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

Chen Lian
Massachusetts Institute of Technology

Yueran Ma
University of Chicago Booth School of Business

Carmen Wang
Harvard University

How do low interest rates affect investor behavior? We demonstrate that individuals "reach for yield," that is, have a greater appetite for risk-taking when interest rates are low. Using randomized investment experiments holding fixed risk premiums and risks, we show low interest rates lead to significantly higher allocations to risky assets among diverse populations. The behavior is not easily explained by conventional portfolio choice theory or institutional frictions. We then propose and provide evidence of mechanisms related to investor psychology, including reference dependence and salience. We also present results using observational data on household investment decisions. (*JEL* D14, E44, E52, G11, G40)

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Since the global financial crisis, central banks in major developed countries have set benchmark interest rates to historic lows. A widely discussed question

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

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

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

Specifically, we show that individuals demonstrate a stronger preference for risky assets when the risk-free rate is low. We first document this phenomenon in a simple randomized experiment. In 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 Group 2, participants consider investing between a risk-free asset with 1% returns and a risky asset with 6% average returns (the risky payoffs are again approximately normally distributed with 18% volatility). In other words, across the two treatment conditions, we keep the risk premium (i.e., average excess returns) and the risks of the risky asset fixed, and only make a downward shift in the risk-free interest rate. Participants are randomly assigned to one of the two conditions. The investment decision in each condition represents the simplest mean-variance analysis problem, where the solution should not be affected by the risk-free rate based on the textbook mean-variance benchmark (Markowitz 1952; Sharpe 1964).

We find robust evidence that people in the low interest rate condition (Group 2) invest significantly more in the risky asset than people in the high interest rate condition (Group 1). The average investment share in the risky asset increases

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

by about 8 percentage points. This finding holds among large and diverse groups of participants (several thousand participants from the U.S. general population through Amazon's Mechanical Turk platform as well as four hundred Harvard Business School MBA students), and across different settings (hypothetical questions and incentivized experiments). Such behavior by individuals is not explained by institutional frictions. It is also difficult to square with standard portfolio choice theory under fairly general conditions (specifically, absolute-risk aversion is weakly decreasing in wealth).

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

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

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

Second, as further evidence for history-dependent reference points, we find that investment history has a significant impact on investment decisions. For instance, when participants first make investment decisions in the high interest

rate condition and then make decisions in the low interest rate condition, they invest substantially more in the risky asset in the low rate condition.

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

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

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

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

Second, we demonstrate the importance of insights in behavioral economics for questions in monetary economics (i.e., impact of interest rates on investor

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

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

1. Benchmark Experiment

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

1.1 Experiment design and sample description

Our experiment takes the form of an online survey that participants complete using their own electronic devices (e.g., computers and tablets). The survey has two sections: Section 1 presents the investment decision, and Section 2 includes a set of demographic questions. Each experiment has 400 participants, who are randomly assigned to the two interest rate conditions. Internet Appendix provides the survey forms. We conduct the benchmark experiment among two groups of participants. The first group consists of adults in the United States from Amazon's Mechanical Turk (MTurk) platform. MTurk is an online platform for surveys and experiments, which is increasingly used in economic research (Kuziemko et al. 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 United States, completes large-scale enrollment in a short amount of time, and provides response quality similar to that of lab experiments (Casler, Bickel, and Hackett 2013). These features are very helpful for our study. As we show later, our MTurk participants have similar demographics as the U.S. general population, with fewer elderlies and a higher level of education. Figure 1 shows the geographic location of participants in the benchmark experiments, which is representative of the U.S. population. Our experiments on MTurk provide

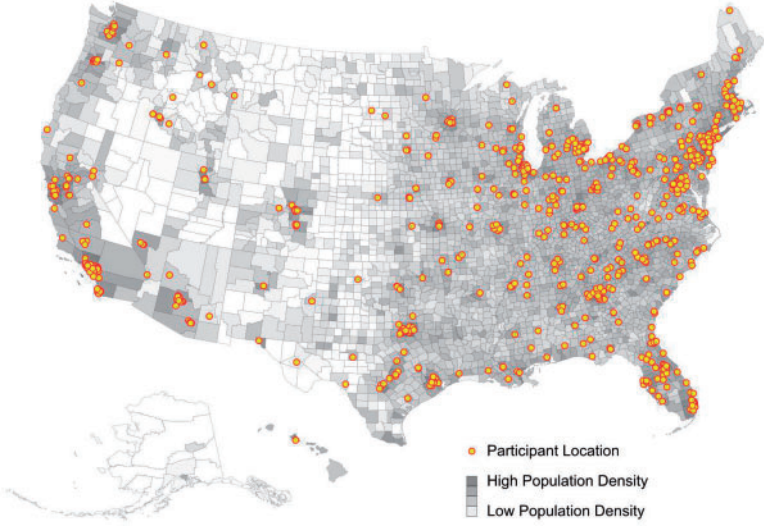

Figure 1
Geographic distribution of MTurk participants
This plot shows the geographic distribution of MTurk participants in the benchmark experiments (Experiments B1 and B2). The dots indicate participant locations. The background coloring is based on log population density in each county.

relatively high payments compared to the MTurk average to ensure quality response.

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

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

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

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

[2] Specifically, at the end of the demographics section, we ask a question in which participants report their favorite lottery among six options: (1) a 50% chance of receiving $22 and a 50% chance of receiving $22; (2) a 50% chance of receiving $30 and a 50% chance of receiving $18; (3) a 50% chance of receiving $38 and a 50% chance of receiving $14; (4) a 50% chance of receiving $46 and a 50% chance of receiving $10; (5) a 50% chance of receiving $54 and a 50% chance of receiving $6; and (6) a 50% chance of receiving $60 and a 50% chance of receiving $0. We categorize risk tolerance as low if participants choose option 1 or 2, medium if they choose option 3 or 4, and high if they choose option 5 or 6.

