Low Interest Rates and Investor Behavior: A Behavioral Perspective*

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Abstract

We discuss the behavioral perspective on "reaching for yield" in financial markets, that is, investors have a greater appetite for risk taking when interest rates are low. We summarize evidence on the intrinsic individual-level reaching for yield motive, from randomized experiments and from observational data. The findings hold among diverse populations, and the effect becomes increasingly pronounced as interest rates decrease below historical norms. We then lay out mechanisms that help to understand such behavior, including reference dependence and salience. The behavioral perspective of reaching for yield points to one venue for the "risk-taking channel" of monetary policy, which highlights the importance of savers' preferences and psychology.

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1 Introduction

Since the global financial crisis, central banks in many countries have set benchmark interest rates to historic lows. A widely discussed question is whether such low interest rates increase investors' appetite for risk taking, a phenomenon often referred to as "reaching for yield." Increased risk taking may help stimulate the economy, and function as a new mechanism of monetary policy transmission. However, it may also pose challenges for financial stability, and call for caution and increased monitoring. Policy makers and investors have highlighted the importance of reaching for yield (Bernanke, 2013; Stein, 2013; Rajan, 2013; Fink, 2016; Powell, 2017). Researchers also posit the "risk-taking channel" of monetary policy (Borio and Zhu, 2012; Bruno and Shin, 2015; Brunnermeier and Schnabel, 2016).

What drives reaching for yield? In this paper, we summarize findings from the behavioral perspective, based on Lian, Ma, and Wang (2018) and other results from recent work. The evidence suggests that reaching for yield is significant when people invest for themselves (without institutional frictions), and can arise from investors' preferences and psychology. Such behavior holds across large and diverse populations, and points to new implications for understanding the impact of low interest rates.

In Section 2, we begin by presenting evidence of individual-level reaching for yield behavior. We show that, all else equal, individuals demonstrate a stronger preference for risky assets when the risk-free rate is low. We first use simple randomized experiments to isolate such behavior, which allow us to cleanly control for investment returns and risks and utilize random assignment. We then present additional evidence using observational data on household investment decisions. The analysis focuses on individuals and households to isolate inherent individual-level tendencies, without confounds from agency and institutional frictions. As we discuss later, the behavioral mechanisms may also affect investors in financial institutions.

In the baseline experiment, we present a simple investment problem with one safe asset and one risky asset, and randomly assign participants to one of two treatment conditions. 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 (again approximately normally distributed with 18% volatility). In other words, we hold fixed the

excess returns of the risky asset and only make a downward shift in the level of the risk-free rate. The investment decision in each condition represents the simplest mean-variance analysis problem, where the solution should not be affected by the risk-free rate based on the textbook mean-variance benchmark (Markowitz, 1952; Sharpe, 1964).

We find robust evidence that people in the low interest rate condition invest significantly more in the risky asset than people in the high interest rate condition. This finding holds among several thousand participants from the US general population (through Amazon's Mechanical Turk platform) as well as four hundred Harvard Business School MBA students, and across different settings (hypothetical questions as well as incentivized experiments).

Furthermore, when we extend the test to a wider range of interest rate conditions, from -1% to up to 15% (holding fixed the excess returns of the risky asset as before, and randomly assign participants to one of these conditions), we find that reaching for yield is particularly pronounced when interest rates are low relative to historical norms and dissipates when interest rates are sufficiently high. In a recent replication of the study, the Dutch Authority for the Financial Markets (AFM) find very similar results among 900 Dutch households tracked by the AFM consumer panel (Ma and Zijlstra, 2018).

Such behavior by individuals is not explained by institutional frictions. The patterns are also hard to square with standard portfolio choice theory, which does not naturally predict the treatment effect and its non-linearity (i.e. strong in the low interest region and weak when interest rates are very high).

In addition to randomized experiments, we also find consistent evidence from observational data. Using monthly portfolio allocations data reported by members of the American Association of Individual Investors (AAII), we find that allocations to stocks decrease with interest rates and allocations to safe interest-bearing assets increase with interest rates, controlling for proxies of returns and risks in the stock market and general economic conditions. The magnitude is close to results in the benchmark experiment. We also use data on flows into equity and high yield corporate bond mutual funds, and find higher inflows when interest rates fall. Using data on European households' investment in structured retail products, Célérier and Vallée (2017) show increased demand for structured investment products with high headline returns as interest rates decline.

In Section 3, we lay out two categories of mechanisms that can contribute to reaching for yield in individual investment decisions. We also present additional supportive evidence for these mechanisms.

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

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

Both history-dependent reference points and salience are consistent with the non-linearity in reaching for yield we observe (i.e. reaching for yield especially pronounced in the low interest rate region). Specifically, history-dependent reference points predict that investors would reach for yield if interest rates are lower than the reference level of returns formed over their previous experiences. Salience and proportional thinking predict more reaching for yield when interest rates are low, where the proportions of investment returns are more sensitive to changes in the interest rate.

In addition, in line with history-dependent reference points, we find that investment history has a significant impact on investment decisions. For instance, when participants first make investment decisions in the high interest rate condition and then make decisions in the low interest rate condition, they invest substantially more in the risky asset in the low rate condition. In line with salience, we find that risk taking decreases and reaching for yield is dampened if investment payoffs are presented using gross returns (e.g. instead of saying 6%, we say that one gets 1.06 units for every unit invested). In this case, the proportion of average returns shrinks (from 6/1 and 10/5, to 1.06/1.01 and 1.1/1.05), especially in the low interest rate condition; as the higher average returns of the risky asset become much less

salient, risk-taking in the low interest rate condition diminishes.

One question is whether the reaching for yield behavior is more sensitive to nominal interest rates or real interest rates. Are reference points based on nominal interest rates or real interest rates? Is salience focused on nominal interest rates or real interest rates? We find that nominal interest rates seem to matter more, both through additional experiments and in observational data. Indeed, in some countries with higher inflation, when inflation and nominal interest rates fall while real interest rates rise, savers express strong dissatisfaction with lower nominal interest rates (Rajan, 2017).

In Section 4, we discuss the importance of recognizing the behavioral perspective of reaching for yield and the inherent individual-level yield-seeking tendencies.

First, the individual-level tendencies are relevant to households, who are the end investors that allocate savings between safe and risky assets (Campbell, 2006; Frazzini and Lamont, 2008; Lou, 2012). Moreover, while a large volume of research studies how expansionary monetary policies affect borrowers (Di Maggio, Kermani, Keys, Piskorski, Ramcharan, Seru, and Yao, 2017; Auclert, 2016; Greenwald, 2018; Wong, 2018), there has been much less focus on savers. The perspective and findings we present suggest the relevance of saver behavior for understanding the impact of low interest rates. Savers' reaching for yield propensity also points to the need for supervision of financial products: investors may not fully understand the risks they are taking; in addition, security issuers may design products that highlight returns and shroud risks to further exploit customers' preferences (Célérier and Vallée, 2017).

Second, the individual-level tendencies can also affect financial institutions. End investors' preferences can shift investment decisions by institutions, which often cater to clients' tastes. The yield chasing flows could also intensify institutional and agency frictions (Feroli, Kashyap, Schoenholtz, and Shin, 2014). Furthermore, the preferences and psychology we document may affect professional investors as well. Reaching for yield is significant among financially well-educated individuals like HBS MBAs, and does not appear to diminish with wealth, investment experience, or work experience in finance.

Third, the increased demand for risky assets can push up asset prices, consistent with findings that low interest rates tend to be associated with compressed equity risk premium and asset price booms (Bernanke and Kuttner, 2005; Bianchi, Lettau, and Ludvigson, 2017; Brunnermeier and Schnabel, 2016).

Taken together, the behavioral perspective of reaching for yield offers one possible channel for the "risk-taking channel" of monetary policy. It may function as an additional transmis-

sion mechanism of monetary policy beyond the traditional framework.

The focus of our analysis is how interest rates affect investors' appetite for *risk taking*. Another related topic is how low interest rate environments affect investors' demand for financial securities with stable streams of payments (e.g. dividends), often referred to as "reaching for income." Recent research also offers empirical evidence and behavioral explanations for "reaching for income" (Hartzmark and Solomon, 2017; Daniel, Garlappi, and Xiao, 2018). This phenomenon also reflects unconventional behavior of savers in a low interest rate world, but may come from different mechanisms (e.g. confusion between dividend income and capital gains, commitment problems). Below we mainly discuss "reaching for yield," defined as low interest rates increasing investors' general propensity of risk taking, but recognize that there are a set of interesting questions to understand about how investors respond to interest rates.

2 Low Interest Rates and Investor Behavior

Since major central banks set interest rates to historic lows following the global financial crisis, the financial press has been filled with observations that low interest rates push investors into riskier assets. Such behavior is not confined to financial institutions, but also appears prevalent at the individual level. For example, a number of reports suggest that households display reaching for yield tendencies in their personal investment decisions.[1]

Analyzing individual-level reaching for yield behavior faces a number of challenges. First, it is challenging to find large exogenous variations in interest rates in observational data (Ramey, 2016). Second, it is also difficult to measure investors' beliefs about returns and risks of assets in capital markets (Greenwood and Shleifer, 2014), which further complicates the analysis.

To isolate the individual-level reaching for yield behavior in a clean and stark manner, we begin with simple randomized experiments in Section 2.1. We present people with the simplest investment question with one safe asset and one risky asset, and randomly assign them into different interest rate conditions. In all conditions, we always hold constant the excess returns of the risky asset. We find significantly higher allocations to the risky assets in the low interest rate conditions. These experiments have been conducted in different settings

[1] "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.

and among large and diverse populations, and yield remarkably consistent results.

We summarize complementary evidence from observational data in Section 2.2, drawing on a variety of data sources. Despite challenges and caveats, the findings seem to systematically point to reaching for yield behavior by households and end investors, which attest to the individual-level yield-seeking tendencies.

2.1 Simple Randomized Experiments

Below we present results of our benchmark experiments. The 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 interest rate condition has around 200 participants, and participants are randomly assigned to different interest rate conditions.

