [9] Next we turn to the general case which also takes into account the potential impact of the higher order terms.

General Case. Now we discuss how the optimal allocation to the risky asset ϕ^{*} changes with the risk-free rate r_f given the distribution of the excess returns x. Under fairly general conditions—specifically, weakly decreasing absolute risk aversion—that are satisfied by most of the commonly studied utility functions (e.g. CRRA), we show that the conventional portfolio choice analysis does not explain the reaching for yield phenomenon we document in Section 2.

Assumption 1. *u is twice differentiable and concave. The investor has (weakly) decreasing absolute risk aversion.*[10]

Proposition 2. *Under Assumption 1, for a given distribution of the excess returns x, the optimal allocation to the risky asset ϕ^{*} is (weakly) increasing in r_f.*

[9]The 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 although x has a log normal distribution, the portfolio returns $1 + r_p = 1 + r + \phi x$ are not necessarily distributed log normally.

[10]In the literature of decision under uncertainty, evidence for increasing *relative* risk aversion is sometimes documented, but (weakly) decreasing *absolute* risk aversion appears to be a consensus (Holt and Laury, 2002).

The intuition behind the 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". The wealth effect, however, is not first order and it drops out in the mean variance approximation.[11]

One may wonder whether increasing absolute risk aversion is a possible explanation of the reaching for yield phenomenon we document. In the literature of choice under uncertainty, evidence of increasing relative risk aversion is sometimes documented, but (weakly) decreasing absolute risk aversion appears to be a consensus (Holt and Laury, 2002). Furthermore, 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 analysis summarized in Proposition 2 does not seem to naturally generate predictions in line with the reaching for yield phenomenon we document in Section 2.

3.2 Reference Dependence

In the following, we discuss two categories of potential mechanisms that may 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 for higher returns. This captures the view some investors hold that 1% interest rates are "too low" (where the notion "too low" implies comparison to some reference level and discomfort in light of that). This intuition can be formalized in the framework of loss aversion around reference points (Benartzi and Thaler, 1995), an important component of the Prospect Theory (Kahneman and Tversky, 1979; Barberis et al., 2001). The dependence on reference points generates additional predictions that we will test in Section 4. In the following, we first analyze the investment decision problem in a framework featuring loss aversion around the reference point following the

[11] One may wonder why 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).

work by He and Zhou (2011), and show how it can generate predictions of reaching for yield. We then discuss different theories of reference point formation and their relevance in our setting. Finally we discuss the empirical predictions and novel implications.

We use the same set-up as before, but now instead of Assumption 1, we assume the utility function u features loss aversion captured by a kink around the reference point:

Assumption 2.

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

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 essence of our mechanism relies on the reference point and loss aversion around the reference point. We discuss the case with diminishing sensitivity in the Supplementary Appendix. Probability reweighting does not affect our key result in Proposition 3 about responses to changes in the risk-free rate; see He and Zhou (2011) for a more detailed discussion.

Proposition 3. *Under Assumption 2, 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 3 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, optimal allocations 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 increases with interest rates. In other words, the investor would "reach against yield" in this case with $r_f > r_r$.

In Section 4, we will provide results as we move the risk-free rate from low (e.g. -1%) to high (e.g. 15%) to shed light on predictions in Proposition 3.

Proposition 3 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 2, 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 allocations to the risky asset. The intuition of Corollary 1 is similar to that of Proposition 3. 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. On the other hand, 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.

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 extensive discussions in the Supplementary Appendix.

In the framework of Kahneman and Tversky (1979), the reference point is the status quo wealth level ($r_r = 0$). This, however, falls into the second case of Proposition 3. Thus, loss aversion around zero *alone* might lead to "reaching against yield" in the setting of our benchmark experiment, opposite of the empirical evidence.[12]

[12] That said, we are not suggesting that loss aversion at zero does not matter. It is perhaps important

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.[13]

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., 2015b). 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. This case falls in the first case of Proposition 3, 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 investor community's popular view that 1% or 0% interest rates are "too low".[14]

Together with Corollary 1, history dependent reference point suggests a novel implication: the degree of reaching for yield may depend on prior economic conditions—how much people invest in risky assets when interest rates are low may be different if they used to live in an environment of high interest rates (e.g. 5%) versus if they used to live in an environment of modest interest rates (e.g. 2%). It might also be different when rates decline sharply as opposed to gradually. These observations have potential implications for the impact of monetary policy on risk taking and financial stability.

In Section 4, we provide evidence that investment history and reference points do appear to have a significant impact on investment decisions.

Another possible question is whether a form of "nominal illusion" may explain the behav-

for many behavior (e.g. aversion to small risks), but it does not appear to be the key driver of reaching for yield, if not partially offsetting it.

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

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

ior 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 average 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.[15] 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. We provide brief discussions in Sections 4 and 5 that reference points appear to be largely nominal in our data.

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 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 (4) 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:

$$\phi_s^* \triangleq \arg\max_{\phi\in[0,1]} \; \delta \mathbb{E} r_p - \frac{\gamma}{2} Var\left(r_p\right), \tag{4}$$

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 (4) embeds the idea that investors' perception of the risky asset's compensation

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

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 (4) 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.[16] We adopt a specification of δ following Bordalo et al. (2013a).