Table 1
Demographics of benchmark experiment samples

		Low		High		Low - high		
		N	%	*N*	%	%	[*t*]	*U* test (*p*)
A. Experiment B1: MTurk, hypothetical								
Gender	Male	82	40.0	102	52.3	−12.3	[−2.48]	.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]	.99
	College	112	54.6	118	60.5	−5.9	[−1.19]	
	High school	53	25.9	45	23.1	2.7	[.62]	
Age	Below 30	103	50.2	98	50.3	−.0	[−.00]	.97
	30–40	63	30.7	56	28.7	2.0	[.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	[−.62]	.54
	Medium	67	32.7	64	32.8	−.1	[−.03]	
	Low	106	51.7	96	49.2	2.5	[.49]	
Financial wealth (excluding housing)	200K+	10	4.9	17	8.7	−3.8	[−1.52]	.65
	50K–200K	56	27.3	56	28.7	−1.4	[−.31]	
	10K–50K	57	27.8	43	22.1	5.7	[1.33]	
	0–10K	59	28.8	51	26.2	2.6	[.59]	
	In debt	23	11.2	28	14.4	−3.1	[−.94]	
Investing experience	Extensive	7	3.4	6	3.1	.3	[.19]	.69
	Some	61	29.8	60	30.8	−1.0	[−.22]	
	Limited	88	42.9	75	38.5	4.5	[.91]	
	No	49	23.9	54	27.7	−3.8	[−.86]	
Total		205		195				
B. Experiment B2: MTurk, incentivized								
Gender	Male	116	56.6	111	56.9	−.3	[−.07]	.98
	Female	89	43.4	84	43.1	0.3	[.07]	
Education	Graduate school	30	14.6	33	16.9	−2.3	[−.63]	.13
	College	122	59.5	125	64.1	−4.6	[−.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]	.57
	30–40	54	26.3	66	33.9	−7.5	[−1.64]	
	40–50	30	14.6	23	11.8	2.8	[.84]	
	Above 50	18	8.8	18	9.2	−.5	[−.16]	
Risk tolerance	High	33	16.1	27	13.9	2.3	[.63]	.71
	Medium	73	35.6	72	36.9	−1.3	[−.27]	
	Low	99	48.3	96	49.2	−1.0	[−.19]	
Financial wealth (excluding housing)	200K+	25	12.2	22	11.3	1.0	[.28]	.36
	50K–200K	47	22.9	55	28.2	−5.3	[−1.21]	
	10K–50K	60	29.3	58	29.7	−.5	[−.10]	
	0–10K	42	20.5	35	17.9	2.5	[.64]	
	In debt	31	15.1	25	12.8	2.3	[.66]	
Investing experience	Extensive	6	2.9	6	3.1	−.2	[−.09]	.98
	Some	68	33.2	66	33.9	−.7	[−.14]	
	Limited	83	40.5	75	38.5	2.0	[.41]	
	No	48	23.4	48	24.6	−1.2	[−.28]	
Total		205		195				

(continued)

Table 1
Continued

		Low		High		Low - high		
		N	%	*N*	%	%	[*t*]	*U* test (*p*)
C. Experiment B3: HBS MBA, incentivized								
Gender	Male	117	58.2	129	64.8	−6.7	[−1.36]	.17
	Female	84	41.8	70	35.2	6.7	[1.36]	
Past 15 years of life	United States	140	69.7	133	66.8	2.8	[.60]	.55
	Abroad	61	30.4	66	33.2	−2.8	[−.60]	
Primary educational field	Humanities	26	12.9	23	11.6	1.4	[.42]	.04
	Social science	64	31.8	43	21.6	10.2	[2.32]	
	Science and engineering	80	39.8	95	47.7	−7.9	[−1.60]	
	Other	31	15.4	38	19.1	−3.7	[−.97]	
Risk tolerance	High	116	57.7	107	53.8	3.9	[.79]	.55
	Medium	48	23.9	56	28.1	−4.3	[−.97]	
	Low	37	18.4	36	18.1	.3	[.08]	
Investment experience	Extensive/professional	22	10.9	25	12.6	−1.6	[−.50]	.47
	Some	71	35.3	60	30.2	5.2	[1.10]	
	Limited	70	34.8	68	34.2	.7	[.14]	
	No	38	18.9	46	23.1	−4.2	[−1.03]	
Worked in finance	Yes	84	41.8	86	43.2	−1.4	[−.29]	.77
	No	117	58.2	113	56.8	1.4	[.29]	
Total		201		199				

Panels A, B, and C tabulate demographics for Experiments B1, B2, and 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 return of the risky asset is 5% in both conditions. The final three columns show the following respectively: 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, which might be sensitive information. Risk tolerance is measured through a question that asks participants to choose their favorite lottery from six options increasing in risks and expected payoffs. We group risk tolerance into low, medium, and high based on the lottery chosen.

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

1.1.2 Experiment B2: MTurk, incentivized. In Experiment B2, participants consider allocating an experimental endowment of 100,000 Francs between the risk-free asset and the risky asset. The investment horizon is 1 year. Participants are recruited on MTurk in February 2016. They receive a participation payment of \$0.7, and could earn a bonus payment proportional to their investment

outcomes, with every 8,950 Francs converted to one dollar of bonus payment.[3] The bonus payment is on the scale of $12, which is very high on MTurk. After the experiment is completed, participants see the investment outcome (the return of the safe asset is fixed and the return of the risky asset is randomly drawn based on the distribution). We follow prior investment experiments and implement the decision of 10% randomly selected participants, who will receive the bonus payment. The payment structure is clearly explained throughout the experiment. Cohn et al. (2015) review payment schemes with random implementation and argue "there is solid evidence showing that these schemes do not change behavior."[4] We verify that results are unchanged whether the bonus payment is provided to all participants or a random subset of participants. Table A2 shows comparison experiments that test robustness to payment structure. Given the 1-year investment horizon, in our baseline specification the bonus payment is delivered a year after participation. In Table A2, we also verify that behavior is not affected by the delayed bonus.

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

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

Table 1, panel C, shows that about 60% of participants are male, roughly 70% are from the United States (and 30% are international students), and roughly 70% have primary educational background in social science or science

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

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

and engineering. The MBA participants have a higher level of risk tolerance than MTurk participants, according to both lottery choice-based assessment and subjective assessment. More than 40% report having some or extensive investment experience. The vast majority, 80%, own stocks; a significant fraction, 40%, have worked in finance. Participant characteristics across the two treatment conditions are generally balanced in Experiment B3.

1.2 Results

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

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

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

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

[5] To check for robustness to extreme observations, in addition to the nonparametric test in panel A, Column 5, we also run least absolute deviation regressions with controls (using the same specification used in panel A, Column 6, and Equation (1)). The coefficient on the low interest rate condition in Experiments B1, B2, B3 is 6.56, 12.70, and 10.00 (t-statistic = 1.74, 3.80, and 3.17) respectively. The results are similar to those obtained using an OLS regression.

Table 2
Low interest rates and risk-taking: Benchmark experiment results

A. Allocations to risky asset (%)

	High (1)	Low (2)	**Dif** (Raw) (3)	[t] (4)	U test (p) (5)	**Dif** (OLS) (6)	[t] (7)	**Dif** (Match) (8)	[t] (9)
B1: MTurk, hypo.	48.15	55.32	7.17	[2.52]	(.02)	7.69	[2.74]	7.27	[2.66]
B2: MTurk, incen.	58.58	66.64	8.06	[3.06]	(.00)	8.14	[3.23]	8.66	[2.81]
B3: HBS MBA, incen.	66.79	75.61	8.83	[3.13]	(.00)	8.76	[3.19]	8.91	[3.30]

B. Regressions with individual characteristics

	% allocated to risky asset		
	B1 (MTurk)	B2 (MTurk)	B3 (HBS)
Low rate condition	**7.69**	**8.14**	**8.76**
	[2.74]	[3.23]	[3.19]
Male	−1.04	6.63	6.25
	[−0.36]	[2.49]	[2.14]
College	−3.09	3.32	
	[−.92]	[1.00]	
Grad school	0.51	1.31	
	[.11]	[.29]	
Age (30—40)	3.69	.86	
	[1.16]	[.29]	
Age (40—50)	7.51	1.87	
	[1.48]	[.47]	
Age (50+)	1.26	6.63	
	[.22]	[1.35]	
Risk tolerance med	12.30	10.15	5.56
	[3.97]	[3.62]	[1.36]
Risk tolerance high	18.22	15.28	15.39
	[4.46]	[4.25]	[4.01]
Wealth (0—10K)	−6.07	−8.69	
	[−1.41]	[−1.88]	
Wealth (10K—50K)	.27	−4.87	
	[.06]	[−1.13]	
Wealth (50K—200K)	−5.29	−2.85	
	[−1.20]	[−.63]	
Wealth (200K+)	.75	3.40	
	[.11]	[.67]	
More experience	5.80	2.95	4.41
	[1.71]	[1.05]	[1.28]
Worked in finance			3.34
			[1.00]
Constant	41.03	54.44	55.81
	[8.91]	[9.82]	[14.27]
Obs	400	400	400
R^2	.118	.136	.115