Baseline Experiment: Two Interest Rate Conditions

Design and Samples. The baseline experiment has two conditions. In the high interest rate condition, the safe asset offers 5% interest rates and the risky asset offers 10% average returns. In the low interest rate condition, the safe asset offers 1% interest rates and the risky asset offers 6% average 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 visualize the distribution; the volatility of the risky asset's returns is 18% (about the same as the volatility of the US stock market).

We perform this benchmark test in three main settings.

1. Experiment B1: MTurk, Hypothetical.

   The first setting is a hypothetical question with participants from across the US through Amazon's online Mechanical Turks (MTurk) platform.[2] Participants consider a question about investing total savings of $100,000 between the risk-free asset and the risky asset, and report their most preferred allocation. The investment horizon is one year. Participants receive a fixed participation payment of $1. Experiment B1 was conducted in June 2016.

[2]MTurk is a popular platform for surveys and experiments, which is increasingly used in economic research (Kuziemko, Norton, Saez, and Stantcheva, 2015; Ambuehl, Niederle, and Roth, 2015; D'Acunto, 2015; Cavallo, Cruces, and Perez-Truglia, 2017; DellaVigna and Pope, 2017a,b). It allows access to a diverse group of participants from across the US, completes large-scale enrollment in a short amount of time, and provides response quality similar to that of lab experiments (Casler, Bickel, and Hackett, 2013).

The geographic distribution of participants is very representative of the US general population, as shown in Figure A1 in Appendix A. The demographics are also generally similar to U.S. general population, slightly younger and better educated, as shown in Table A1 Panel A in Appendix A. Roughly half of the participants are male. About 75% of participants report they have college or graduate degrees. The majority of participants are between 20 to 40 years old. Their attitudes toward risk taking are relatively conservative.[3] The wealth distribution is largely in line with the US population. Most participants have some amount of investment experience; 56.5% own stocks, slightly higher than the stock ownership rate of 51.9% from the 2016 Survey of Consumer Finances.

2. Experiment B2: MTurk, Incentivized.

   The second setting is an incentivized experiment on MTurk, where we provide participants experimental endowment of 100,000 experimental currency (Francs) to invest,[4] and provide bonus payment proportional to their investment payoffs. The participation payment is \$0.7, and bonus payment is on the scale of \$12 (very high on MTurk). We follow prior investment experiments and implement the decision of 10% randomly selected participants, who will receive the bonus payment after the experiment.[5] Experiment B2 was conducted in February 2016.

   Table A1 Panel B in Appendix A shows the demographics of participants in Experiment B2, which are very similar to the demographics in Experiment B1.[6]

[3] At the end of the demographics section, we ask a question where participants report their favorite lottery among six options. The majority prefer safe lotteries with lower expected payoffs to risky lotteries with higher expected payoffs. We also ask participants' subjective evaluation of risk tolerance, and the majority select they are "somewhat risk averse but willing to hold some risky assets."

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

[5] Cohn, Engelmann, Fehr, and Maréchal (2015) review payment schemes with random implementation and argue "there is solid evidence showing that these schemes do not change behavior." From an ex ante perspective, participants should make their optimal decisions, in case they are chosen and their choices are implemented. We also verify that results are unchanged whether the bonus payment is provided to all participants or a random subset of participants.

[6] One limitation in incentivized experiments is that the stake size is modest given researchers' budget constraints. We make three observations in light of concerns about modest stake size. First, this issue does not affect the hypothetical experiment, and results on reaching for yield are robust across different settings. Second, to the extent that small stakes make participants more risk neutral and decrease variations in investment decisions, it works against us finding significant treatment effects. Third, prior research also finds that risk preferences with respect to small stakes are meaningful and consistent with participants' risk preferences in general. In Lian, Ma, and Wang (2018) we show that participants' risk tolerance in the incentivized experiments is significantly correlated with allocations of their household financial wealth.

3. Experiment B3: Harvard Business School (HBS) MBAs, Incentivized

   The third setting is a similar incentivized experiment with HBS MBAs. Participants are recruited via email from all enrolled HBS MBA students. They consider allocating an experimental endowment of 1,000,000 Francs to the safe asset and the risky asset. They receive a $12 dining hall lunch voucher in appreciation for their participation, and could earn a bonus payment proportional to their investment outcomes, on the scale of $210. Similar to Experiment B2, we implement the decision of 10% randomly selected participants and they receive the bonus payment. Experiment B3 was conducted in April 2016.

   Table A1 Panel C in Appendix A2 shows the demographics of this sample, which closely reflect the composition of MBA students at HBS. The vast majority, 80%, own stocks; a significant fraction, 40%, have worked in finance. The MBA participants generally have a higher level of risk tolerance than MTurk participants. More than 40% report having some or extensive investment experience.

More details and sample survey questionnaires are available in Lian, Ma, and Wang (2018). A sample experimental interface is available here: https://hbs.qualtrics.com/jfe/form/SV_agcXRndpmLz5VHL (test with HBS MBAs).

Results. Table 1 reports results of the benchmark experiments. In Panel A, the first four columns show mean allocations to the risky asset in the high and low interest rate conditions, the difference between the two conditions, and the t-stat that the difference is significantly different from zero. The final column shows p-values from non-parametric Mann-Whitney-Wilcoxon tests. We find that the mean allocation to the risky asset is about 7 to 9 percentage points higher in the low interest rate condition. Specifically, the mean allocation to the risky asset increases from 48.15% in the high rate condition to 55.32% in the low rate condition in Experiment B1 (difference is 7.17%), from 58.58% to 66.64% in Experiment B2 (difference is 8.06%), and from 66.79% to 75.61% in Experiment B3 (difference is 8.83%). It is natural that the general level of risk tolerance can vary across these experiments depending on the subject pool and the setting (e.g. HBS MBAs are more risk tolerant than MTurk participants; MTurk participants are more risk tolerant investing experimental endowments than investing a significant amount of savings), so the *level* of mean allocations is different in Experiments B1 to B3. However, these differences in risk tolerance do not seem to affect the pattern of reaching for yield (i.e. the treatment effect).

Panel B shows mean differences in allocations controlling for individual characteristics, through OLS regressions as well as propensity score matching (estimates of average treatment effects are reported). The covariates include gender, education, age, risk tolerance, wealth, investment experience in the MTurk samples; and gender, risk tolerance, investment experience, and work experience in finance in the HBS MBA sample. The treatment effect is very similar with controls. Figure A2 in Appendix A plots the distribution of allocations to the risky asset in the high and low interest rate conditions for Experiments B1 to B3. The distributions are fairly smooth, with an upward shift in allocations in the low rate condition relative to the high rate condition.

Table 1: Low Interest Rates and Risk Taking: Benchmark Experiment Results

This table presents results of the benchmark experiments. In Panel A, the first four columns show mean allocations to the risky asset in the high and low interest rate conditions, the difference in mean allocations between the two conditions, and the corresponding t-statistics. Column (5) shows p-values from the Mann–Whitney–Wilcoxon test, against the null that allocations in the high and low interest rate conditions are the same. In Panel B, columns (1) and (2) show the mean difference in allocations controlling for individual characteristics through OLS; columns (3) and (4) show the difference through propensity score matching (ATE). In the MTurk samples, covariates include dummies for gender, age group, education level, risk tolerance, investment experience, wealth level. In the HBS MBA sample, covariates include dummies for gender, risk aversion level, investment experience, and work experience in finance.

Panel A. Allocations to Risky Asset (%)

	High (1)	Low (2)	Dif (Raw) (3)	[t] (4)	U test (p) (5)
B1: MTurk, Hypo.	48.15	55.32	7.17	[2.52]	(0.02)
B2: MTurk, Incen.	58.58	66.64	8.06	[3.06]	(0.00)
B3: HBS MBA, Incen.	66.79	75.61	8.83	[3.13]	(0.00)

Panel B. Controlling for Individual Characteristics

	Dif (OLS) (1)	[t] (2)	Dif (Match) (3)	[t] (4)
B1: MTurk, Hypo.	7.69	[2.74]	7.27	[2.66]
B2: MTurk, Incen.	8.14	[3.23]	8.66	[2.81]
B3: HBS MBA, Incen.	8.76	[3.19]	8.91	[3.30]

The increase of mean allocations to the risky asset of around 8 percentage points is economically meaningful. It is a roughly 15% increase on the base of about 60% allocations to the risky asset. We also translate the differences in portfolio shares to equivalents in terms of changes in the effective risk premium. Specifically, we calculate, for a given coefficient of relative risk aversion γ, how much the risk premium (i.e. average excess returns) on the risky asset, μ, needs to change to induce this much shift in portfolio allocations, ϕ, in a conventional

mean-variance analysis problem if we apply the formula $\phi = \mu/\gamma\sigma^2$. For $\gamma = 3$,[7] for instance, the treatment effect is equivalent to μ changing by about 0.7 percentage points (on a base of about 5 percentage point risk premium).

Our results on reaching for yield are consistent in different settings and subject pools. We find that HBS MBAs and MTurks reach for yield by a similar degree. Nor do we find that reaching for yield declines with wealth, investment experience, or education among MTurks, or with investment and work experience in finance among MBAs. Among the HBS MBAs who have worked in finance (42% of the sample), for example, the difference in mean allocations to the risky asset between the high and low interest rate conditions is 10 percentage points (t-stat 2.47).

More Interest Rate Conditions

In addition to the two baseline interest rate conditions, we also perform tests with a wider range of interest rate conditions, with the risk-free rate ranging from -1% to up to 15%. The excess returns on the risky asset are the same as before (mean excess returns is 5%, and volatility is 18%). Participants are randomly assigned to one of these conditions.

Samples. We present results of this test from two samples.

1. MTurk, Incentivized

   The first sample is 1,400 participants from MTurk, randomly assigned to conditions with -1%, 0%, 1%, 3%, 5%, 10% and 15% interest rates. As in Experiment B2, participants invest experimental endowment of 100,000 Francs, and the payment structure also follows Experiment B2. The experiment was conducted in June 2016. The demographics are similar to those in Experiment B1 and Experiment B2.