Assumption 3. *We require that the risk-free rate $r_f > 0$ throughout this subsection. Following Bordalo et al. (2013a), define*

$$\delta(r_f + \mathbb{E}x, r_f, Var\left(x\right), 0) = f\left(\left|\frac{(r_f + \mathbb{E}x) - r_f}{(r_f + \mathbb{E}x) + r_f}\right| - \left|\frac{Var\left(x\right) - 0}{Var\left(x\right) + 0}\right|\right), \tag{5}$$

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, Gennaioli, and Shleifer (2015a).[17] 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 risky asset has a

[16] In our context, Salience Theory and proportional thinking is broadly the same. In the Supplementary Appendix, 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 alternative models related to salience or proportional thinking such as Bordalo, Gennaioli, and Shleifer (2012), Bordalo, Gennaioli, and Shleifer (2013b), and Bushong et al. (2015).

[17] In the original set-up, either the risk dimension is more salient or the return dimension is more salient, and the more salient dimension receives a fixed weight. When there is a risk-free asset, the risk dimension is always more salient, by a fixed amount. Accordingly, returns of the risk-free asset 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 $f\left(t\right) = \begin{cases} \beta & t > 0 \\ \frac{1}{\beta} & t < 0 \end{cases}$, where $\beta > 1$. In addition, the decision problem in Bordalo et al. (2013a) and Bordalo et al. (2015a) is a discrete choice problem. We generalize it to settings where the decision is continuous, which applies to the portfolio choice problem here. See Supplementary Appendix for more discussions.

constant variance and the safe asset has zero variance).

Proposition 4. *Under Assumption 3, 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 4 is straightforward. Holding average excess returns $\mathbb{E}x$ constant, the proportion of average expected 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 with a larger set of parameter values in addition to our benchmark parameter values. Specifically, we keep the excess returns of the risky asset fixed, and vary the risk-free rate from -1% to up to 15%. The average excess returns is 5%, the same as in the benchmark experiment, and the distribution is also the same as in the benchmark experiment. For example, in the condition with the lowest interest rate, participants consider allocations 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 allocations 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 a pool of participants to one of these different conditions.

Through this experiment, we would like to examine two main questions. The first question is how allocations to the risky asset change along the gradient—whether allocations to the risky asset increase in a linear fashion or increase more sharply when interest rates fall below a certain range. Both reference dependence and proportional thinking/salience predict such non-linearity in portfolio allocations. In particular, in the reference dependence model specified in Section 3.2, whether allocations to the risky asset increase when interest rates fall depends crucially on whether the risk-free rate r_f is above or below the reference point r_r. In the model of proportional thinking/salience discussed in Section 3.3, the ratio of the average returns $(r_f + \mathbb{E}x)/r_f$ becomes less sensitive to r_f when r_f is high. 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 conventional Prospect Theory formulation discussed in Section 3.2 Proposition 3.

We conduct Experiment T1 in June 2016. Participants are recruited on MTurk. Similar to Experiment B2 (Benchmark Incentivized, MTurk), they consider allocating experimental endowment of 100,000 Francs to the risk-free asset and the risky asset. They receive participation payment of \$0.7, and 10% randomly chosen participants receive bonus payment proportional to their investment outcome, with every 8,950 Francs converted to one dollar (so the bonus payment is on the scale of \$12). Each condition has 200 participants (same as the benchmark experiments). Table A4 in the Supplementary 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 have not participated in our other experiments. In other words, we do not allow participants to participate more than once.[18]

Table 4 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. Mean allocation to the risky asset is 57% when the risk-free rate moves to 5%, which is about 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%.

In sum, results in Table 4 show that allocations to the risky asset increase steeply when the risk-free rate is below 3%, but are not as sensitive to interest rates when rates are relatively high. The cut-off at around 3% is interesting, especially since that average interest

[18]For incentivized experiments in this section, participants receive their bonus payment within a week after participation. While ideally we would like to have a one year investment horizon, this is logistically more challenging to implement on MTurk, given that some people may no longer be on MTurk in one year's time and it takes extra effort to deliver payment to them. In Section 2, we already tested that results are robust to the payment horizon. Therefore, for the additional experiments we run in this section, we pay the bonus shortly after the experiment to simplify the logistics.

rates in the US are about 3% in the past two to three decades, and 3% interest rates are roughly in line with what most people have been used to. The cut-off around 3% is also broadly 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 is not consistent 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 increases as interest rates decline) as interest rates get into the low range, we do not observe reaching against yield when the risk-free rate approaches the high end, as would be predicted by the baseline Prospect Theory formulation discussed in Section 3.2 Proposition 3. One possibility is this reaching against yield effect is modest in magnitude, and our sample size of 200 per condition does not have enough power to detect it (this effect could be further dampened by salience/proportional thinking). Another possibility is that the reaching against yield prediction is not very robust, and it depends on the specific functional form used to model reference dependence. For example, another way to formulate reference dependence is that people experience discomfort/loss aversion when the average return of the portfolio is below the reference point. (In contrast, in the baseline Prospect Theory formulation discussed in Section 3.2, investors suffer from loss aversion for each state where the realized return is below the reference point.) This alternative formulation of reference dependence predicts reaching for yield when interest rates are low, but does not predict reaching against yield when interest rates are high. We present this alternative formulation in the Supplementary Appendix.

4.2 Experiment T2 (History Dependence)

In Experiment T2, we examine how investment history and reference point 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%

[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 used in Assumption 3 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 return $\mathbb{E}x$ is 5%. But more generally, how to generalize models of salience/proportional thinking to negative quantities is still an open question in the literature.

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 ultra 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 Corollary 1 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 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 participation payment of \$1.2, and 10% randomly chosen participants receive 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 has been completed. Making payments according to outcomes from one randomly chosen round is standard in prior experimental work (e.g. Holt and Laury (2002); Mormann and Frydman (2016)). To check the robustness of this result, we also report results in 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 A5 in the Supplementary Appendix shows the demographics of participants in Experiment T2.

