Empirical Analyses in Finance and Macroeconomics

Empirical Analyses in Finance and Macroeconomics

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Empirical Analyses in Finance and Macroeconomics

Abstract

This thesis has three essays which are empirical studies at the intersection of finance and macroeconomics. The topics include low interest rates and financial markets, debt contracts and corporate borrowing constraints, and expectations in finance and macro. The essays hope to provide empirical evidence, using diverse approaches, to better understand the connections as well as differences between classic theories and economic activities in practice.

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To my parents

Introduction

This thesis has three essays which are empirical studies at the intersection of finance and macroeconomics. The topics include low interest rates and financial markets, debt contracts and corporate borrowing constraints, and expectations in finance and macro. The essays hope to provide empirical evidence, using diverse approaches, to better understand the connections as well as differences between classic theories and economic activities in practice.

The first essay is “Low Interest Rates and Risk Taking: Evidence from Individual Investment Decisions," joint with Chen Lian and Carmen Wang. In this research, we demonstrate that individuals “reach for yield," that is, have a greater appetite for risk taking when interest rates are low. Using randomized investment experiments holding fixed risk premia and risks, we show low interest rates lead to significantly higher allocations to risky assets, among MTurk subjects and HBS MBAs. This effect also displays non-linearity, and becomes increasingly pronounced as interest rates decrease below historical norms. The behavior is not easily explained by conventional portfolio choice theory or institutional frictions. We then propose and provide evidence for mechanisms related to investor psychology, including reference dependence and salience. We also present results using observational data on household investment decisions.

The second essay is “Anatomy of Corporate Borrowing Constraints," joint with Chen Lian. A common perspective in macro-finance analyses links firms’ borrowing constraints to the liquidation value of physical assets firms pledge as collateral. We empirically investigate borrowing by non-financial firms in the US. We find that 20% of corporate debt by value is collateralized by specific physical assets (“asset-based lending" in creditor parlance), while 80% is based predominantly on cash flows from firms' operations ("cash flow-based lending"). In this setting, a standard form of borrowing constraint restricts a firm's total debt as a function of cash flows measured using operating earnings ("earnings-based borrowing constraints," or EBCs). The features of corporate borrowing illuminate how financial variables affect firms' borrowing constraints and outcomes on the margin. First, with cash flow-based lending, cash flows in the form of operating earnings directly relax EBCs, and enable firms to both borrow and invest more. Second, as corporate borrowing overall does not rely heavily on physical assets such as real estate, firms could be less vulnerable to collateral damage from asset price shocks, and fire sale amplifications may be mitigated. In the Great Recession, for example, property value declines did not trigger a deleveraging cycle among major US non-financial firms due to collateral damage. Finally, results in the US contrast with those in Japan, where corporate borrowing historically emphasizes physical assets.

The third essay is "New Experimental Evidence on Expectations Formation," joint with Augustin Landier and David Thesmar. In this research, we utilize simple experiments to isolate key patterns in expectations formation. In the experiment, participants make forecasts of stable and basic AR(1) processes. We find strong rejections of rational expectations. Both over-reaction to news and anchoring around past beliefs are present in the data, and the former quantitatively dominates. The findings are consistent across different experimental settings, process parameters, and individual characteristics. Large and systematic deviations from rationality occur even though the forecasting exercise is simple and transparent.

Chapter 1

Low Interest Rates and Risk Taking: Evidence from Individual Investment Decisions[1]

1.1 Introduction

Since the global financial crisis, central banks in major developed countries have set benchmark interest rates to historic lows. A widely discussed question is whether such low interest rates increase investors' appetite for risk taking, a phenomenon often referred to as "reaching for yield."[2] 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;

[1] Joint with Chen Lian and Carmen Wang

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

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 et al., 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 et al., 2017).

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

Specifically, we show that individuals demonstrate a stronger preference for risky assets when the risk-free rate is low. We first document this phenomenon in a simple randomized experiment. In Treatment Group 1, participants consider investing between a risk-free asset with 5% returns and a risky asset with 10% average returns (the risky payoffs are approximately normally distributed with 18% volatility). In Treatment Group 2, participants consider investing between a risk-free asset with 1% returns and a risky asset with 6% average returns (the risky payoffs are again approximately normally distributed with 18% volatility). In other words, across the two treatment conditions, we keep the risk premium (i.e. average excess returns) and the risks of the risky asset fixed, and only make a downward shift in the risk-free interest rate. Participants are randomly assigned to one of the two conditions. The investment decision in each condition represents the simplest mean-variance analysis problem, where the solution should not be affected by the risk-free rate based on the textbook mean-variance benchmark (Markowitz, 1952; Sharpe, 1964).