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

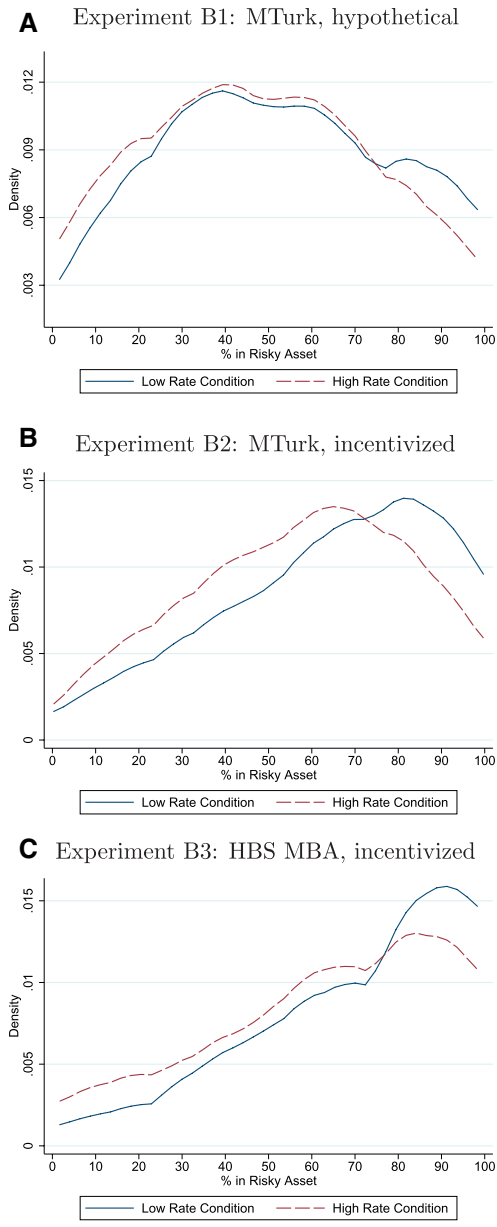

Figure 2
Distribution of allocations to the risky asset in benchmark experiments
Density plots of allocations to the risky asset in the benchmark experiments. Panels A, B, and C present plots for Experiments B1, B2, and B3, respectively. The solid line is the distribution of allocations to the risky asset in the low interest rate condition, and the dashed line is that in the high interest rate condition.

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

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

Our results on reaching for yield are consistent in different settings and subject pools. Some previous studies find the influence of psychological forces and certain biases may diminish with education and experience(List and Haigh 2005; Cipriani and Guarino 2009; Kuchler and Zafar 2017), whereas others do not find such an effect or find the opposite effect (Haigh and List 2005; Abbink and Rockenbach 2006; Cohn et al. 2015). In our data, HBS MBAs and MTurks reach for yield by a similar degree. Nor do we find that reaching for yield declines with wealth, investment experience, or education among MTurks or with investment and work experience in finance among MBAs, as shown in Internet Appendix Table A1. 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-statistic $= 2.47$).

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

[7] In the experiment, participants make decisions about investing a fixed amount of money. In practice, interest rates may also affect the consumption/saving decision and therefore the amount of money people decide to invest. Prior empirical studies, however, often do not find significant responses of consumption and savings to interest rates (Mankiw, Rotemberg, and Summers 1985; Hall 1988; Campbell and Mankiw 1989). In Section 4, we also present suggestive evidence that lower interest rates appear to be associated with both higher portfolio shares and higher dollar amounts invested in risky assets.

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

We make three observations in light of concerns about modest stake size. First, this issue does not affect the hypothetical experiment. The treatment effect is consistent across hypothetical and incentivized tests, which suggests the robustness of the result. Second, to the extent that small stakes make participants more risk neutral and decrease variations in investment decisions, it works against us finding significant differences between different interest rate conditions. Third, experimental research finds that risk preferences with respect to small stakes are meaningful and consistent with participants' risk preferences in general (Holt and Laury 2002). Previous studies find informative results based on experimental stakes (Andersen et al. 2008; Andreoni and Sprenger 2012; Charness, Gneezy, and Imas 2013; Bossaerts, Plott, and Zame 2007; Cohn et al. 2015), and we use stake size in line with prior work. We also find that participants' risk tolerance in the incentivized experiments is significantly correlated with allocations of their household financial wealth, as shown in Internet Appendix Table A3.

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

2. Potential Mechanisms

In this section, we discuss potential explanations of our findings in Section 1. We first show that conventional portfolio choice theories may not easily explain the reaching for yield behavior we document. We then suggest two categories of possible explanations, reference dependence and salience, which we test in Section 3.

2.1 Conventional portfolio choice theory

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

optimal $\phi^* \in [0,1]$ to maximize expected utility:

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

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

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

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

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

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

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

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

The intuition for this result is that, for a given distribution of x, when r_f increases the investor effectively becomes wealthier. If absolute-risk aversion

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

[9] In Section 2, we focus on the partial derivative of investment allocations with respect to the risk-free rate, holding inflation and inflation expectations constant, like in our randomized experiment. We discuss other issues related to inflation outside of the experiment in Internet Appendix Section 2.7.

is decreasing in wealth, the investor would be less risk averse and more willing to invest in the risky asset. In other words, the investor would "reach against yield," which is the opposite of what we document in Section 1. This wealth effect, however, is not first order and it drops out in the mean-variance approximation.[10]

Proposition 1 assumes weakly decreasing absolute-risk aversion, a property shared by commonly used utility functions (e.g., constant relative-risk aversion [CRRA]). The prediction of Proposition 1 would be reversed if investors instead have increasing absolute-risk aversion. Is this a possible explanation for the reaching for yield phenomenon we document? In studies of choice under uncertainty, increasing relative-risk aversion is sometimes observed, but (weakly) decreasing absolute-risk aversion appears to be a consensus (Holt and Laury 2002). Moreover, increasing absolute-risk aversion is difficult to square with additional experimental results we present in Section 3 to test mechanisms.

In the above we follow the experiment in Section 1 and study a static portfolio choice problem in (2). The static design helps us cleanly tease out the behavioral mechanisms that may generate reaching for yield behavior. In Internet Appendix Section 2.7, we discuss the impact of interest rates on portfolio allocations more generally, such as in dynamic portfolio choice problems with hedging or life-cycle motives. These explanations do not seem to explain the experimental results in Section 1 and further tests of mechanisms in Section 3.

2.2 Reference dependence

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

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

One way to specify reference dependence is through a framework of loss aversion around the reference point, as formulated in the prospect theory (Kahneman and Tversky 1979). In the following, we first use this type of framework to analyze the investment decision and predictions for reaching for

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

yield. We then discuss reference point formation in our setting and additional empirical implications.

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

Assumption 1.