Table 5 presents results of Experiment T2 and shows several findings. First, there is evidence of reaching for yield both within group and across group. Within both Group 1 and Group 2, allocations to the risky asset is 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.[20]

The finding suggests potential path dependence of reaching for yield. Experiences of high interest rate environment, which likely increase people's reference point, may aggravate reaching for yield behavior. With some degree of extrapolation, the evidence hints at a novel implication that the degree of reaching for yield in a low interest rate setting may depend on previous economic environment: how much people shift into risky assets when interest rates are low may be different if they used to live in an environment of high interest rates, versus if they used to live in an environment of modest interest rates. This observation connects to prior work by Malmendier and Nagel (2011, 2016) that shows the importance of past experiences in economic decision making.

In this experiment, we do not find that experience of the low rate condition has 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, a decrease in 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. 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

[20]These findings are consistent across hypothetical and incentivized settings. The hypothetical results cannot be explained by increasing absolute risk aversion. The incentivized results are also hard to be explained by increasing absolute risk aversion, given that payments depend on one randomly chosen round and investment returns are displayed after both rounds are completed. For instance, when considering decisions in the second round, there is 1/2 chance that the first round will be chosen so the second round does not matter, and 1/2 chance that the second round will be chosen so the first round does not matter. Thus the decision in the second round does not depend on what happened 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.

is not very robust, and depends on the functional form of the traditional Prospect Theory specification. As discussed in Section 4.1, an alternative formulation of reference dependence features loss aversion when the average return of the portfolio is below the reference point. This formulation predicts reaching for yield when the interest rates are low, but not reaching against yield when interests are high, and experience of the low rate condition will not have a significant impact on investment decisions in the high rate condition.

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 are different 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 investment. 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 through examples. In the examples, we describe the probability that one will get a certain number of Francs if one invested 100 or 1000 Francs. The investment descriptions look 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.
>
> For another example, suppose you put 1,000 Francs into this investment, you will get 1,050 Francs.
>
> **Investment B**: Investment B has nine possible outcomes. Its average return is **10%**. The volatility of the investment return 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.
>
> For another example, suppose you put 1,000 Francs into this investment, you will get 1,100 Francs on average. There is uncertainty about the exact amount of money you will get. The second row of the chart below describes the nine possible outcomes: there is a 19% chance that you will get 1,200 Francs, there is a 12% chance that you will get 900 Francs, etc.

Gross Framing: In the gross framing conditions, instead of using the commonly used net returns, we describe the investments' payoffs as 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 invested 100 (1,000) Francs. The investment descriptions look as follows:

> **Investment A**: For every Franc you put into Investment A, you will get **1.05** Francs with certainty.
>
> For example, suppose you put 100 Francs into this investment, you will get 105 Francs.
>
> For another example, suppose you put 1,000 Francs into this investment, you will get 1,050 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 payoff is 18%. The chart below shows the nine possible outcomes, 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 the baseline and gross framing conditions tests the influence of salience and proportional thinking. In particular, a corollary of Proposition 4 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 more pronounced in the low interest rate condition (see Supplementary 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.[21] In

[21] To understand how 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 risky assets through examples, instead of describing them as getting certain Francs for every 100 (or 1000) Francs invested, we describe them as gaining or losing certain Francs. The investment descriptions look as follows:

> **Investment A**: Investment A's return is **5%** for sure.
>
> For example, suppose you put 100 Francs into this investment, you will earn 5 Francs.
>
> For another example, suppose you put 1,000 Francs into this investment, you will earn 50 Francs.

addition, the results can also help to further differentiate with conventional portfolio choice theory with increasing absolute risk aversion, in which case results should not be affected by framing.

In Experiment T3, we randomly assign a pool of participants into 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. Similar to Experiment B2 (Benchmark Incentivized, MTurk) and Experiment T1, they consider allocating experimental endowment of 100,000 Francs to the risk-free asset and the risky asset. They receive participation payment of $0.7, and 10% randomly chosen participants receive bonus payment proportional to investment outcomes, with every 8,950 Francs converted to one dollar (so the bonus payment is on the scale of $12). Table A6 in the Supplementary Appendix shows the demographics of participants in Experiment T3.

Table 6 presents results of Experiment T3. With baseline framing, mean allocations to the risky asset are 64.51% in the low interest rate condition, and 57.13% in the high interest rate conditions. With gross framing, mean allocations to the risky assets are 54.44% and 52.65% low and high 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.[22]

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 behavior. The

> **Investment B**: Investment B has nine possible outcomes. Its average return is **10%**. The volatility of the investment payoff is 18%. The chart below shows the nine possible outcomes, 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 earn 10 more 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 earn 20 Francs, there is a 12% chance that you will lose 10 Francs, etc. ...

We find reaching for yield behavior is similar with net framing and with baseline framing. Please see the Supplementary Appendix for results and detailed discussions.

[22]Results in Experiment T3 are inconsistent with conventional portfolio choice theory with increasing absolute risk aversion. One may wonder whether the results could be explained by reference dependence: 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 rate may appear particularly low relative to experience, but this comparison could be less instinctive when investment payoffs are described in gross returns. Accordingly, risk taking in the low interest rate condition would be more pronounced with baseline framing than with gross framing. This logic, however, cannot easily explain why allocations to the risky asset in the high interest rate condition are also noticeably higher with baseline framing than with gross framing.

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 very 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 point. 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 completely described in gross returns. In the experiments, we also ask participants to explain their investment decisions. Based on the explanations they give, it also seems 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 from three different sources, we document that low interest rates appear to be associated with higher shares of investors' personal portfolios allocated to risky assets, as well as increased flows into risky assets. The patterns and the magnitude are in line with findings in our experiment.