2. Dutch Households, Hypothetical

   The second sample is 900 Dutch households from a panel by the Dutch Authority for the Financial Markets (AFM). The AFM conducted a replication study using the hypothetical survey in Lian, Ma, and Wang (2018), translated into Dutch. Participants are randomly assigned into conditions with interest rates with -1%, 0%, 1%, 3%, 5%, 10% and 15% interest rates. Respondents did not receive financial payments, but do have high response rates (>50%). The experiment was conducted by the AFM in August 2017. The demographics in the AFM panel tilts toward the elderly, and 58%

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

are 60 years old or above. Participants are predominantly male. They are well-educated and financially well-off, and most have some investment experiences (see Lian, Ma, and Wang (2018) and Ma and Zijlstra (2018) for more details).

Results. Figure 1 shows results in the US (Panel A) and the Netherlands (Panel B). The results point to notable non-linearity in how investment decisions respond to interest rates (statistical tests can reject linearity with high significance). Reaching for yield is particularly pronounced when interest rates are low, roughly below 3%. The patterns are very consistent across settings.

2.2 Observational Data

The experiments provide a simple and stark illustration of individual-level reaching for yield tendencies. We also observe indications of such behavior based on observational data on households' portfolio allocations and investment flows, which we summarize below.

Household Allocations to Risky Assets. We begin with monthly portfolio shares reported by members of the American Association of Individual Investors (AAII). We have time series data on the mean allocation to stocks (direct holdings and mutual funds) and "cash" (which in investor terminology refers to interest-bearing liquid assets, such as savings accounts, CDs, money market funds as explained in the AAII survey form), available since November 1987.

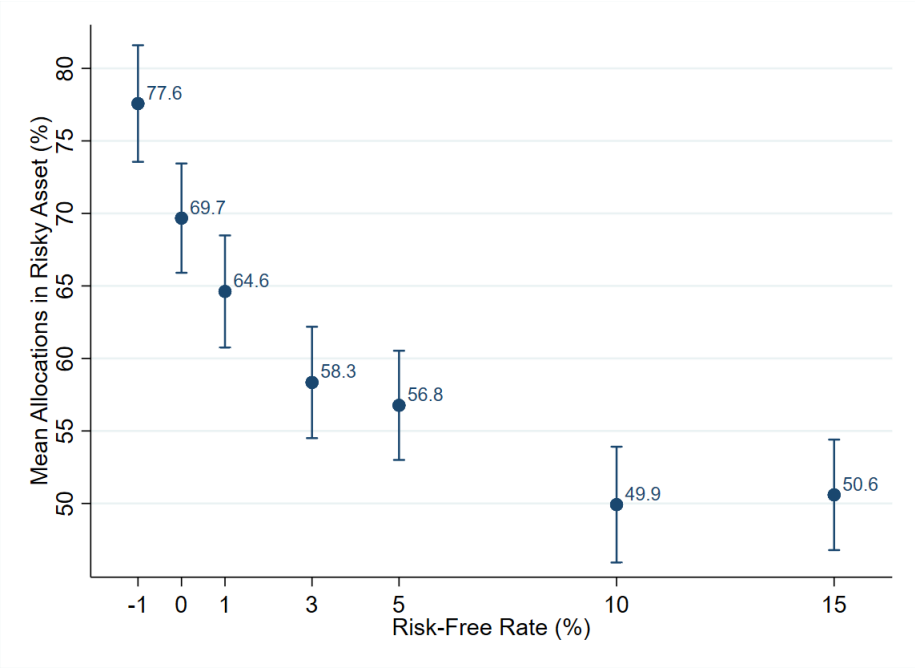
We use the three-month Treasury rate for the risk-free rate. For control variables, we use several model-based measures of expected stock returns, including the Campbell-Shiller price-earnings ratio (P/E10), the surplus consumption ratio ($Surp$) of Campbell and Cochrane (1999), as well as predicted next twelve-month excess stock returns (estimated using past twelve-month stock returns and surplus consumption).[8] In addition, we control for proxies of subjective expectations using investor sentiment measured in the AAII survey, as in Greenwood and Shleifer (2014). Finally, we control for VIX^2 (the square of VIX, which measures expected variance of the S&P 500 index), and commonly used proxies for general economic conditions: past year real GDP growth, and the credit spread (Gilchrist and Zakrajšek, 2012). We lag all the right hand side variables by one period, as opposed to using

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

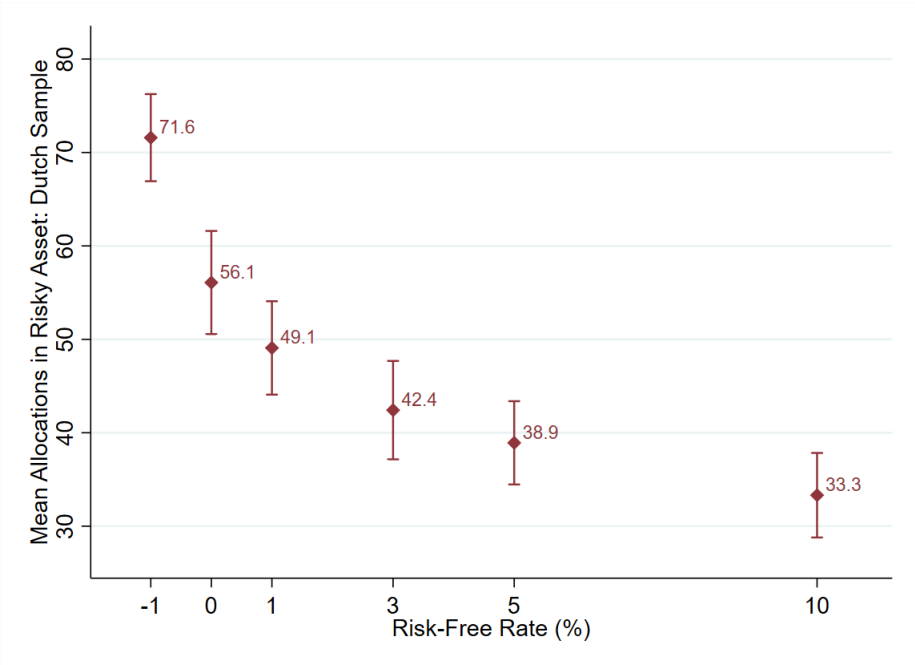
Figure 1: Mean Allocations Across Interest Rate Conditions

Mean allocations to the risky asset across various interest rate conditions. Panel A shows results in the US (MTurk, Incentivized). Panel B shows results in the Netherlands (Dutch households from AFM panel, hypothetical). The x-axis shows the risk-free rate in each condition. The mean excess returns on the risky asset is 5% in all conditions. The y-axis is the mean allocation to the risky asset. The vertical bar shows the 95% confidence interval for the mean allocation.

Panel A. MTurk, Incentivized



Panel B. Dutch Households, Hypothetical



contemporaneous ones, since allocation decisions may affect contemporaneous asset prices (so using contemporaneous controls could be problematic).

Table 2 presents results using portfolio allocations data from AAII. We find that lower interest rates are associated with higher allocations to stocks and lower allocations to "cash." A one percentage point decrease in interest rates is associated with a roughly 1.4 to 2 percentage points increase in allocations to stocks and a similar size fall in allocations to "cash." In our benchmark experiments, the treatment is a 4 percentage points difference in the level of interest rates, which is associated with a roughly 8 percentage points change in the mean allocation to the risky asset. The magnitude of investment allocations' response to interest rates appears similar in the experiment and in the observational data. Results are also similar in regressions using changes in allocations and changes in interest rates.[9]

We also use standard structural VAR to study the impulse response of investment allocations to innovations in interest rates, as shown in Appendix A Figure A3. Results are similar and the impulse response suggests persistent impact in the medium run.

Household Investment Flows. Similar results hold using data on household investment flows. We study monthly flows into risky assets including equity mutual funds and high-yield corporate bond mutual funds since 1985, from the Investment Company Institute (ICI). We also study quarterly household sector flows into stocks and interest-bearing safe assets since 1985, from the Flow of Funds (FoF). Appendix A Table A3 and Figure A4 show that decreases in interest rates are consistently associated with flows into risky assets and out of safe interest-bearing assets.[10]

Choi and Kronlund (2017) study risk-taking by corporate bond mutual fund, and find that funds which reach for yield during periods of low interest rates attract more inflows (although their returns tend to be negative on a risk-adjusted basis). The results also point to reaching for yield tendencies of end investors, which may influence financial institutions' investment decisions as well as they cater to clients.

Household Investment in Structured Financial Products. Finally, in Europe and Asia, households have access to structured financial products. Célérier and Vallée (2017)

[9]In the past two decades, stock market participation rate declined secularly while interest rates fell. The falling stock market participation rate can be driven by a number of demographic factors (e.g. inequality, income and unemployment conditions), and appears most pronounced among young households based on the SCF data. However, both investment by stock market participants and aggregate stock market participation in dollar terms do not seem to secularly decline.

[10]One question is who takes the other side of these household flows. Using data from the Flow of Funds, Lian, Ma, and Wang (2018) find that the flows are accommodate by foreign investors and corporate issuers.

Table 2: Interest Rates and AAII Portfolio Allocations

Monthly time series regressions:

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

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

Panel A. Interest Rates and Mean Allocations to Stocks

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

Newey-West t-statistics in brackets

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

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

Newey-West t-statistics in brackets

show structured products highlight high headline returns in periods of low interest rates, and increase complexity to shroud risks. Similarly, during Japan's period of low interest rates since early 2000s, complex retail structured products such as the power reverse dual currency (PRDC) notes were created to cater to end investors' yield seeking behavior (Rule, Garratt, and Rummel, 2004). These developments in investment products also suggest end investors have strong reaching for yield tendencies.

3 Mechanisms

What drives the individual-level reaching for yield behavior? In Lian, Ma, and Wang (2018), we discuss in detail that the evidence is not easily explained based on conventional portfolio choice theories (under traditional expected utility framework). In particular, in the simple randomized experiments, we hold constant the excess returns of the risky asset across different conditions, and only make parallel shifts in the risk-free rate. Conventional portfolio choice theories do not naturally predict significant changes in investment allocations, and are even harder to square with the substantial non-linearity we observe in Figure 1.