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

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

Here, we include the reference point component, but not the additional features of the prospect theory, such as diminishing sensitivity and probability reweighting, because the gist of our observation relates to the reference point and loss aversion around the reference point. We discuss the case with diminishing sensitivity in the Internet Appendix Section 2.2.[11] Probability reweighting does not affect our key result in Proposition 2 about responses to changes in the risk-free rate (see He and Zhou (2011) for a more detailed discussion). We also discuss other functional forms for modeling reference dependence in Internet Appendix Section 2.

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

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

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

[11] Internet Appendix Section 2.2 explains the theoretical prediction of whether diminishing sensitivity contributes to reaching for yield is ambiguous. We then evaluate the results numerically based on standard prospect theory parameter values (Tversky and Kahneman 1992). We find that it is difficult for diminish sensitivity *alone* to account for the evidence in Section 1 without the loss aversion component. Some recent research also questions diminishing sensitivity, especially the convexity of the utility function in the loss domain, in the investment context (Bracha 2016).

asset. This result suggests a potential explanation for the findings in Section 1 that participants in the low interest rate condition invest more in the risky asset.

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

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

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

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

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

Reference Point Formation A natural question is where investors' reference points come from. In the following, we discuss the leading theories of reference points, and explain why people's past experiences may be the main contributor to the type of reference dependence that generates reaching for yield. We provide proofs and more discussions in Internet Appendix Section 2.4.

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

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

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

Another form of reference point that can be important in our setting highlights the impact of past experiences (Simonsohn and Loewenstein 2006; Bordalo, Gennaioli, and Shleifer 2017; DellaVigna et al. 2017). Specifically, people form reference investment returns that they have become accustomed to. When the risk-free rate drops below what they are used to, people experience discomfort and become more willing to invest in risky assets.[14] This falls in the first case of Proposition 2, which predicts reaching for yield. Given the economic environment in the decades prior to the Great Recession, reference points from past experiences appear in line with investors' view that 1% or 0% interest rates are "too low."[15]

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

2.3 Salience and proportional thinking

The second category of mechanisms is that investment decisions could be affected by the salience of the higher average returns of the risky asset, which may vary with the interest rate environment. Specifically, 6% average returns might appear to be more attractive compared to 1% risk-free returns than 10% average returns compared to 5% risk-free returns. This intuition can be formalized by a version of the Salience theory of

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

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

[15] In the incentivized experiments, if participants mingle the experimental returns with other returns and monetary payoffs in their lives, one question is whether they compare the experimental returns or the sum of all monetary payoffs with respect to their reference points. As Barberis, Huang, and Thaler (2006) highlight, narrow framing—the tendency to consider an investment problem in isolation as opposed to mingling it with other risks (e.g., labor income risks, other investments)—appears to be a robust element of investor behavior. To the extent that participants are inclined to frame narrowly and evaluate the investment problem on its own, we can directly apply the predictions of the reference dependence mechanisms studied in this section. The same holds for the salience and proportional thinking mechanism in Section 2.3.

Bordalo, Gennaioli, and Shleifer (2013b). It also connects to the well documented phenomenon that people tend to evaluate stimuli by proportions (i.e., 6/1 is much larger than 10/5) rather than by differences (Weber's law; Tversky and Kahneman (1981), Kőszegi and Szeidl (2013), Cunningham (2013), Bushong, Rabin, and Schwartzstein (2016)).

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

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

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

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

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

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

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

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

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

[16] In our context, the salience theory and proportional thinking are broadly the same. In the Internet Appendix Section 2.6, we discuss a subtle difference between the way "salience" is defined in Bordalo, Gennaioli, and Shleifer (2013b) and proportional thinking. We also explain the relationship between our framework and other related models, such as Bordalo, Gennaioli, and Shleifer (2012), Bordalo, Gennaioli, and Shleifer (2013a), Bushong, Rabin, and Schwartzstein (2016), and Kőszegi and Szeidl (2013).

[17] In the original setup, either the risk dimension is more salient or the return dimension is more salient, and the more salient dimension receives a fixed weight. When there is a risk-free asset, the risk dimension is always

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

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

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

3. Testing Mechanisms

In this section, we perform three additional experiments to test explanations for the reaching for yield behavior discussed in Section 2. We find evidence supportive of both reference dependence and salience.

3.1 Experiment T1 (nonlinearity)

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

Through this experiment, we would like to examine two main questions. The first is whether reaching for yield exhibits nonlinearity and is most pronounced when interest rates are low. Both reference dependence and salience/proportional thinking predict such nonlinearity. In the model of reference point and loss aversion in Section 2.2, reaching for yield occurs when interest rates are below the reference point. In the model of salience/proportional thinking in Section 2.3, allocations to the risky asset would be more sensitive to interest rates when interest rates are low, where the ratio of the average returns $(r_f+\mathbb{E}x)/r_f$ changes more with the risk-free rate. The second question is whether we observe "reaching against yield" (i.e., allocations to the risky

more salient by a fixed amount. Accordingly, returns of the risk-free asset do not change the salience of the return dimension relative to the risk dimension. We generalize Bordalo, Gennaioli, and Shleifer (2013b) to a continuous salience function that allows salience to move even with a risk-free asset. Our formulation nests the original salience function as a special case $f(t)=\begin{cases}\beta & t>0\\ \frac{1}{\beta} & t<0\end{cases}$, where $\beta>1$. In addition, the decision problem in Bordalo, Gennaioli, and Shleifer (2013b) and Bordalo, Gennaioli, and Shleifer (2016) is a discrete choice problem. We generalize it to continuous decisions. See Internet Appendix Section 2.6 for more discussions.

Table 3
Allocations in various interest rate conditions

Risk-free rate (%)	−1	0	1	3
Mean returns of the risky asset (%)	4	5	6	8
Mean allocations to the risky asset (%)	77.58	69.67	64.62	58.34
95% CI	(73.53, 81.62)	(65.88, 73.46)	(60.72, 68.51)	(54.48, 62.21)
Risk-free rate (%)	5	10	15	
Mean returns of the risky asset (%)	10	15	20	
Mean allocations to the risky asset (%)	56.77	49.92	50.59	
95% CI	(52.98, 60.55)	(45.90, 53.93)	(46.76, 54.43)	

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

asset increasing in the risk-free rate) when interest rates are sufficiently high, as predicted by the traditional prospect theory formulation in Proposition 2.

We conducted Experiment T1 in June 2016. Participants are recruited on MTurk. Like in the benchmark experiments, each interest rate condition has 200 participants. Similar to Experiment B2 (Benchmark Incentivized, MTurk), participants consider allocating experimental endowment of 100,000 Francs to the risk-free asset and the risky asset. The payment structure follows Experiment B2. The participation payment is $0.7. Participants may also receive a bonus payment proportional to their investment outcomes, with every 8,950 Francs converted to one dollar (so the bonus payment is on the scale of $12). We implement the decision of 10% randomly chosen participants and they receive the bonus payment. Table A6 in the Internet Appendix shows the demographics of participants in Experiment T1, which are similar to those in the benchmark experiments. In all of our experiments, we use participants who did not participate in any of our previous experiments.[18]

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

Results in Experiment T1 suggest notable nonlinearity in how investment decisions respond to interest rates. Reaching for yield is particularly pronounced when interest rates are low, roughly below 3%. Statistical tests can reject

[18] For incentivized experiments in Section 3, participants receive their bonus payments shortly after participation. Delaying the bonus by 1 year requires us to collect MTurk participants' contact information, in case they no longer work on MTurk in 1 year's time. In Section 1 and Internet Appendix Table A2, we have tested that the results are robust to payment timing. Therefore, in the additional experiments we pay the bonus within 1 week to simplify the logistics.