Before we proceed to describing the data and presenting the results, we would like to note the key challenges in testing our hypothesis using observational data. These issues factor into our data selection and empirical analysis, and while we work to address these issues, we hold results in this section as just suggestive. First, it is challenging to know people's perception of returns and risks associated with assets in capital markets. For example, Greenwood and Shleifer (2014) document that subjective expectations of future stock returns tend to be negatively correlated with expected returns based on rational expectations models. To address this challenge, we draw on proxies for both rational expected returns and subjective expectations to approximate a setting of roughly holding risk premium constant. Second, most of the variations in interest rates in observational data happen over time (and our inference largely relies on asymptomatics in the time dimension), so we need to measure investment decisions over an extended period of time and with sufficient frequency. This makes it hard to use data such as Survey of Consumer Finances which takes place infrequently, or data based on brokerage accounts (e.g. Barber and Odean (2001)) that tend to only cover a short period of time. Instead, relatively high frequency data that cover a long period of time are more desirable. The following section discusses the data we use to address these challenges to the extent possible.

5.1 Data Sources

Our first source is monthly data on portfolio allocations reported by members of the American Association of Individual Investors (AAII). We have time series data on the mean allocations to stocks (direct holdings and stock mutual funds), bonds (direct holdings and bond mutual funds), and "cash" (which in investor terminology generally refers to interest-bearing liquid assets, such as savings accounts, CDs, money market funds as explained in the AAII survey form). The series starts in November 1987 and we use data till the end of 2014. This data has several nice features. One is that its focus is portfolio allocations, which maps directly into quantities in our experiment. This helps us to assess the magnitude of allocations' response to interest rates in the experiment compared to that in the observational data. In addition, the data is at relatively high frequency and the time series is sufficiently long, which provides an adequate amount of variations in interest rates. Moreover, AAII's monthly member survey also asks about views of the stock market (bullish, neutral, bearish), which helps to gauge subjective perceptions of future stock market performance. Greenwood and Shleifer (2014) show that investor sentiment based on AAII data 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. We use the same sentiment measure using AAII data as in Greenwood and Shleifer (2014), which is % bullish - % bearish.

The second source is monthly data on flows into equity mutual funds and high yield corporate bond mutual funds obtained from the Investment Company Institute (ICI). We use data from January 1985 to December 2014. The third source is quarterly data of the household sector's flows into stocks (direct holdings and mutual funds) and deposits from the Flow of Funds. For comparability with data from the other two sources (and to minimize influences of major structural changes in financial investment, such as the rise of mutual funds), we use data from 1985Q1 to 2014Q4. Section A3 in the Supplementary Appendix provides a summary of data sources and variable definitions for observational data. Table 7 displays summary statistics of the main variables used in this section's analysis.

5.2 Results

In this section, we study the relationship between personal investment decisions and interest rates in the observational data. We start with simple OLS regressions to document the basic patterns. In the OLS setting, omitted variable problems will likely bias against us, since interest rates tend to be low in economic recessions, during which time investors are more risk averse, more pessimistic, and less willing to invest in risky assets. Nonetheless, we find that with simple controls of economic conditions (e.g. GDP growth) and objective and subjective expected excess returns (e.g. dividend yield and investor sentiment), the data suggest that portfolio shares of stocks and flows into risky assets increase (while portfolio shares of safe assets and flows into deposits fall) when interest rates decrease. We then use standard structural VAR (sVAR) to document the same patterns in response to innovations in interest rates, and we find persistent effect in the medium run.

A. Evidence from Portfolio Shares

Table 8 presents time series regressions of mean portfolio share in stocks (or in "cash") on short-term interest rates. We report results using both the Fed Funds Rate and the 3-month Treasury bill rate, which are very similar. Our main controls include proxies for subjective and objected expected returns of the stock market: AAII sentiment and the P/E ratio, as well as commonly used proxies for general economic conditions and business cycles: past year real GDP growth and the credit spread (Gilchrist and Zakrajšek, 2012). We lag all the right hand side variables by one quarter, as opposed to using contemporaneous ones, since allocation decisions may affect contemporaneous asset prices (so using contemporaneous controls could be problematic). The outcome variable is mean allocations to stocks in Panel A and mean allocations to "cash" in Panel B. The AAII survey 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), but we will examine high yield bonds later using high yield bond fund flow data.

Table 8 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 about 1.5 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 about eight percentage points change in mean allocations to the risky asset. Interestingly, the magnitude of allocations' response to interest rates seems to be similar in the experiment and in the observational data. We can also run regressions using changes in allocations on changes in interest rates, which are shown in Table A8 in the Supplementary Appendix, and results are similar.

In addition, Figure 2 presents the impulse response of allocations to innovations in interest rates from a standard sVAR. We use standard inputs in macro VARs (monthly inflation and industrial production), the Fed Funds Rate, P/E ratio and investor sentiment, and allocations. We order the macro variables as slowest moving (inflation, followed by industrial production), followed by mean allocations and sentiment in the month, then the P/E ratio which is measured at the end of the month. We order Fed Funds Rate last to be most conservative in our identification of interest rate innovations. Results are similar if we drop some variables or use alternative orderings. Figure 2 shows that higher rates are associated with persistent decreases in allocations to stocks and persistent increases in allocations to "cash", and vice versa.