In the following, we lay out two categories of mechanisms that can be important for understanding individual-level reaching for yield tendencies, and present additional findings in support of each mechanism. We finally discuss the relevance of nominal interest rates vs. real interest rates for reaching for yield behavior.

3.1 Reference Dependence

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

One way to specify reference dependence is through a framework of loss aversion around the reference point, as formulated in the Prospect Theory (Kahneman and Tversky, 1979). Specifically, we assume the utility function u features loss aversion captured by a kink around the reference point:

Assumption 1.

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

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

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

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

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

Proposition 1 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. In other words, we observe reaching for yield behavior. The intuition is that when interest rates are below the reference point and drop further, investing in the safe asset will make the investor bear the entire increase in the first-order loss (i.e. utility loss from loss aversion). The risky asset, however, provides some chance to avoid the increase in the first-order loss. As a result, the lower the interest rates, the higher the incentive to invest in the risky asset.

On the other hand, when the risk-free rate r_f is above the reference point r_r, the optimal allocation to the risky asset ϕ^* is (weakly) increasing in r_f. In other words, the investor would "reach against yield." The intuition is that when the risk-free rate is above the reference point, investing in the safe asset can avoid the first-order loss with certainty. If interest rates fall but stay above the reference point, the safe asset still does not generate any first-order loss, but there is a higher chance that the risky investment gets into the region with the first-order loss. This prediction, however, depends on the functional form in the traditional Kahneman and Tversky (1979) framework (where the investor evaluates gain/loss state by state). Lian, Ma, and Wang (2018) show that with alternative specifications of reference dependence (e.g. reference points about average returns), the investors displays reaching for yield behavior when interest rates are low, but allocations do not change with interest rates (i.e. no "reaching against yield") when interest rates are sufficiently high.

Proposition 1 focuses on how investment decisions change with the risk-free rate r_f, fixing the reference point r_r. The mirror image is how decisions change with the reference point r_r, for a given level of interest rate r_f.

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

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

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

Corollary 1 shows that if the risk-free rate r_f is below the reference point r_r, the higher the reference point, the higher the allocation to the risky asset. The intuition is the same as that of Proposition 1.

A natural question is where investors' reference points come from. In the setting of low interest rates, an important form of reference points highlights the impact of past experiences. Specifically, people form reference investment returns that they have become accustomed to. When the risk-free rate drops below what they are used to, people experience discomfort and become more willing to invest in risky assets. This falls in the first case of Proposition 1, which predicts reaching for yield. Given the economic environment in the decades prior to the Great Recession, reference points from past experiences appear in line with investors' view that 1% or 0% interest rates are "too low." Such history-dependent reference points could be psychological; the same formulation could also capture saving or investment targets that people aim for to cover certain expenses, which are commonly formed based on past experiences as well.

The observation of history-dependent reference points connects to a growing number of studies that point to the importance of personal history and experiences in economic decisions (Malmendier and Nagel, 2011; Simonsohn and Loewenstein, 2006; Bordalo et al., 2017; DellaVigna et al., 2017). The literature since Kahneman and Tversky (1979) has also studied several other forms of reference points, such as status quo wealth level ($r_r = 0$), the risk-free rate (Barberis, Huang, and Santos, 2001), and rational expectations of outcomes in choice set (Kőszegi and Rabin, 2006; Pagel, 2017). While these formulations have applications in a variety of settings, they do not appear to be the main forces behind the reaching for yield behavior documented in Section 2, as explained in Lian, Ma, and Wang (2018).

Together with Corollary 1, history-dependent reference points suggest a novel implication: the degree of reaching for yield may depend on prior economic conditions. If the world has always had zero percent interest rates, reactions to 0% or 1% interest rates could be different. Indeed, in 19th century Britain, an observation attributed to the famed journalist and editor of *The Economist* Walter Bagehot is that "John Bull can stand many things but he cannot stand two per cent," which captures savers' dissatisfaction with low interest rates. At the time, the Bank of England routinely keeps benchmark interest rate around 5% and 2% was the minimum level very occasionally reached. Today, 2% interest rate would be considered fairly reasonable. Through this perspective, what constitutes "low interest rates" is *relative*

and history-dependent.

Evidence. History-dependent reference points are consistent with the non-linearity we observe in Figure 1. As discussed above, this mechanism predicts that reaching for yield would be pronounced when the risk-free rate is below people's reference points, but not when the risk-free rate is sufficiently high. In Figure 1, for conditions where interest rates are very high relative to what most participants are used to, reaching for yield indeed dissipates; in conditions where interest rates are very low relative to experience over the past few decades, reaching for yield is highly significant.

Furthermore, we design additional experiments to examine how investment history and reference dependence affect investment decisions. Specifically, participants in this experiment make two rounds of investment decisions: half of the participants (Group 1) first make decisions in the high interest rate condition (5% safe returns and 10% average risky returns, same as the benchmark experiment), and then make decisions in the low interest rate condition (1% safe returns and 6% average risky returns); the other half of the participants (Group 2) do the reverse. Group 1 mimics the situation where people move from a high interest rate environment to a low interest rate environment, which is a particularly relevant case for the recent discussions about investor reactions to low interest rates. After being placed in the high interest rate condition, participants in Group 1 are likely to carry a relatively high reference point when they move to the low interest rate condition. Accordingly, participants in Group 1 may invest more aggressively in the risky asset in the low interest rate condition.

We conduct both hypothetical and incentivized versions of this experiment, with participants on MTurk. Table 3 presents the results, which show several findings. First, there is reaching for yield both within group and across groups. Within each of Group 1 and Group 2, allocations to the risky asset are higher in the low rate condition than in the high rate condition. Across Group 1 and Group 2, when making the first decision, the group facing the low rate condition (Group 2) has significantly higher allocations to the risky asset. This is analogous to the benchmark experiments.

Second and importantly, participants in Group 1—who consider the high rate condition first—have particularly high allocations to the risky asset in the low rate condition. On average, they invest roughly 10 percentage points more in the low rate condition than participants in Group 2. These results are in line with predictions in Corollary 1 and history-dependent reference points. Similar results are also found in alternative tests of history dependence, as shown in Appendix A Table A4.

Table 3: Path Dependence of Investment Decisions

In this experiment, half of the participants are randomly assigned to Group 1, and they first make investment decisions in the high interest rate condition (5% risk-free rate and 10% average risky returns), and then make decisions in the low interest rate condition (1% risk-free rate and 6% average risky returns). The other half of the participants are assigned to Group 2, and they first make investment decisions in the low rate condition, and then make decisions in the high rate condition. Mean allocations to the risky asset (%) are presented.

G1	High: 5—10	Low: 1—6
Mean Alloc. to Risky	49.23	**66.12**
G2	Low: 1—6	High: 5—10
Mean Alloc. to Risky	55.64	46.98
G1 (Low) - G2 (Low)	Difference	$[t]$
	10.48	[3.40]

(a) Hypothetical

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

(b) Incentivized

History-dependent reference points could be affected by both short-term and long-term experiences.[11] The experiment studies the mechanism by exploiting differences in short-term experiences. We also test whether heterogeneity in long-term lifetime experiences may affect reference points and investment decisions, using data from the Survey of Consumer Finances and the empirical strategy of Malmendier and Nagel (2011).[12] In Appendix A Table A5, we present suggestive evidence that, at each point in time, individuals who experienced higher interest rates over their lifetime appear less satisfied with safe assets and exhibit a higher propensity to invest in risky assets like stocks. While there are several caveats in the observational data (e.g. hard to fully control for potential differences in perceived risks and returns of risky assets), the overall pattern seems consistent with predictions of history-dependent reference points.

3.2 Salience and Proportional Thinking

Theory. The second category of mechanisms captures the observation 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. For instance, when interest rates are 1%, 6% average returns on a risky asset may look quite attractive; when interest rates are

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

[12] In our experiments, due to relative homogeneity in age, variations in lifetime experiences are limited (the interquartile difference is average experienced interest rates, for example, is about 1%). Moreover, given we only have one cross-section, we cannot separate experience effects from age effects.

5%, 10% average returns on a risky asset may not stand out as much. Taken to an extreme, if interest rates are 80% and a risky asset offers 85% average returns, the additional payoffs may look trivial. Similarly, investors tend to think of 25 basis points of extra returns as meaningful when interest rates are 1%, but much less so when interest rates are 5%.

This intuition can be formalized by a version of the Salience Theory of Bordalo, Gennaioli, and Shleifer (2013). It also connects to the well documented phenomenon that people tend to evaluate stimuli by proportions (i.e. 6/1 is much larger than 10/5) rather than by differences (Weber's law; Tversky and Kahneman (1981); Kőszegi and Szeidl (2013); Cunningham (2013); Bushong, Rabin, and Schwartzstein (2016)). Equation (2) outlines a representation of this idea, which uses a variant of the mean-variance analysis. The investor still trades off expected returns and risks. The relative weight between these two dimensions, however, is affected by the ratio of the assets' average returns:

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

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 (2) embeds the idea that investors' perception of the risky asset's compensation for risk is not exactly the *difference* between the average returns on the risky asset and the risk-free rate (as in the conventional mean-variance analysis). Instead, it is also affected by the *proportion* of the average returns of the two assets. When the proportion is large, investors perceive compensation for risk taking to be better, and behave as if the return dimension in Equation (2) gets a higher weight.

We adopt a specification of δ following Bordalo, Gennaioli, and Shleifer (2013):

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

$$\delta(r_f + \mathbb{E}x, r_f, Var\left(x\right), 0) = f\left(\left|\frac{(r_f + \mathbb{E}x) - r_f}{(r_f + \mathbb{E}x) + r_f}\right| - \left|\frac{Var\left(x\right) - 0}{Var\left(x\right) + 0}\right|\right), \tag{3}$$

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

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

The intuition of Proposition 2 is straightforward. Holding average excess returns $\mathbb{E}x$

constant, the proportion of the average returns $(r_f + \mathbb{E}x)/r_f$ increases as r_f decreases. Accordingly, δ is larger and the investor is more willing to invest in the risky asset.[13]

Evidence. Salience and proportional thinking are also generally consistent with the non-linearity we observe in Figure 1. In the low interest region, the proportions of average returns are more sensitive to changes in the interest rate, which would be associated with larger changes in allocations across conditions.