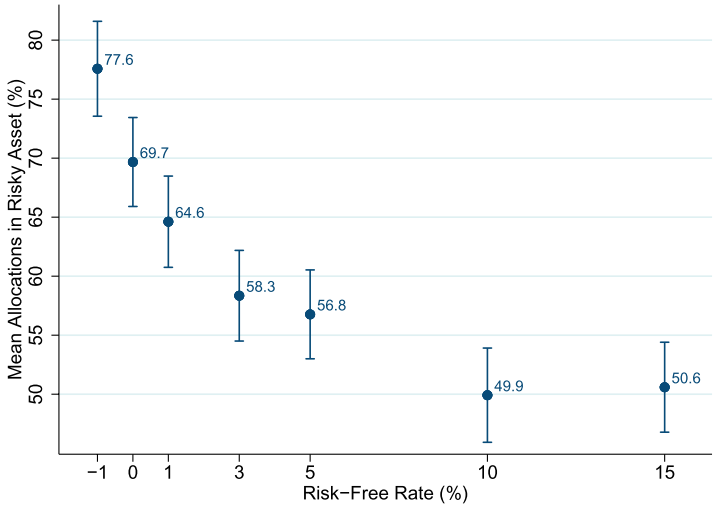

Figure 3
Mean allocations across interest rate conditions
Mean allocations to the risky asset across various interest rate conditions in Experiment T1. Each condition has 200 participants. The x-axis shows the risk-free rate in each condition. The mean excess returns on the risky asset is 5% in all conditions. The y-axis is the mean allocation to the risky asset. The vertical bar represents the 95% confidence interval for the mean allocation.

linearity with high significance.[19] The shape of the nonlinear response is in line with reasonable reference points based on the average level of interest rates and investment returns most participants were used to prior to the Great Recession. The pattern is also generally consistent with salience/proportional thinking, as the ratio of the average returns $(r_f+\mathbb{E}x)/r_f$ becomes significantly less sensitive to r_f when r_f is high.

On the other hand, the substantial nonlinearity we observe is difficult to square with conventional portfolio choice theories with increasing absolute-risk aversion, life-cycle motives, or hedging motives. In these cases, it is not clear why differences in allocations are substantial between conditions with 0% versus 5% interest rates, for instance, but are absent between conditions with 10% versus 15% interest rates.

In addition, while we see clear patterns of reaching for yield when interest rates get into the low range, we do not observe reaching against yield when interest rates approach the high end. In Proposition 2 in Section 2, we show the baseline prospect theory formulation does predict reaching against yield when the risk-free rate is higher than the reference point. One possibility is that reaching against yield is modest in magnitude, and our sample size of 200

[19] For instance, in a quadratic specification of $Y_i=\alpha+\beta r_{f,i}+\gamma r_{f,i}^2+\epsilon_i$, where Y_i is individual i's allocation to the risky asset and $r_{f,i}$ is the risk-free rate in individual i's assigned condition, the t-statistic of γ being different from zero is 5.67 (p-value $<$ .001). We can also test the null that the piecewise slopes between all the adjacent interest rate conditions are the same, and the null can be rejected with p-value $<$ .001.

per condition does not have enough power to detect it; this effect could be further dampened by salience/proportional thinking. Another possibility is that the reaching against yield prediction is not very robust, and is specific to the functional form in the traditional prospect theory formulation. For example, an alternative formulation of reference dependence is that people experience discomfort/loss aversion when the average return of the portfolio is below the reference point (as opposed to experiencing loss aversion for each state where the realized return is below the reference point, like in the traditional formulation in Section 2.2). This alternative formulation predicts reaching for yield when interest rates are low, but does not predict reaching against yield when interest rates are high. We present this alternative formulation in Internet Appendix Section 2.3.[20]

The results of reaching for yield and nonlinearity are robust across different settings and different populations. In August 2017, the Dutch Authority for the Financial Markets replicated the test using 900 Dutch households. They used the hypothetical version of our protocol (translated into Dutch) and six interest rate conditions from −1% to 10%. Internet Appendix Section 3.2 and Ma and Zijlstra (2018) provide the Dutch results.

3.2 Experiment T2 (history dependence)

In Experiment T2, we examine how investment history and reference dependence affect investment decisions. Specifically, participants in this experiment make two rounds of investment decisions: half of the participants (Group 1) first make decisions in the high interest rate condition (5% safe returns and 10% average risky returns, same as the benchmark experiment), and then make decisions in the low interest rate condition (1% safe returns and 6% average risky returns); the other half of the participants (Group 2) do the reverse. Group 1 mimics the situation where people move from a high interest rate environment to a low interest rate environment, which is a particularly relevant case for the recent discussions about investor reactions to low interest rates. After being placed in the high interest rate condition, participants in Group 1 are likely to carry a relatively high reference point when they move to the low interest rate condition. As Section 2.2 suggests, allocations to the risky asset in a low rate environment would increase when people have higher reference points. Accordingly, participants in Group 1 may invest more aggressively in the risky asset in the low interest rate condition.

We conduct two versions of Experiment T2. In the incentivized version, in each round participants consider allocating experimental endowment of

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

Table 4
Path dependence of investment decisions

G1	High: 5–10	Low: 1–6	G1	High: 5–10	Low: 1–6
Mean alloc. to the risky asset	49.23	**66.12**	Mean Alloc. to Risky	57.24	**71.57**
G2	Low: 1–6	High: 5–10	G2	Low: 1–6	High: 5–10
Mean alloc. to the risky asset	55.64	46.98	Mean Alloc. to Risky	62.99	55.40
G1 (low) - G2 (low)	Difference	[t]	G1 (Low) - G2 (Low)	Difference	[t]
	10.48	[3.40]		8.58	[3.14]
(a) Hypothetical			(b) Incentivized		

This table presents results from Experiment T2. Half of the participants are randomly assigned to Group 1. 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. They first make investment decisions in the low rate condition and then make decisions in the high rate condition. We perform this experiment using both hypothetical questions and incentivized tests.

100,000 Francs to the safe asset and the risky asset (the outcomes of the risky asset in the two rounds are uncorrelated). Participants are recruited on MTurk in June 2016. They receive a participation payment of $1.2. They may also receive a bonus payment proportional to their investment outcome in one randomly chosen round, with every 8,950 Francs converted to one dollar (so the bonus payment is on the sale of $12). Investment outcomes for both rounds are displayed after the entire experiment is completed. Participants are then informed which round the bonus payment would depend on, and whether they are among the 10% randomly selected participants to receive the bonus payment. Making payments based on randomly chosen outcomes is standard in prior experimental work (e.g., Holt and Laury (2002), Frydman and Mormann (2016)).[21] To check the robustness of this result, we also report results from a hypothetical version. In the hypothetical version, in each round, participants consider hypothetical questions about investing total savings of $10,000 between the safe asset and the risky asset. Participants are recruited from MTurk in August 2015. They receive $0.5 for participation. In both versions, 200 participants compose Group 1 and 200 participants compose Group 2. Internet Appendix Table A7 shows the demographics in Experiment T2.