As discussed in Sections 3 and 4, one question is whether risk taking behavior is mainly affected by nominal interest rates or by real interest rates. In the experiment, we find nominal interest rates play a more important role. Similarly, in the observational data, we also find results to be stronger with nominal interest rates. Table A9 shows results using real interest rates instead of nominal interest rates. We find qualitatively similar results using real returns but the coefficients are smaller in magnitude.

B. Evidence from Fund Flows

We perform similar analyses using data on household investment flows into various types of assets. Table 9 presents the results using monthly equity mutual fund flows (Panel A), monthly high yield corporate bond fund flows (Panel B), Flow of Funds quarterly household sector flows into stocks (Panel C) and into interest-bearing deposits (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 same as before, and all right hand side variables are lagged by one period. Figure 3 shows the impulse response plots for the corresponding variables. We see that across different data sources, decreases in interest rates are associated with flows into risky assets and out of safe interest-bearing assets.

One question about results using household investment flows is who takes the other side, and whether the flows reflect shifts in household demand or other changes in the market (e.g. shifts in security demand by other types of market participants or shifts in security supply). To shed light on this question, we examine investment flows of other sectors (domestic financial sector and rest of the world) and flows of security supply (i.e. net issuance by domestic financial and non-financial sectors, and rest of the world). We also study responses of asset prices to interest rate movements. We use data from Flow of Funds on net flows into equities by households and other sectors, which, by accounting identity, sum up to net equity issuance by the corporate sectors.

Table A10 in the Supplementary Appendix shows regression results of flows into equities by sector, along with issuance by sector. There is a modest increase in financial sector flows into equities in response to a fall in interest rates, but not statistically significant. Rest of the world accommodates part of the inflows, and their flows into equities decrease significantly in response to a fall in interest rates in the US. The main actor on the other side of the inflows appears to be corporations in the US, whose net equity issuance increases following a fall in interest rates. Figure A1 turns to the impulse response of *excess* stock returns following interest rate shocks. Lower interest rates are associated with higher excess stock returns in the first few months, followed by lower excess returns in the longer term, consistent with prior findings by Bernanke and Kuttner (2005). Taken together, these patterns 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). Rest of the world accommodates a portion of the inflows and reduces equity holdings in the US market. 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.

A caveat about results using observational data is they pick up investment responses to changes in interest rates *on average*. Reaching for yield behavior, on the other hand, appears particularly pronounced when interest rates are below certain levels, as evidence in Section 4 suggests. Accordingly, historical data on investment responses to interest rates may not fully reflect how people would behave in a low interest rate environment. For similar reasons, we do not place a heavy emphasis on empirical identification using monetary policy shocks. These shocks tend to be small in magnitude, and often come from minor policy changes such as the Fed moving earlier or later than market expectations. It is hard to extrapolate from these exercises whether risk taking behavior may change in a low interest rate environment, or to test the potential mechanisms we laid out in Section 3. In sum, we hold the findings in this section to be merely suggestive and complementary to our experimental evidence, yet we are intrigued that data across several different sources show consistent patterns.

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. We show, in a simple investment experiment, 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 large subject pools including workers on MTurk who are similar to the US general population as well as 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 also find evidence in observational data that risk taking by individual investors increase 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, there appears to be a deeply ingrained notion among many savers 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 increase risk taking in low interest environment could also aggravate reaching for yield by financial institutions, many of which cater to the preferences of their end investors (Gennaioli, Shleifer, and Vishny, 2015b; Harris, Hartzmark, and Solomon, 2015).

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.

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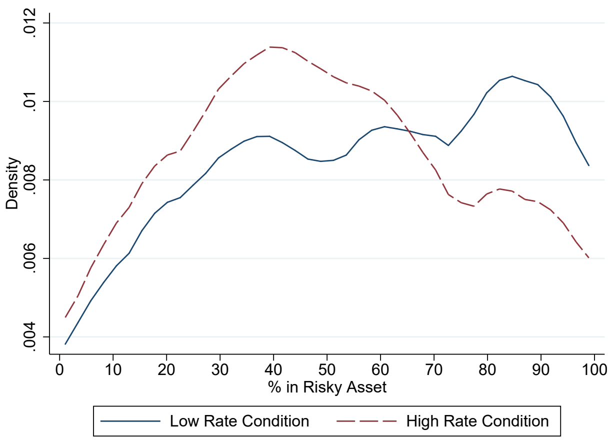
A Figures

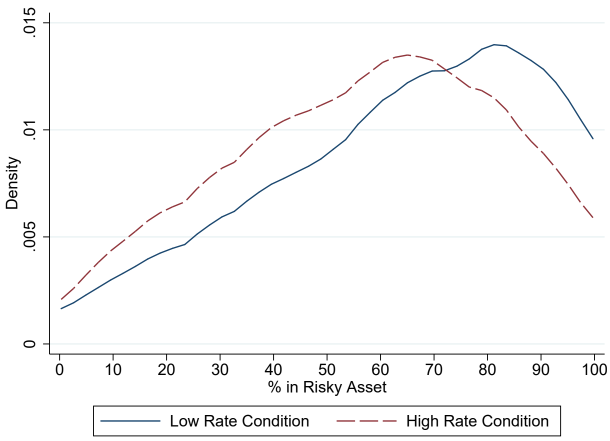
Figure 1: Distributions of Allocations to the Risky Asset in Benchmark Experiments