We also design an additional experiment to examine the influence of salience and proportional thinking. In particular, we study whether results vary when we present investment payoffs using net returns (Baseline Framing) versus gross returns (Gross Framing), as explained below.

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

> **Investment A**: Investment A's return is **5%** for sure.
>
> For example, suppose you put 100 Francs into this investment, you will get 105 Francs.
>
> **Investment B**: Investment B has nine possible outcomes. Its average return is **10%**. The volatility of the investment returns is 18%. The nine possible outcomes are shown by the chart below, where the number inside each bar indicates the probability of that particular outcome.
>
> For example, suppose you put 100 Francs into this investment, you will get 110 Francs on average. There is uncertainty about the exact amount of money you will get. The first row of the chart below describes the nine possible outcomes: there is a 19% chance that you will get 120 Francs, there is a 12% chance that you will get 90 Francs, etc.

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

> **Investment A**: For every Franc you put into Investment A, you will get **1.05** Francs for sure.
>
> For example, suppose you put 100 Francs into this investment, you will get 105 Francs.
>
> **Investment B**: Investment B has nine possible outcomes. For every Franc you put into Investment B, you will get **1.1** Francs on average. The volatility of the investment returns is 18%. The nine possible outcomes are shown by the chart below, where the number inside each bar indicates the probability of that particular outcome.

[13] While intuitively it may seem that negative interest rates are quite "salient," existing models do not provide a clear way to deal with negative quantities. The salience function in Assumption 2 can work with r_f that is modestly negative, as long as $(r_f + \mathbb{E}x) + r_f > 0$.

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

The comparison between baseline framing and gross framing tests the influence of salience and proportional thinking. A corollary of Proposition 2 is that for any given interest rate, allocations to the risky asset would be higher with baseline framing than with gross framing, and this difference would be more pronounced in the low interest rate condition. Intuitively, the ratio of average returns between the risky asset and the risk-free asset with gross framing (e.g. 1.06/1.01) is much smaller than its counterpart with baseline framing (e.g. 6/1). This change is larger for the low rate condition (i.e. 6/1 to 1.06/1.01) than for the high rate condition (i.e. 10/5 to 1.1/1.05). Correspondingly, salience and proportional thinking could lead to less reaching for yield with gross framing than with baseline framing, as the proportions of average returns become very similar across the two conditions with gross framing.

Table 4: Baseline and Gross Framing

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

Panel A. Mean Allocations to Risky Asset (%)

	High: 5—10	Low: 1—6	Difference	[t]	U test (p-val)
Baseline	56.77	64.62	7.85	[2.85]	(0.00)
Gross	52.70	54.59	1.89	[0.69]	(0.45)
Baseline - Gross	4.06	10.03	5.96	-	-
[t]	[1.46]	[3.70]	[1.54]	-	-
U test (p-val)	(0.17)	(0.00)	-	-	-

Panel B. Differences Controlling for Individual Characteristics

	Dif (OLS)	[t]	Dif (ATE)	[t]
Baseline: Low − High	7.17	[2.75]	6.41	[2.30]
Gross: Low − High	1.83	[0.68]	0.92	[0.29]
High: Baseline − Gross	4.61	[1.75]	6.34	[1.94]
Low: Baseline − Gross	10.04	[3.79]	9.68	[3.40]

In this experiment, we randomly assign 800 MTurk participants to different framing conditions and different return conditions (i.e. baseline high, baseline low, gross high, gross

low), with 200 participants in each condition.

Table 4 presents the results. Allocations to the risky asset are lower with gross framing than with baseline framing, especially in the low rate condition. The mean allocation in the risky asset decreases by 4.06% from baseline framing to gross framing in the high interest rate condition, and by 10.03% in the low interest rate condition. This result is consistent with predictions of salience and proportional thinking. Correspondingly, reaching for yield is dampened with gross framing.

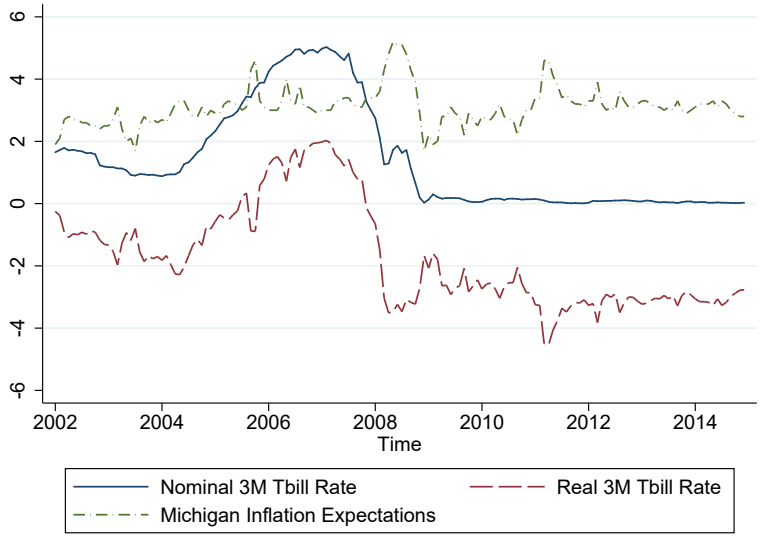
The impact of salience and proportional thinking may also be inferred from the advertisement of investment products. As examples from Célérier and Vallée (2017) show, investment products are commonly advertised as offering 6% returns (or yield), for example, rather than invest $1 get $1.06.

3.3 Nominal vs. Real Interest Rates

An additional question is whether reaching for yield is triggered by low nominal interest rates, or low real interest rates, or both play a role?

Figure 2: Nominal and Real Interest Rates in the US

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



In recent years in the US, inflation and inflation expectations have stayed relatively stable, and both nominal and real interest rates declined as shown in Figure 2. Similarly, in our benchmark experiments in Section 2.1, we study how investment allocations change with

respect to interest rates, holding constant inflation.[14] Participants in all treatment conditions face the same inflation environment; different treatment conditions lead to differences in both nominal and real returns.

One may be interested in separating the role of low nominal interest rates vs. low real interest rates. In the two mechanisms we discussed above, this question relates to whether reference points are more about nominal returns or real returns, and whether investors apply salience and proportional thinking to nominal returns or real returns.

Below we investigate this question through additional experiments, observational data, and some anecdotes. The results suggest that nominal interest rates are important for driving the reaching for yield behavior; real interest rates may have some additional impact, but appears weaker in comparison. The combined impact of low nominal interest rates and low real interest rates is strongest.

Some Evidence. We first design an additional experiment to test the impact of changes in nominal vs. real interest rates. We perform a hypothetical experiment with three conditions. 600 participants from MTurk are randomly assigned to one of these conditions.

1. High nominal interest rates + High real interest rates:
    - Nominal returns: 5% on the safe asset, 10% average on the risky asset.
    - Real returns: 5% on safe asset, 10% average on risky asset.
    - Expected inflation: 0%.
2. High nominal interest rates + Low real interest rates:
    - Nominal returns: 5% on the safe asset, 10% average on the risky asset.
    - Real returns: 1% on safe asset, 6% average on risky asset.
    - Expected inflation: 4%.
3. Low nominal interest rates + Low real interest rates:
    - Nominal returns: 1% on the safe asset, 6% average on the risky asset.
    - Real returns: 1% on safe asset, 6% average on risky asset.
    - Expected inflation: 0%.

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

In other words, between condition 1 and condition 2, we hold fixed nominal returns and change real returns. If real returns are important for reaching for yield, we would expect significantly different behavior across these two conditions. Between condition 2 and condition 3, we hold fixed real returns and change nominal returns. If nominal returns are important for reaching for yield, we would expect significantly different behavior across these two conditions.

To make sure participants clearly understand concepts related to inflation, we provide detailed explanation at the beginning of the investment problem. For 4% inflation, we write "Suppose also that expected inflation in the next year is 4%. In other words, goods that cost $100 today (e.g. cloths, furniture, etc) will cost $104 on average in the next year." In addition, in the demographic section after the investment decision, we ask three standard questions to test participants' understanding of inflation, as shown in Appendix B. The tests show that most participants have a reasonably good understanding of inflation. 64% participants provided correct answers to all three questions, and another 84% participants gave correct answers to at least two questions.

By displaying information about expected inflation in a prominent part of the question, this design could make participants think more about inflation than they otherwise would in daily economic decisions. Thus the experiment could overestimate the impact of real returns. When we ask "How often do you typically think about inflation for your economic and financial decisions (e.g. consumption, financial investments, retirement savings)?" 8% chose "a lot," 35% chose "somewhat," 41% chose "a little," 16% chose "never."

Table 5 shows the difference in mean allocations to the risky asset among the three conditions above. The comparison between condition 1 and condition 2 (C2-C1) shows the impact of lowering real interest rates (holding nominal fixed); the comparison between condition 2 and condition 3 (C3-C2) shows the impact of lowering nominal interest rates (holding real fixed); the comparison between condition 1 and condition 3 (C3-C1) shows the impact of lowering both nominal and real interest rates. The results show that lowering real returns has some positive impact, but not statistically significant given our sample size. Lowering nominal returns has a larger and statistically significant impact. The combined impact of lowering both nominal and real returns (analogous to the recent situation in the US as discussed above) has the largest and most significant impact.

We also test the impact of nominal vs. real interest rates in observational data. In Table 6, we run the same regressions as in Section 2.2 Table 2, but replace nominal interest rate with

Table 5: Nominal Returns vs. Real Returns

Columns (1) and (2) show the raw difference in mean allocations across conditions, and the associated t-statistic. Column (3) shows the p-values from the Mann–Whitney–Wilcoxon test, against the null that allocations across the conditions are the same. Columns (4) and (5) show the mean difference in allocations controlling for individual characteristics through OLS; columns (6) and (7) show the difference through propensity score matching (ATE). Matching covariates include dummies for gender, age group, education level, risk tolerance, investment experience, wealth level.