Table 4 and Figure 4 present the results, which show several findings. First, reaching for yield is present both within group and across groups. Within each of Group 1 and Group 2, allocations to the risky asset are higher in the low rate condition than in the high rate condition. Across Group 1 and Group 2, when making the first decision, the group facing the low rate condition (Group 2) has significantly higher allocations to the risky asset. This is analogous to the benchmark experiment.

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

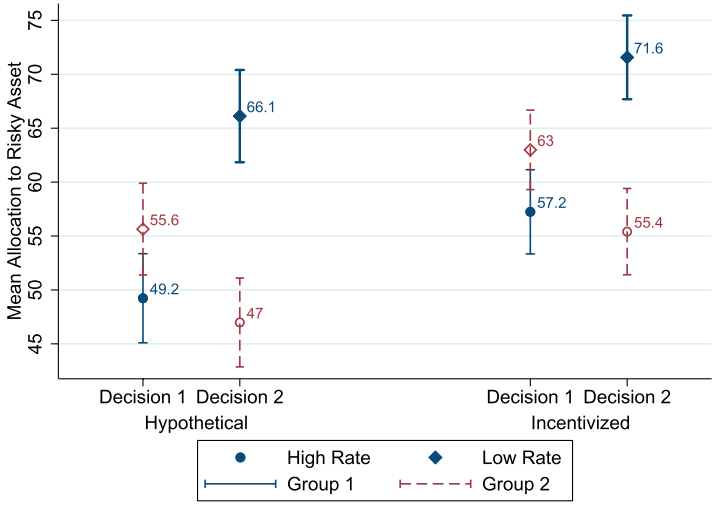

Figure 4
Path dependence of investment fecisions
This plot shows mean allocations in Experiment T2. In Group 1, participants first make investment decisions in the high interest rate condition (5% risk-free rate and 10% average risky returns) and then make decisions in the low interest rate condition (1% risk-free rate and 6% average risky returns). In Group 2, participants first make investment decisions in the low rate condition and then make decisions in the high rate condition. The circles are mean allocations in the high interest rate condition; the diamonds are mean allocations in the low interest rate condition. The vertical bar shows the 95% confidence interval for the mean allocation. We perform this experiment using both hypothetical questions and incentivized tests.

Second and importantly, participants in Group 1—who consider the high rate condition first—have particularly high allocations to the risky asset in the low rate condition. On average, they invest roughly 10 percentage points more in the low rate condition than participants in Group 2. These results are in line with predictions of reference dependence in Section 2.2 Corollary 1 and history-dependent reference points.[22]

Internet Appendix Section 2.5 presents alternative designs to test history dependence, which produce similar findings. In these tests, all participants face the same interest rate environment in the final round, but prior to that, one group starts with an environment with higher interest rates, while another group starts with an environment with lower interest rates. Our discussant Cary Frydman performed a hypothetical experiment on MTurk. We performed an incentivized version with slightly different interest rate specifications. The results show a consistent pattern: when participants consider the final medium interest rate

[22] In this experiment, we do not find that experiences of the low rate condition have a significant influence on allocations in the high rate condition. According to Corollary 1, with the traditional prospect theory formulation, a decrease in the reference point should increase risk-taking when the reference point is lower than the risk-free rate. In this case, Group 2 would be expected to invest more in the risky asset in the high rate condition, which we do not observe in the data. Since Corollary 1 follows from Proposition 2, this prediction is equivalent to the reaching against yield prediction we discussed in Experiment T1. Thus it shares the same explanations for the lack of evidence in our data, as elaborated at the end of Section 3.1.

condition, those who start in a high interest rate setting invest more aggressively in the risky asset than those who start in a low interest rate setting.

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

History-dependent reference points could be affected by both short-term and long-term experiences.[23] Experiment T2 studies the mechanism by exploiting differences in short-term experiences. We make two observations about the impact of long-term experiences. First, as discussed in Section 3.1, the nonlinearity in Experiment T1 is in line with reference points from prior life experiences. Second, we also test whether heterogeneity in lifetime experiences, which may result in different reference points, can help explain differences in investment decisions. In our experiments, due to relative homogeneity in age, variations in lifetime experiences are limited (the interquartile difference is average experienced interest rates, for example, is about 1%). Moreover, given we only have one cross-section, we cannot separate experience effects from age effects. To shed further light on this issue, in Internet Appendix Section 3.3.2 we use panel data from the Survey of Consumer Finances and apply the empirical strategy of Malmendier and Nagel (2011). We present suggestive evidence that, at each point in time, individuals who experienced higher interest rates over their lifetime appear less satisfied with safe assets and exhibit a higher propensity to invest in risky assets like stocks. The observational data present several caveats (e.g., fully controlling for potential differences in perceived risks and returns of risky assets is difficult), but the overall pattern seems consistent with history-dependent reference points.

3.3 Experiment T3 (salience and proportional thinking)

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

[23] An analogy is a person's reference point for weather (e.g., winter temperature). This can be affected by both long-term experiences—whether $30^\circ F$ is cold is different for a New Yorker versus a Floridian—and short-term experiences—$30^\circ F$ 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 versus Montreal, who will come back with different temporary reference points about weather.

The baseline framing is what we use in the benchmark experiments and in Experiments T1 and T2. Specifically, we first explain the (average) returns of the investments, in terms of net returns (e.g., 1%, 5%) 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 experiments, instead of using the commonly used net returns, we describe the investments' payoffs using gross returns. Instead of 5%, we say for every Franc invested one would get 1.05 Francs. We keep everything else the same. The descriptions read as follows:

> **Investment A**: For every Franc you put into Investment A, you will get 1.05 Francs for sure.
>
> For example, suppose you put 100 Francs into this investment, you will get 105 Francs. ...
>
> **Investment B**: Investment B has nine possible outcomes. For every Franc you put into Investment B, you will get 1.1 Francs on average. The volatility of the investment returns is 18%. The nine possible outcomes are shown by the chart below, where the number inside each bar indicates the probability of that particular outcome.
>
> For example, suppose you put 100 Francs into this investment, you will get 110 Francs on average. There is uncertainty about the exact amount of money you will get. The first row of the chart below describes the nine possible outcomes: there is a 19% chance that you will get 120 Francs, there is a 12% chance that you will get 90 Francs, etc.

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

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

In Experiment T3, we randomly assign participants to different framing conditions and different return conditions (i.e., baseline high, baseline low, gross high, gross low), with 200 participants in each condition. Participants are recruited on MTurk in June 2016. Experiment T3 and Experiment T1 are run together; all procedures and payment structures are the same. Internet Appendix Table A8 shows the demographics in Experiment T3.