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

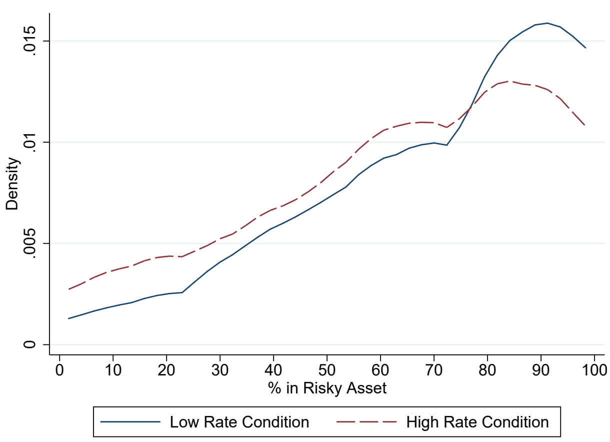
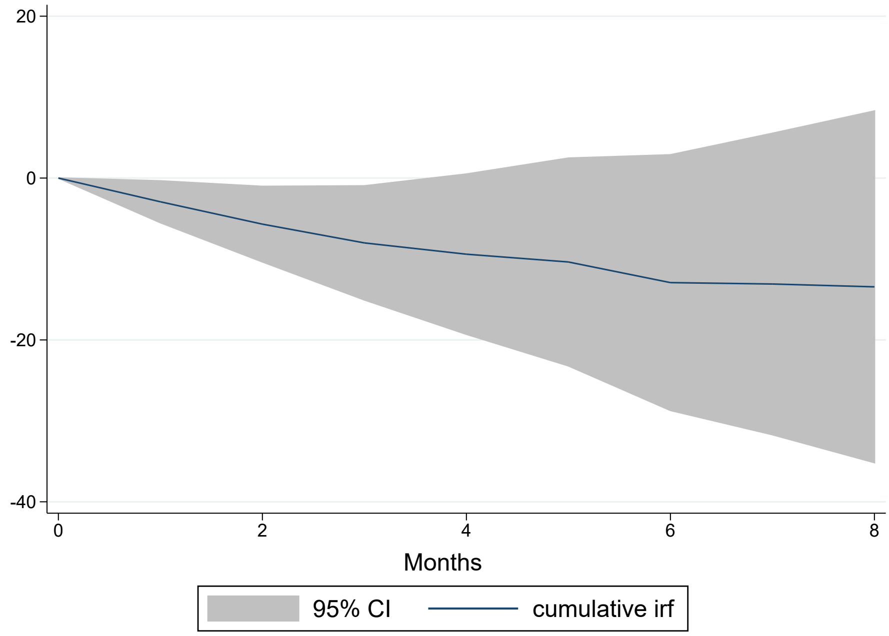


Figure 2: Interest Rates and AAII Portfolio Allocations: sVAR Impulse Responses

Impulse response plots of AAII member portfolio allocations to innovations in interest rates. Variables include (in VAR ordering sequence): inflation rate, industrial production growth, allocations (stocks in Panel A and "cash" in Panel B), AAII Sentiment (% Bullish - % Bearish), P/E10, and the Fed Funds Rate. Eight lags are used. Monthly from November 1987 to December 2014.

Panel A. Mean Allocations to Stocks



Panel B. Mean Allocations to "Cash"

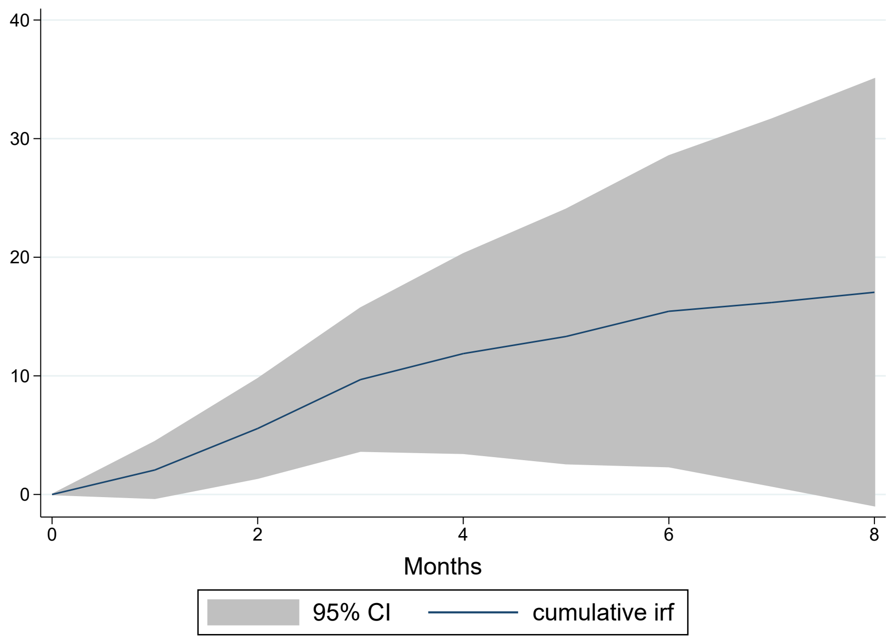
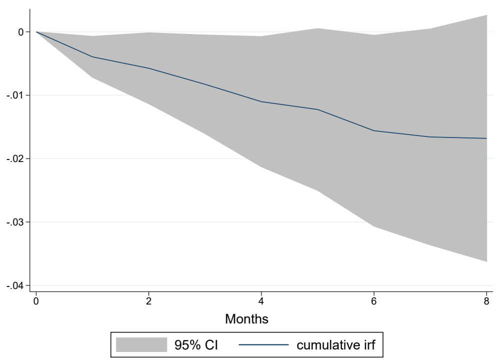
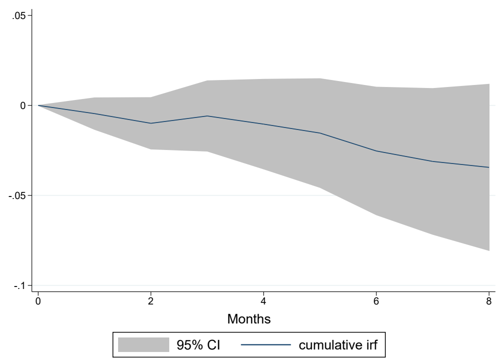