	Dif (Raw) (1)	[t] (2)	U (3)	Dif (OLS) (4)	[t] (5)	Dif (Match) (6)	[t] (7)
C2-C1 (change real, fix nominal)	3.64	[1.26]	(0.17)	2.72	[0.97]	4.67	[1.62]
C3-C2 (change nominal, fix real)	5.80	[2.01]	(0.04)	5.43	[1.93]	6.26	[1.97]
C3-C1 (change nominal & real)	9.44	[3.12]	(0.00)	8.11	[2.75]	8.18	[2.55]

real interest rate. The results are much weaker in both magnitude and statistical significance.

Finally, anecdotally low nominal interest rates also seem to weigh on savers more prominently. For example, Rajan (2017) documents that as nominal interest rates in India declined thanks to lower inflation, many savers felt upset, even though real interest rates increased. As we show above, even for individuals with reasonably good understanding of inflation, they may not pay much attention to inflation in everyday economic decisions and may anchor more on nominal returns. In many other situations, such as those discussed by Rajan (2017), individuals may not have a good understanding of real returns to begin with, which would further increase the relative importance of nominal returns.

4 Implications

Finally, we discuss implications of the behavioral perspective on reaching for yield for understanding the impact of low interest rates, from the viewpoint of savers, financial institutions, and capital markets. We highlight that savers' preferences and psychology, through their direct impact on investment decisions and through their additional influence on institutions, can be an important source for the "risk-taking channel" of monetary policy.

4.1 Savers in a Low Interest Rate World

The extraordinary monetary policy actions since the Great Recession has stimulated a vibrant stream of research in recent years. Most studies analyze how these policies affect borrowers (Di Maggio et al., 2017; Auclert, 2016; Greenwald, 2018; Wong, 2018; Beraja, Fuster, Hurst, and Vavra, 2017). There has been less focus on savers. The findings we present suggest there is also much to be understood about savers' behavior.

Table 6: Real Interest Rates and AAII Portfolio Allocations

Monthly time series regressions:

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

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

Panel A. Interest Rates and Mean Allocations to Stocks

	Mean Allocations to Stocks			
	(1)	(2)	(3)	(4)
L.r^{real}_f	0.42	-0.65	0.04	-0.19
	[0.49]	[-1.76]	[0.05]	[-0.27]
L.P/E10		0.91		
		[7.71]		
L.$Surp$			-10.47	
			[-0.60]	
L.$E[rx^1_{stk}2]$				0.07
				[0.38]
L.AAII Sentiment		0.06	0.22	0.2245
		[2.27]	[4.50]	[4.40]
L.VIX^2		-21.56	-38.09	-42.89
		[-2.32]	[-2.47]	[-2.54]
L.Past 12M GDP Growth		-0.26	1.70	1.5739
		[-0.57]	[2.00]	[1.91]
L.Credit Spread		-1.60	1.23	1.47
		[-1.60]	[0.64]	[0.76]
Constant	59.93	43.29	54.13	52.75
	[29.76]	[11.52]	[9.67]	[9.28]
Observations	326	326	326	326

Newey-West t-statistics in brackets

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

	Mean Allocations to "Cash"			
	(1)	(2)	(3)	(4)
L.r^{real}_f	0.06	0.65	-0.18	0.56
	[0.10]	[1.61]	[-0.39]	[0.90]
L.P/E10		-0.54		
		[-4.02]		
L.$Surp$			32.12	
			[2.83]	
L.$E[rx^1_{stk}2]$				-0.30
				[-1.97]
L.AAII Sentiment		-0.05	-0.16	-0.1690
		[-1.69]	[-4.78]	[-3.66]
L.VIX^2		25.51	27.14	43.81
		[2.60]	[2.59]	[2.75]
L.Past 12M GDP Growth		0.62	-1.07	-0.78
		[1.24]	[-1.91]	[-1.02]
L.Credit Spread		1.48	0.22	-0.61
		[1.38]	[0.18]	[-0.34]
Constant	23.92	30.90	22.83	27.99
	[16.67]	[7.29]	[6.18]	[5.41]
Observations	326	326	326	326

Newey-West t-statistics in brackets

Indeed, many savers appear to have a deeply ingrained notion that saving is the preservation of wealth, and wealth should grow at a "decent" rate. Savers also have a tendency to be influenced by the salience of investment returns, and perceive and evaluate returns proportionally. Such mindset could lead to saver behavior that is at odds with predictions of canonical models. As we show, savers may reach for yield and demonstrate a stronger propensity of risky taking in their financial investments in a low interest environment. Saving targets savers (such as retirees) aim to achieve may also prompt them to cut back on consumption in order to achieve their savings target (Powell, 2017; Gross, 2015).

In addition, savers' yield-seeking behavior draws attention to monitoring investment products and to consumer protection. If savers do not have a clear notion of the risks they take, they may suffer losses beyond their regular capacity to bear. Financial engineering of investment products may also exploit savers' reaching for yield tendencies and their desire for alternative investments with high returns in low interest rate environments. Célérier and Vallée (2017) show that retail structured products in Europe become increasingly complex to masks risks and highlight high headline returns, during periods of low interest rates. Accordingly, it would be important for financial regulators to require adequate information and disclosure about the risks investment products entail.

4.2 Impact on Financial Institutions

The individual-level behavioral mechanisms for reaching for yield may also affect financial institutions in several ways.

First, they may directly affect decision-makers in financial institutions. Results in Section 2.1 suggest that the intrinsic reaching for yield motive is significant among financially well-educated individuals like HBS MBA students, including those who have worked in the finance industry. Anecdotally, the key mechanisms we study—reference dependence, and salience and proportional thinking—also appear common among finance professionals.

Second, as shown in Section 2.2, end investors' yield-seeking behavior drives flows into financial institutions. Institutions may also need to adjust their investment decisions to cater to clients' taste and attract flows (Di Maggio and Kacperczyk, 2017; Choi and Kronlund, 2017). Moreover, the return and yield chasing flows may aggravate agency frictions and relative performance frictions such as those studied in Feroli et al. (2014).

Third, end investors' reference points may also play a role in financial institutions promising fixed returns to clients. As interest rates fall, the stickiness of reference points and

promises may push institutions to take more risks in order to meet their promises.

Finally, financial institutions may engineer investment products to cater to investors' yield as mentioned above; to the extent institutions have residual exposures to the risks associated with these products, they may suffer losses in adverse scenarios, as illustrated by the subprime crisis (Acharya, Schnabl, and Suarez, 2013; Duffie, 2018).

4.3 Asset Prices and Capital Markets

As low interest rates increase investors' demand for risky assets, they can drive up asset prices and drive down expected excess returns going forward. This mechanisms is consistent with findings that low interest rates tend to be associated with low conditional equity risk premium (Bernanke and Kuttner, 2005; Bianchi, Lettau, and Ludvigson, 2017; Lian, Ma, and Wang, 2018), which are not explained by changes in economic fundamentals . Recent research also suggests that low interest rates in the US lead to increased inflows to emerging market assets and affect their risk premia (Miranda-Agrippino and Rey, 2018).

Taken together, reaching for yield behavior by US savers may have ramifications in capital markets domestically and internationally, through end investors' investment allocation decisions and through impact on financial institutions as discussed above. This perspective suggests one possible venue for the "risk-taking channel" of monetary policy, which ties to the preferences and psychology of savers.

5 Summary

We present the behavioral perspective on low interest rates and risk taking in financial markets, which points to intrinsic individual-level reaching for yield motives driven by investors' preferences and psychology. We summarize evidence from a variety of sources, including simple randomized experiments among diverse populations, asset allocations by individual investors, and household flows into several risky asset classes. We apply two main behavioral mechanisms, reference dependence and salience, to explain such behavior. These mechanisms are central to individuals' decision making in many domains, and we show they are important for understanding the key problem of investors' response to interest rates.

The behavioral mechanisms also offer additional implications that can be relevant to policy. For instance, history-dependent reference points suggest the potential path dependence of reaching for yield—what is "low" interest rate is relative to investors' past experiences.

As low interest rates persist going forward, investors may gradually adjust to such an environment (e.g. reference points may decrease), although the path of adjustment could be hard to test. Salience and proportional thinking suggest the relevance of framing for investors' evaluation of investment returns. If regulators perceive the necessity to mitigate reaching for yield in certain market segments, e.g. retail financial products, the form of investment descriptions and framing could have an impact.

Overall, the behavioral mechanism indicates the role of savers in understanding the "risk-taking channel" of monetary policy. Besides monetary policy, low interest rates can arise from a confluence of factors, such as low productivity growth (Gordon, 2015), weak aggregate demand (Summers, 2015), or shortage of assets (Caballero, Farhi, and Gourinchas, 2008). These forces that drive down interest rates may also interact with investors' intrinsic reaching for yield motives.

There are naturally concerns that investors' reaching for yield behavior and the ensuing asset price booms may pose challenges to financial stability. The upshot of asset price booms is hard to foresee in each episode, but recognizing the intrinsic individual-level yield seeking tendencies may suggest possible vulnerabilities to attend to, such as end investors and retirees. It may also suggest ex ante prudential analyses and measures in these directions (Ma and Zijlstra, 2018).

References

Acharya, Viral V, Philipp Schnabl, and Gustavo Suarez, 2013, Securitization without risk transfer, *Journal of Financial Economics* 107, 515–536.

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

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

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

Beraja, Martin, Andreas Fuster, Erik Hurst, and Joseph Vavra, 2017, Regional heterogeneity and monetary policy, Working paper.

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

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

Bianchi, Francesco, Martin Lettau, and Sydney C Ludvigson, 2017, Monetary policy and asset valuation, Working paper.

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

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

Borio, Claudio, and Haibin Zhu, 2012, Capital regulation, risk-taking and monetary policy: A missing link in the transmission mechanism?, *Journal of Financial Stability* 8, 236–251.

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

Brunnermeier, Markus, and Isabel Schnabel, 2016, Bubbles and central banks: Historical perspectives, in *Central Banks at a Crossroads–What Can We Learn from History?*, 493–562 (Cambridge University).

Bruno, Valentina, and Hyun Song Shin, 2015, Capital flows and the risk-taking channel of monetary policy, *Journal of Monetary Economics* 71, 119–132.