Table 5 and Figure 5 present results from Experiment T3. With baseline framing, the mean allocation to the risky asset is 56.77% in the high interest rate condition, and 64.62% in the low interest rate condition. With gross framing, the mean allocation to the risky assets is 52.70% and 54.59% in the high and low interest rate conditions respectively. Allocations to the risky asset are lower with gross framing than with baseline framing, especially in the low rate condition. The mean allocation in the risky asset decreases by 4.06% 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.[25]

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[24] To understand how the reaching for yield behavior may change with framing, we also test another framing that we refer to as "net framing." In the net framing conditions, we explain the investments' headline returns in net returns, just like with the baseline framing. When we explain the distribution of the risky asset's returns through examples, instead of describing them as getting a certain amount of Francs for every 100 Francs invested, we describe them as gaining or losing a certain amount of Francs. For instance, the description of Investment A becomes "Investment A's return is 5% for sure. For example, suppose you put 100 Francs into this investment, you will earn 5 Francs." We find that the reaching for yield behavior is similar using net framing and baseline framing (see Table A5).

[25] What is the relationship between results in Experiment T3 and reference dependence? One observation is that since reference points from the natural environment are most likely about net returns, gross framing may dampen the influence of reference points. Specifically, when using net returns, 1% interest rates may appear particularly

Table 5
Baseline and gross framing

A. Mean allocations to the risky asset (%)

	High: 5–10	Low: 1–6	Difference	[t]	U test (p-value)
Baseline	56.77	64.62	7.85	[2.85]	(.00)
Gross	52.70	54.59	1.89	[.69]	(.45)
Baseline - gross	4.06	10.03	5.96	–	–
[t]	[1.46]	[3.70]	[1.54]	–	–
U test (p-value)	(.17)	(.00)	–	–	–

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	[.68]	.92	[.29]
High: Baseline − gross	4.61	[1.75]	6.34	[1.94]
Low: Baseline − gross	10.04	[3.79]	9.68	[3.40]

This table presents results from 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 amount of wealth. 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.

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

4. Suggestive Evidence from Observational Data

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

When using the observational data in the analysis, we need to address two important challenges. First, assessing investors' beliefs about the returns and risks of risky assets is difficult. Ideally, we would like to control for investors' expectations of excess returns and risks of the risky asset and isolate the impact of shifts in the risk-free rate. Even if investors have rational expectations, it could be difficult to find exact measures of asset properties. Moreover, recent research

low relative to experience, but this comparison could be less instinctive when investment payoffs are described in gross returns. Thus, results in Experiment T3 may not be inconsistent with reference dependence. Can reference dependence and the observation above fully *explain* results in Experiment T3? Probably not, given that allocations to the risky asset in the high interest rate condition are also higher with baseline framing than with gross framing.

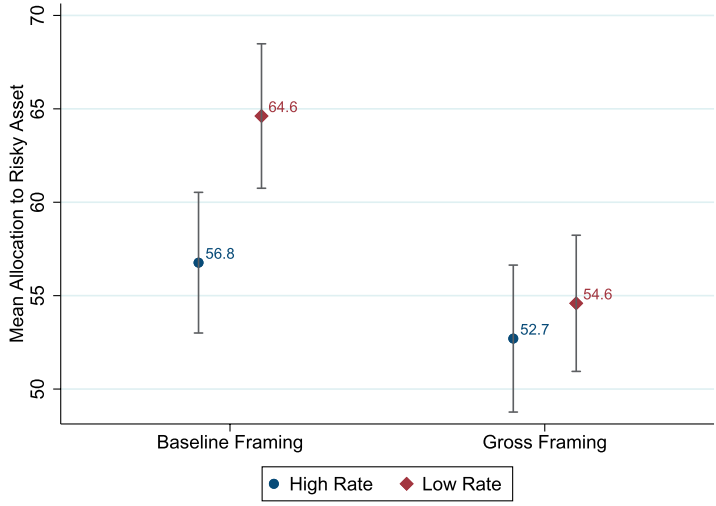

Figure 5
Mean allocations with baseline and gross framing
Mean allocations to the risky asset in Experiment T3. The circles are mean allocations in the high interest rate condition; the diamonds are mean allocations in the low interest rate condition. The vertical bar shows the 95% confidence interval for the mean allocation.

documents that households' subjective expectations of stock returns differ from model-based expected returns (Greenwood and Shleifer 2014; Amromin and Sharpe 2013). In light of this issue, we control for both model-based measures and subjective expectations from investor surveys. Second, interest rate variations can be correlated with other drivers of investment decisions, such as general economic conditions and investors' risk tolerance. To the extent that investors are more risk averse in recessions, this bias would work against us. We include controls of economic conditions (e.g., gross domestic product [GDP] growth, credit spreads (Gilchrist and Zakrajšek 2012)). In the data, these controls strengthen our results.[26]

Main Variables We measure household investment decisions using data from three sources. The first data source is monthly portfolio allocations reported by members of the American Association of Individual Investors (AAII). We have time-series data on the mean allocation to stocks (direct holdings and

[26] One may also consider using monetary policy shocks as instruments. In our sample period, monetary policy shocks by Romer and Romer (2004) and Gertler and Karadi (2015) are strong instruments for interest rate changes at the monthly frequency (our data on household investment allocations are at monthly or quarterly frequencies). We find results with slightly larger coefficients but less power using the Romer and Romer (2004) and Gertler and Karadi (2015) shocks, shown in Internet Appendix Table A12. A caveat is, to the extent that monetary policy shocks may affect stock market conditions, they are not perfect instruments unless we can find precise measures of expectations of stock returns and risks. In addition, it also could be difficult to rule out that monetary policy shocks may affect investors' risk tolerance for other reasons (e.g., by influencing economic conditions).

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

We use the 3-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 12-month excess stock returns (estimated using past 12-month stock returns and surplus consumption).[27] In addition, we control for proxies of subjective expectations using investor sentiment measured in the AAII survey, like in Greenwood and Shleifer (2014). Finally, we control for VIX^2 (the square of VIX, which measures expected variance of the S&P 500 index), and commonly used proxies for general economic conditions: past year real GDP growth, and the credit spread (Gilchrist and Zakrajšek 2012). We lag all the right-hand side variables by one period, as opposed to using contemporaneous ones, since allocation decisions may affect contemporaneous asset prices (so using contemporaneous controls could be problematic).

Internet Appendix Section 4 provides a summary of variable definitions and data sources. Table 6 presents summary statistics of the main variables used in this section.

Results Table 7 presents results using portfolio allocations data from AAII. We find that lower interest rates are associated with higher allocations to stocks and lower allocations to "cash." A 1-percentage-point decrease in interest rates is associated with a roughly 1.4- to 2-percentage-point increase in allocations to stocks and a similar size fall in allocations to "cash." In our benchmark experiments, the treatment is a 4-percentage-point difference in the level of interest rates, which is associated with a roughly 8-percentage-point 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

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

Table 6
Summary statistics of observational data

	Mean	SD	25%	50%	75%	Start	End	*N*
Portfolio share data from AAII								
% in stocks	60.18	8.35	53.27	61.25	66.91	1987M11	2014M12	326M
% in "cash" (AAII)	23.96	6.32	19.00	22.69	28.00	1987M11	2014M12	326M
Mutual fund flow data from ICI								
Equity Fund Flows/NAV (%)	.39	.77	−.12	.28	.90	1985M1	2014M12	360M
HY CB Fund Flows/NAV (%)	.65	1.90	−.58	.75	1.77	1985M1	2014M12	360M
Household investment flows data from FoF								
Flows into stocks/HH fin. ast. (%)	−.19	.82	−.72	−.22	.27	1985Q1	2014Q4	120Q
Flows into deposits/HH fin. ast. (%)	.71	.87	.15	.75	1.36	1985Q1	2014Q4	120Q
Interest rates								
3-month Treasury rate	3.66	2.53	1.13	4.31	5.53	1985M1	2014M12	360M
Controls								
Stock market sentiment (AAII)	8.57	15.30	−1.81	9.36	18.75	1987M8	2014M12	329M
P/E10	23.44	7.54	18.31	22.41	26.46	1985M1	2014M12	360M
$Surp$	.113	.098	.081	.157	.185	1985M1	2014M12	360M
VIX^2	.049	.051	.023	.035	.056	1986M1	2014M12	348M
Past 4Q GDP growth	2.70	1.68	1.80	3.02	3.96	1985Q1	2014Q4	360M
Credit spread	2.31	.74	1.73	2.17	2.75	1985M1	2014M12	360M

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

the observational data. In Internet Appendix Table A11, we present regressions using changes in allocations and changes in interest rates, which show similar results. We also find that results are weaker using real interest rates, suggesting nominal interest rates may play a more important role.