Figure 3: Interest Rates and Household Investment Flows: sVAR Impulse Responses

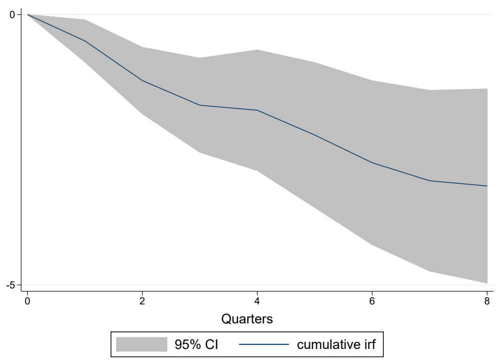
Impulse response plots of household investment flows to innovations in interest rates. Plot (a) shows monthly sVAR results of equity mutual fund flows (normalized by equity mutual fund net asset value) using data from the Investment Company Institute (ICI). Plot (b) shows monthly sVAR results of high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



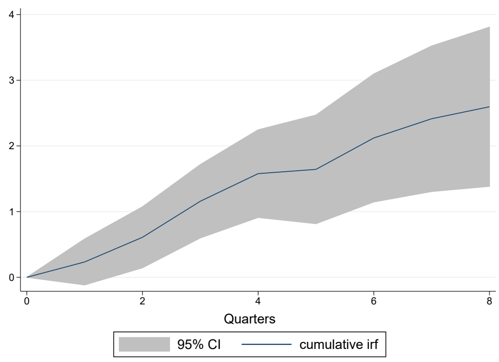
(a) Equity Mutual Fund Flows (ICI)



(b) High Yield Mutual Fund Flows (ICI)



(c) Household Flows into Stocks (FoF)



(d) Household Flows into Deposits (FoF)

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	40.00	102	52.31
	Female	123	60.00	93	47.69
Education	Graduate school	38	18.54	30	15.38
	College	112	54.63	118	60.51
	High school	53	25.85	45	23.08
Age	Below 25	59	28.78	51	26.15
	25–45	116	56.59	120	61.54
	45–65	29	14.15	24	12.31
	Above 65	1	0.49	0	0.00
Investing exper.	Extensive experience	7	3.41	6	3.08
	Some experience	61	29.76	60	30.77
	Limited experience	88	42.93	75	38.46
	No experience	49	23.90	54	27.69
Fin wealth (ex. hous)	In debt	23	11.22	28	14.36
	0–10K	59	28.78	51	26.15
	10K–50K	57	27.80	43	22.05
	50K–200K	56	27.32	56	28.72
	200K+	10	4.88	17	8.72
Total		205		195	

Panel B. Experiment B2: MTurk, Incentivized

		Low		High	
		N	%	N	%
Gender	Male	116	56.59	111	56.92
	Female	89	43.41	84	43.08
Education	Graduate school	30	14.63	33	16.92
	College	122	59.51	125	64.10
	High school	52	25.37	35	17.95
Age	Below 25	51	24.88	39	20.00
	25–45	123	60.00	127	65.13
	45–65	30	14.63	27	13.85
	Above 65	1	0.49	2	1.03
Investing exper.	Extensive experience	6	2.93	6	3.08
	Some experience	68	33.17	66	33.85
	Limited experience	83	40.49	75	38.46
	No experience	48	23.41	48	24.62
Fin. wealth (ex. hous)	In debt	31	15.12	25	12.82
	0–10K	42	20.49	35	17.95
	10K–50K	60	29.27	58	29.74
	50K–200K	47	22.93	55	28.21
	200K+	25	12.20	22	11.28
Total		205		195	

Panel C. Experiment B3: MBA, Incentivized

		Low		High	
		N	%	N	%
Gender	Male	117	58.21	129	64.82
	Female	84	41.79	70	35.18
Past 15 years of life	US	140	69.65	133	66.83
	Abroad	61	30.35	66	33.17
Primary educational field	Humanities	26	12.94	23	11.56
	Social Science	64	31.84	43	21.61
	Science and Engineering	80	39.80	95	47.74
	Other	31	15.42	38	19.10
Investment exper.	Extensive/professional	22	10.95	25	12.56
	Some experience	71	35.32	60	30.15
	Limited experience	70	34.83	69	34.67
	No experience	38	18.91	45	22.61
Worked in finance	Yes	84	41.79	86	43.22
	No	117	58.21	113	56.78
		201		199	

Table 3: 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 across 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 4: 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 forth row shows its 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 5: 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 a high interest rate environment (5% risk-free rate and 10% average risky returns), and then make decisions in a low interest rate environment (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 6: 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 across 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. Reaching for Yield Controlling for Individual Characteristics