Bushong, Benjamin, Matthew Rabin, and Joshua Schwartzstein, 2016, A model of relative thinking, Working paper.

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

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

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

Campbell, John Y, 2006, Household finance, *Journal of Finance* 61, 1553–1604.

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

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

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

Cavallo, Alberto, Guillermo Cruces, and Ricardo Perez-Truglia, 2017, Inflation expectations, learning, and supermarket prices: Evidence from survey experiments, *American Economic Journal: Macroeconomics* 9, 1–35.

Célérier, Claire, and Boris Vallée, 2017, Catering to investors through security design: Headline rate and complexity, *Quarterly Journal of Economics* 132, 1469–1508.

Choi, Jaewon, and Mathias Kronlund, 2017, Reaching for yield in corporate bond mutual funds, *Review of Financial Studies* 31, 1930–1965.

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

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

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

Daniel, Kent, Lorenzo Garlappi, and Kairong Xiao, 2018, Monetary policy and reaching for income, Working paper.

DellaVigna, Stefano, Attila Lindner, Balázs Reizer, and Johannes F Schmieder, 2017, Reference-dependent job search: Evidence from Hungary, *Quarterly Journal of Economics* 132, 1969–2018.

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

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

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

Di Maggio, Marco, Amir Kermani, Benjamin Keys, Tomasz Piskorski, Rodney Ramcharan, Amit Seru, and Vincent Yao, 2017, Monetary policy pass-through: Mortgage rates, household consumption and voluntary deleveraging, *American Economic Review* 107, 3550–3588.

Duffie, Darrell, 2018, Prone to fail: The pre-crisis financial system, Working paper.

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

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

Frazzini, Andrea, and Owen A Lamont, 2008, Dumb money: Mutual fund flows and the cross-section of stock returns, *Journal of Financial Economics* 88, 299–322.

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

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

Greenwald, Daniel L, 2018, The mortgage credit channel of macroeconomic transmission, Working paper.

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

Gross, Bill, 2015, Saved by zero?, Janus Capital investment outlook.

Hartzmark, Samuel M, and David H Solomon, 2017, The dividend disconnect, Working paper.

Kahneman, Daniel, and Dale T Miller, 1986, Norm theory: Comparing reality to its alternatives, *Psychological Review* 93, 136–153.

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

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

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

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

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

Lian, Chen, Yueran Ma, and Carmen Wang, 2018, Low interest rates and risk taking: Evidence from individual investment decisions, *Review of Financial Studies* forthcoming.

Lou, Dong, 2012, A flow-based explanation for return predictability, *Review of Financial Studies* 25, 3457–3489.

Ma, Yueran, and Wilte Zijlstra, 2018, A new take on low interest rates and risk taking VOX column.

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

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

Miranda-Agrippino, Silvia, and Hélene Rey, 2018, US monetary policy and the global financial cycle, Working paper.

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

Pagel, Michaela, 2017, Expectations-based reference-dependent life-cycle consumption, *Review of Economic Studies* 84, 885–934.

Powell, Jerome, 2017, Low interest rates and the financial system, Speech at the 77th Annual Meeting of the American Finance Association.

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

Rajan, Raghuram G, 2017, *I Do What I Do*.

Ramey, Valerie A, 2016, Macroeconomic shocks and their propagation, *Handbook of Macroeconomics* 2, 71–162.

Rule, David, Adrian Garratt, and Ole Rummel, 2004, Structured note markets: Products, participants and links to wholesale derivatives markets, *Financial Stability Review* .

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

Simonsohn, Uri, and George Loewenstein, 2006, Mistake# 37: The effect of previously encountered prices on current housing demand, *Economic Journal* 116, 175–199.

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

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

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

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

Wong, Arlene, 2018, Population aging and the transmission of monetary policy to consumption, Working paper.

A Additional Figures and Tables

Figure A1: Geographic Distribution of MTurk Participants

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

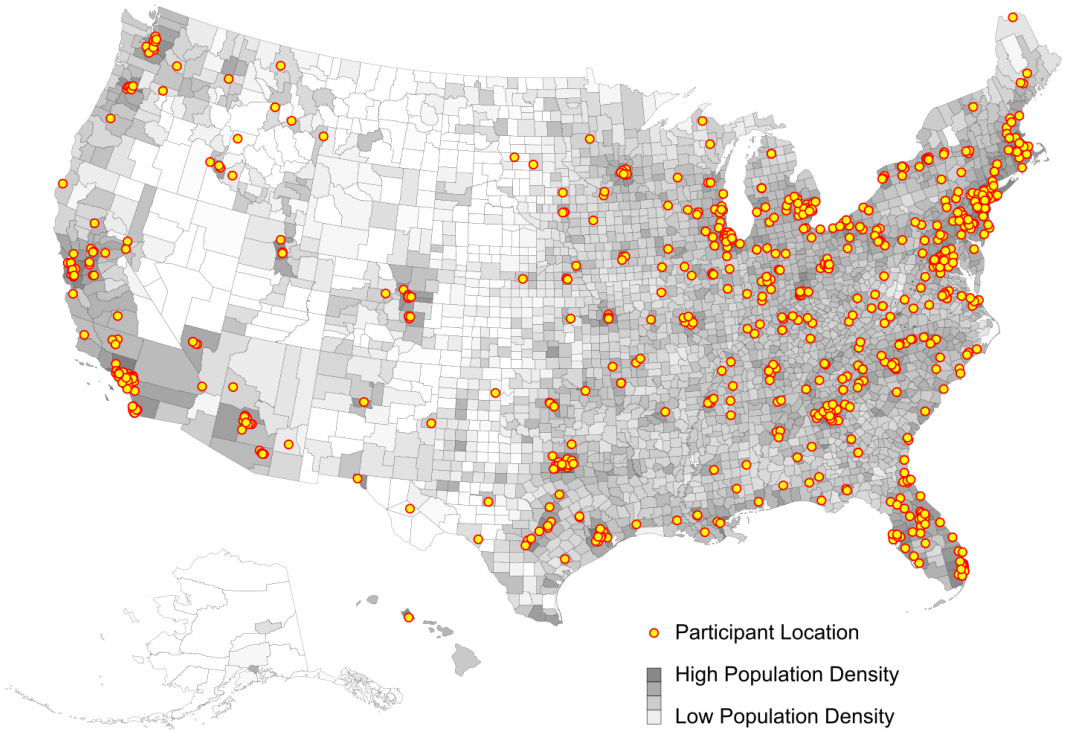
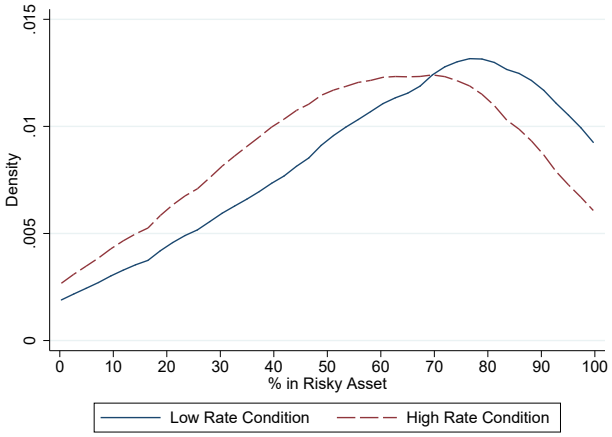


Figure A2: Distribution of Allocations to the Risky Asset in Benchmark Experiments

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

Panel A. Experiment B1: MTurk, Hypothetical

Panel B. Experiment B2: MTurk, Incentivized



Panel C. Experiment B3: HBS MBA, Incentivized

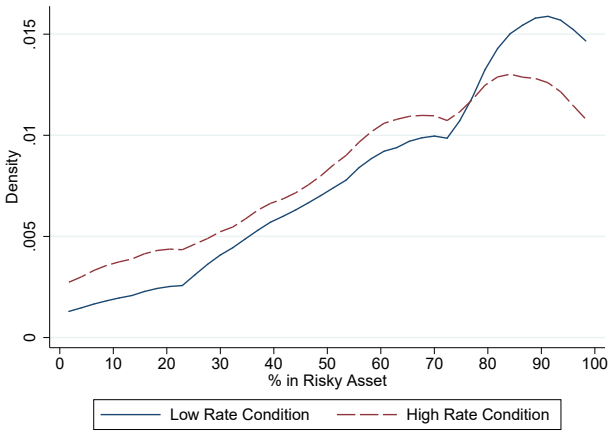
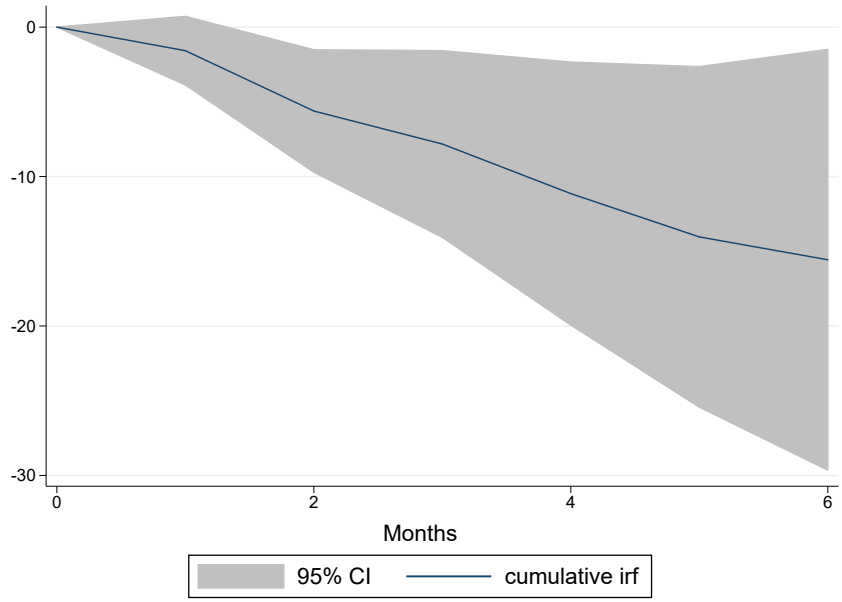