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

We also use standard structural VAR (sVAR) to study the impulse response of investment decisions to innovations in interest rates, presented in Internet Appendix Figure A5 and Figure A6. The sVAR analysis yields the same results. The impulse response suggests persistent impact in the medium run.

[28] In the past two decades, stock market participation rate secularly declined, 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.

Table 7
Interest rates and AAII portfolio allocations

A. Interest rates and mean allocations to stocks

	Mean allocations to stocks			
	(1)	(2)	(3)	(4)
L.r_f	−.38	−1.47	−1.92	−2.00
	[−.51]	[−4.49]	[−2.46]	[−2.57]
L.P/E10		.84		
		[9.16]		
L.$Surp$			6.79	
			[.40]	
L.$E[rx^{12}_{stk}]$				−.12
				[−.60]
L.AAII sentiment		.04	.17	.16
		[1.66]	[4.01]	[3.67]
L.VIX^2		−6.34	−14.45	−5.73
		[−.78]	[−.96]	[−.27]
L.past 12M GDP growth		.34	2.11	2.17
		[.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

B. Interest rates and mean allocations to "cash"

	Mean allocations to "cash"			
	(1)	(2)	(3)	(4)
L.r_f	.62	1.51	1.19	1.28
	[1.21]	[3.85]	[2.26]	[1.99]
L.P/E10		−.47		
		[−4.22]		
L.$Surp$			20.56	
			[1.78]	
L.$E[rx^{12}_{stk}]$				−.21
				[−1.27]
L.AAII sentiment		−.02	−.13	−.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		−.01	−1.33	−1.10
		[−.01]	[−2.45]	[−1.63]
L.credit spread		3.83	2.82	1.69
		[3.56]	[2.11]	[.86]
Constant	21.85	21.32	15.14	19.50
	[9.99]	[4.97]	[3.69]	[3.02]
Observations	326	326	326	326

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. Newey-West t-statistics are in brackets, using the automatic bandwidth selection procedure of Newey and West (1994).

Table 8
Interest rates and household investment flows

A. Equity mutual fund flows (ICI)				
L.D.r_f	−.42	−.42	−.40	−.44
	[−2.51]	[−2.50]	[−2.39]	[−2.13]
Controls	No	Yes	Yes	Yes
Observations	360	328	328	328
B. High-yield corp. bond mutual fund flows (ICI)				
L.D.r_f	−1.01	−.78	−.78	−1.17
	[−2.42]	[−1.69]	[−1.70]	[−2.65]
Controls	No	Yes	Yes	Yes
Observations	360	360	360	360
C. Household flows into stocks (FoF)				
L.D.r_f	−.37	−.47	−.40	−.74
	[−2.63]	[−2.89]	[−2.39]	[−3.51]
Controls	No	Yes	Yes	Yes
Observations	120	109	109	109
D. Household flows into deposits (FoF)				
L.D.r_f	.41	.40	.38	.34
	[3.11]	[2.51]	[2.41]	[1.60]
Controls	No	Yes	Yes	Yes
Observations	120	109	109	109

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, that is, F is flows as a percentage of net asset value) using data from ICI; X includes controls in Table 7. In panel B, F is monthly flows into high-yield corporate bond mutual funds (normalized by net asset value of high-yield corporate bond mutual funds) using data from ICI; X includes past 12-month excess returns of high-yield corporate bonds in Column 2, past 12-month excess returns and high-yield corporate default rates in Column 3, and predicted next 12-month high-yield corporate bond excess returns (estimated using 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 7 (measured at the end of the previous quarter). In panel D, F is quarterly household sector flows into interest-bearing safe assets (time and saving deposits, money market mutual funds, commercial papers, normalized by household financial assets, that is, F is flows as a percentage of household financial wealth) using data from Flow of Funds; X includes controls in Table 7 (measured at the end of the previous quarter). All regressions include four lags of F. Outcome variables are from the beginning of 1985 to the end of 2014, but AAII sentiment is only available starting August 1987. Newey-West t-statistics in brackets, using the automatic bandwidth selection procedure of Newey and West (1994).

Who takes the other side of households' investment flows? In Internet Appendix Table A13, we use data from the Flow of Funds to study net flows into equities by households and other sectors, as well as net equity issuance by firms (net inflows are equal to net issuance by accounting identity). Table A13 shows that following a fall in interest rates, the financial sector tends to have higher inflows to equities, although the increase is not statistically significant. The inflows from U.S. households and institutions are partly accommodated by investors in the rest of the world, who reduce their holdings of U.S. equities. The main player on the other side of the inflows appears to be U.S. corporate issuers, whose net equity issuance increases. We also examine changes in asset prices

to verify that the flows are driven by higher demand for equities (as opposed to higher supply). Internet Appendix Figure A7 plots the response of *excess* stock returns to interest rate movements. Lower interest rates are associated with higher excess stock returns in the first few months (i.e., positive price impact due to inflows), followed by lower excess returns in the long term, consistent with findings by Bernanke and Kuttner (2005) and Bianchi, Lettau, and Ludvigson (2017).

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

5. Conclusion

In this paper, we document intrinsic reaching for yield behavior at the individual level and analyze its drivers. Using simple randomized experiments of investment decision making, we show that allocations to the risky asset are significantly higher when interest rates are low, holding fixed the excess returns of the risky asset. We find consistent results in different settings, and in diverse subject pools including MTurk workers and HBS MBAs. We propose two categories of explanations, reference dependence and salience, and provide evidence that both contribute to the reaching for yield behavior. Despite challenges and caveats, we find complementary evidence in observational data that risk-taking in household investment decisions increases as interest rates fall.

Since the Great Recession, central banks in many countries adopted extraordinary monetary policies. A large volume of research studies how these policies affect borrowers (Di Maggio et al. 2017; Auclert 2016; Greenwald 2018; Wong 2018; Beraja et al. 2017). Less focus has been given to savers. Our findings, along with other recent research (Hartzmark and Solomon 2017), suggest it is also important to understand savers' behavior. Savers' reaching for yield behavior can also influence financial institutions' actions: institutions may invest in riskier assets to cater to clients' demand or may design securities that highlight returns and shroud risks to further exploit these preferences (Célérier and Vallée 2017).

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

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