	Coef.	*t*-stat
Baseline	7.18	2.72
Gross	2.40	0.89

Table 7: 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 American Association of Individual Investors (AAII); equity (high yield corporate bond) mutual fund flows, normalized by respective net asset value, using data from Investment Company Institute (ICI); household sector flows into stocks (both direct holdings and mutual fund holdings) and interest-bearing deposits (include time and saving deposits, money market mutual fund, and commercial paper), normalized by household sector financial wealth, using data from Flow of Funds; short-term interest rates; stock market sentiment (% Bullish - % Bearish) from AAII, P/E10, 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	326
% in "Cash" (AAII)	23.96	6.32	19.00	22.69	28.00	1987M12	2014M12	326
Mutual Fund Flow Data from ICI								
Equity Fund Flows/NAV (%)	0.39	0.77	-0.12	0.28	0.90	1985M1	2014M12	360
HY CB Fund Flows/NAV (%)	0.65	1.90	-0.58	0.75	1.77	1985M2	2014M12	360
Household Investment Flows Data from FoF								
Flows into Stocks/HH Fin. Ast. (%)	-0.19	0.82	-0.72	-0.22	0.27	1985Q1	2014Q4	120
Flows into Deposits/HH Fin. Ast. (%)	0.71	0.87	0.15	0.75	1.36	1985Q1	2014Q4	120
Interest Rates								
Fed Funds Rate	4.00	2.78	1.25	4.71	5.90	1985M1	2014M12	360
3M Treasury Rate	3.66	2.53	1.13	4.31	5.53	1985M1	2014M12	360
Controls								
Stock Market Sentiment (AAII)	8.57	15.30	-1.81	9.36	18.75	1987M8	2014M12	329
P/E10	23.44	7.54	18.31	22.41	26.46	1985M1	2014M12	360
Past 4Q GDP Growth	2.70	1.68	1.80	3.02	3.96	1985Q1	2014Q4	360
Credit Spread	2.31	0.74	1.73	2.17	2.75	1985M1	2014M12	360

Table 8: Interest Rates and AAII Portfolio Allocations

Monthly time series regressions:

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

where i is Fed Funds Rate in columns (1) and (2), and 3-month Treasury rate in columns (3) and (4); X includes AAII stock market sentiment, P/E10, 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.Fed Funds Rate	-0.3975	-1.3412		
	[-0.59]	[-4.74]		
L.3M Treasury Rate			-0.3784	-1.5289
			[-0.51]	[-4.87]
L.AAII Sentiment		0.0349		0.0377
		[1.55]		[1.69]
L.P/E10		0.8464		0.8457
		[9.21]		[9.27]
L.Past 12M GDP Growth		0.3293		0.3263
		[0.81]		[0.81]
L.Credit Spread		-3.9969		-4.2623
		[-5.00]		[-5.27]
Constant	61.6493	52.5138	61.4669	53.3631
	[19.49]	[15.14]	[19.30]	[15.25]
Observations	326	326	326	326
R-squared	0.017	0.783	0.013	0.785

Newey-West t statistics in brackets

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

	Mean Allocations to "Cash"			
	(1)	(2)	(3)	(4)
L.Fed Funds Rate	0.6126	1.4122		
	[1.32]	[4.14]		
L.3M Treasury Rate			0.6226	1.6041
			[1.21]	[4.21]
L.AAII Sentiment		-0.0219		-0.0249
		[-0.91]		[-1.05]
L.P/E10		-0.4768		-0.4764
		[-4.28]		[-4.28]
L.Past 12M GDP Growth		0.0109		0.0176
		[0.02]		[0.04]
L.Credit Spread		4.1623		4.4329
		[4.56]		[4.79]
Constant	21.7032	20.9797	21.8509	20.1231
	[10.04]	[5.02]	[9.99]	[4.75]
Observations	326	326	326	326
R-squared	0.068	0.608	0.059	0.612

Newey-West t statistics in brackets

Table 9: Interest Rates and Household Investment Flows

Time series regressions:

$$F_t = \alpha + \beta \Delta i_{t-1} + X'_{t-1}\gamma + \sum_{s=1}^{8} \eta_{t-s} F_{t-s} + \epsilon_t$$

where i is Fed Funds Rate in columns (1) and (2), and 3-month Treasury rate in columns (3) and (4). 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 8. 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 months excess returns of high yield corporate bonds, 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 8 (measured at the end of the previous quarter). In Panel D, F is quarterly household sector flows into interest-bearing deposits (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 8 (measured at the end of the previous quarter). All regressions include eight lags of the flow variable. Outcome variables are from the beginning of 1985 to the end of 2014, but AAII sentiment is only available starting in 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.Fed Funds Rate	-0.4231	-0.4611		
	[-3.16]	[-3.38]		
L.D.3M Treasury Rate			-0.4077	-0.3408
			[-2.93]	[-2.61]
Controls	No	Yes	No	Yes
Observations	360	328	360	328
R-squared	0.524	0.610	0.522	0.605
Panel B. High Yield Corporate Bond Mutual Fund Flows (ICI)				
L.D.Fed Funds Rate	-0.5448	-0.2922		
	[-1.41]	[-0.71]		
L.D.3M Treasury Rate			-0.9122	-0.7247
			[-2.30]	[-1.75]
Controls	No	Yes	No	Yes
Observations	360	360	360	360
R-squared	0.335	0.347	0.341	0.352
Panel C. Household Flows into Stocks (FoF)				
L.D.Fed Funds Rate	-0.1913	-0.3048		
	[-1.66]	[-2.08]		
L.D.3M Treasury Rate			-0.2938	-0.3953
			[-2.37]	[-2.70]
Controls	No	Yes	No	Yes
Observations	120	109	120	109
R-squared	0.327	0.431	0.342	0.444
Panel D. Household Flows into Deposits (FoF)				
L.D.Fed Funds Rate	0.3774	0.4759		
	[3.55]	[3.52]		
L.D.3M Treasury Rate			0.4391	0.3855
			[3.66]	[2.65]
Controls	No	Yes	No	Yes
Observations	120	109	120	109
R-squared	0.424	0.506	0.428	0.486

Newey-West t statistics in brackets