Figure A3: Interest Rates and AAII Portfolio Allocations: sVAR Impulse Response

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

Panel A. Mean Allocations to Stocks



Panel B. Mean Allocations to "Cash"

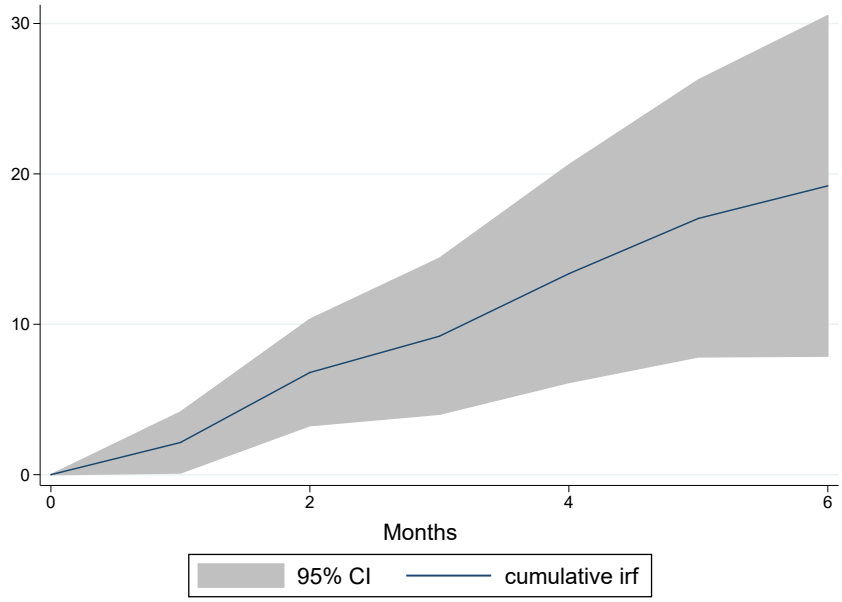
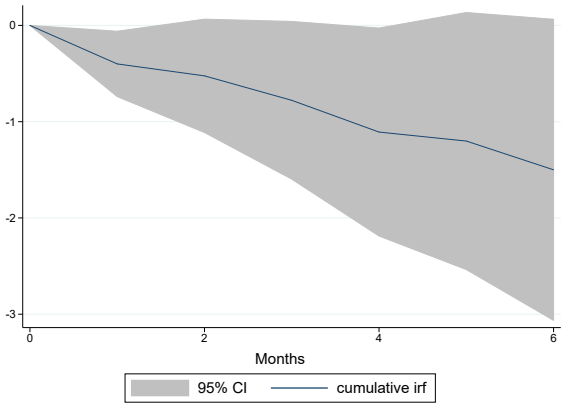
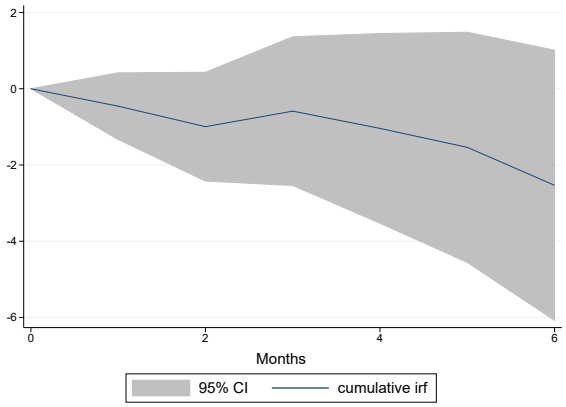


Figure A4: Interest Rates and Household Investment Flows: sVAR Impulse Response

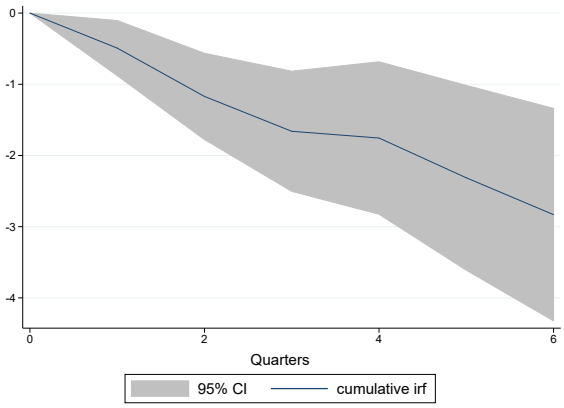
Impulse response plots of household investment flows to innovations in interest rates. Plot (a) shows monthly sVAR results of equity mutual fund flows (normalized by equity mutual fund net asset value) using data from the Investment Company Institute (ICI). Plot (b) shows monthly sVAR results of high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



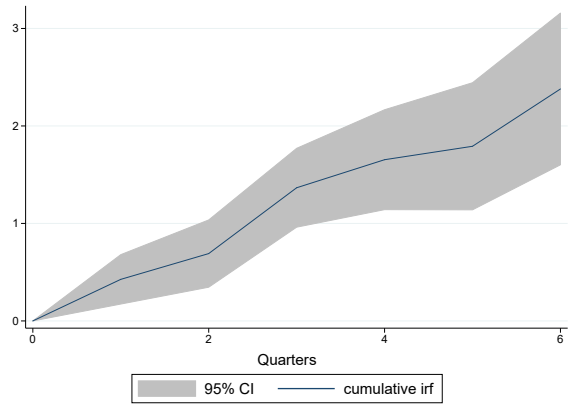
(a) Equity Mutual Fund Flows (ICI)



(b) High Yield Mutual Fund Flows (ICI)



(c) Household Flows into Stocks (FoF)



(d) Household Flows into Deposits (FoF)

Table A1: Demographics of Benchmark Experiment Samples

Panels A, B, C tabulate demographics for Experiments B1, B2, B3 respectively. In the Low condition, the risk-free rate is 1%; in the High condition, the risk-free rate is 5%. The mean excess returns of the risky asset is 5% in both conditions. The final three columns show repetitively: the difference in the percentage of participants in a certain category, the t-statistic associated with the difference, and the p-value from the Mann-Whitney-Wilcoxon test against the null that the distribution of characteristics across the two conditions are the same. For the MBA sample, we do not collect age because of homogeneity, and do not collect wealth as it might be sensitive information. Risk tolerance is measured through a question that asks participants to choose their favorite lottery from six options increasing in risks and expected payoffs: a) 50% chance receive \$22 and 50% chance receive \$22; b) 50% chance receive \$30 and 50% chance receive \$18; c) 50% chance receive \$38 and 50% chance receive \$14; d) 50% chance receive \$46 and 50% chance receive \$10; e) 50% chance receive \$54 and 50% chance receive \$6; f) 50% chance receive \$60 and 50% chance receive \$0. We categorize risk tolerance as low if participants choose option a) or b), medium if they choose option c) or d), and high if they choose option e) or f).

Panel A. Experiment B1: MTurk, Hypothetical

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

Panel B. Experiment B2: MTurk, Incentivized

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

Panel C. Experiment B3: HBS MBA, Incentivized

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

Table A3: Interest Rates and Household Investment Flows

Time series regressions:

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

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

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

Newey-West t-statistics in brackets

Table A4: Additional Results on History Dependence

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

Panel A. Setting 1 (Hypothetical Experiment)

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

Panel B. Setting 2 (Incentivized Experiment)

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

Table A5: Investment Decisions and Interest Rate Experiences

Panel regressions using Survey of Consumer Finance data:

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

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

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

t-statistics in brackets, corrected for multiple imputation

B Questions on Inflation Comprehension

Below are inflation comprehension questions used in the demographic section of the experiment in Section 3.3, to test participants' understanding of inflation, nominal returns, and real returns.

1. Suppose the interest rate on your savings account is 1% a year and inflation is 2% a year. After one year, would the money in the account buy more than it does today, exactly the same, or less than today?

   (More, Same, Less, Don't know) **79.1% chose "less."**

2. If inflation is 2% a year, goods that cost $100 now will cost how many dollars next year on average?

   $_____. **86.0% wrote "102."**

3. Consider two individuals, Ann and Barbara, who graduated from the same college a year apart. Upon graduation, both took similar jobs with publishing firms.

   Ann started with an annual salary of $50,000. During her first year on the job there was no inflation, and in her second year Ann received a 2% raise in salary.

   Barbara also started with an annual salary of $50,000. During her first year on the job there was 4% inflation, and in her second year Barbara received a 5% raise in salary.

   As they entered their second year on the job, who do you think is doing better in economic terms?

   (Ann, Barbara, No difference) **80.0% chose "Ann."**

C List of Experiments

Table A6: List of Experiments

This table summarizes the experiments. Most experiments use non-overlapping samples (participants are allowed to participate in only one experiment; participants from previous experiments are automatically screened out in subsequent experiments). Experiments 2 and 3 are run together (i.e. a given pool of participants are randomly assigned to one of the conditions in these experiments at the same time). Experiments 5, 6, 7, 8 are run together.

	Population	Setting	Test	N	Time
1	Mturk	Hypothetical	Benchmark	400	Jun-16
2	Mturk	Incentivized	Benchmark	400	Feb-16
3	Mturk	Incentivized	Robustness checks (payment methods)	1,200	Feb-16
4	HBS MBA	Incentivized	Benchmark	400	Apr-16
5	Mturk	Incentivized	Gradient & non-linearity	1,400	Jun-16
6	Mturk	Incentivized	Gross framing	400	Jun-16
7	Mturk	Incentivized	Robustness (net framing)	400	Jun-16
8	Mturk	Incentivized	Robustness (binary distribution)	400	Jun-16
9	Mturk	Hypothetical	History dependence	400	Aug-15
10	Mturk	Incentivized	History dependence	400	Jun-16
11	Mturk	Hypothetical	History dependence additional design (by Cary Frydman)	400	Nov-16
12	Mturk	Incentivized	History dependence additional design	400	Dec-16
13	Dutch households	Hypothetical	Gradient & non-linearity (by Dutch AFM)	900	Aug-17
14	Mturk	Hypothetical	Nominal vs. real returns	600	May-18
Total				8,100	