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

We conjecture two categories of mechanisms that may contribute to reaching for yield in individual investment decisions. The first category captures the observation that people may form reference points of investment returns. When interest rates fall below the reference level, people experience discomfort, and become more willing to invest in risky assets to seek higher returns. The reference point can be shaped by what people have become used to over past experiences. The observation connects to the popular view among investors that 1% interest rates are "too low," compared to what they are accustomed to. This intuition can be formalized in the framework of reference dependence (Kahneman and Tversky, 1979), where the reference point may be history-dependent (Kahneman and Miller, 1986; Bordalo et al., 2017b; 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 et al., 2013b). It also connects to the well documented phenomenon, often referred to as Weber's law, that people tend to evaluate stimuli by proportions (i.e. 6/1 is much larger than 10/5) rather than by differences.

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

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

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

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

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

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

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

Third, our paper relates to experimental studies on decision under risk and uncertainty. A number of experiments test elements that affect risk taking (Holt and Laury, 2002; Gneezy and Potters, 1997; Cohn et al., 2015; Kuhnen, 2015; Beshears et al., 2016). 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 study this question and provide new findings. In a contemporaneous experiment with hypothetical questions, Ganzach and Wohl (2017) also find increased risk taking when interest rates are low. We provide a large set of evidence across many different settings, isolate behavior that departs from standard benchmarks, and test the underlying mechanisms in detail.

The remainder of the paper is organized as follows. Section 1.2 presents results of the benchmark experiment. Section 1.3 discusses possible explanations for the reaching for yield behavior we observe, and Section 1.4 tests these mechanisms. Section 1.5 provides results using historical data on household investment decisions. Section 2.5 concludes.

1.2 Benchmark Experiment

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

1.2.1 Experiment Design and Sample Description

Our experiment takes the form of an online survey that participants complete using their own electronic devices (e.g. computers and tablets). The survey has two sections: Section 1 presents the investment decision, and Section 2 includes a set of demographic questions. Each experiment has 400 participants, who are randomly assigned to the two interest rate conditions. The survey forms are available in the Survey Appendix.

We conduct the benchmark experiment among two groups of participants. The first group consists of adults in the US from Amazon's Mechanical Turk (MTurk) platform. MTurk is an online platform for surveys and experiments, which is increasingly used in economic research (Kuziemko et al., 2015; Ambuehl et al., 2015; D'Acunto, 2015a; Cavallo et al., 2017; DellaVigna and Pope, 2017a,b). It allows access to a diverse group of participants from across the US, completes large-scale enrollment in a short amount of time, and provides response quality similar to that of lab experiments (Casler et al., 2013). These features are very helpful for our study. As we show later, our MTurk participants have similar demographics as the US general population, with fewer elderlies and a higher level of education. Figure 1.1 shows the geographic location of participants in the benchmark experiments, which is representative of the US population. Our experiments on MTurk provide relatively high payments compared to the MTurk average to ensure quality response.

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

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

Experiment B1: MTurk, Hypothetical

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

Table 1.1 Panel A shows the summary statistics of participant demographics in Experiment B1. Roughly half of the participants are male. About 75% of participants report they have college or graduate degrees; the level of education is higher than the US general population (Ryan and Bauman, 2015a). 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.[3] In the demographic section, we also ask participants' subjective evaluation of risk tolerance, and the majority select they are "somewhat risk averse but willing to hold some risky assets." About 60% of participants have financial wealth (excluding housing) above $10,000; roughly 10% to 15% of participants are in debt, while 5% to 10% have financial wealth more than $200,000. The wealth distribution is largely in line with the US population (the 2016 Survey of Consumer Finances shows median household financial assets of $23,500). Most participants have some amount of

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

investment experience; 56.5% own stocks, slightly higher than the stock ownership rate of 51.9% from the 2016 Survey of Consumer Finances.

In the final three columns of Table 1.1, we also check whether the random assignment balances participant characteristics across the two treatment conditions. For each characteristic (e.g. gender), we compute the difference in the share of participants in a given category across the two conditions (e.g. difference in the share of males), and the t-statistics associated with the difference. Because many characteristics have several categories (e.g. education has graduate school, college, high school), in the final column we also make an overall assessment by comparing the distribution across the two treatment conditions. We use the non-parametric and ordinal Mann-Whitney-Wilcoxon (rank-sum) test and report the p-value. In Experiment B1, most characteristics are fairly balanced, except that the high interest rate condition happens to have more men.

Experiment B2: MTurk, Incentivized

In Experiment B2, participants consider allocating an experimental endowment of 100,000 Francs between the risk-free asset and the risky asset. The investment horizon is one year. 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.[4] 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."[5] We verify that results

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

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

are unchanged whether the bonus payment is provided to all participants or a random subset of participants. Internet Appendix Table A.2 shows comparison experiments that test robustness to payment structure. Given the one year investment horizon, in our baseline specification the bonus payment is delivered a year after participation. In Table A.2, we also verify that behavior is not affected by the delayed bonus.

Table 1.1 Panel B shows the demographics in Experiment B2. Experiment B2 has slightly more male participants; participants are also slightly wealthier, and have a higher stock ownership rate (64% in Experiment B2, compared to 56.5% in Experiment B1). Overall the demographics are similar to those in Experiment B1. Participant characteristics across the two treatment conditions are fairly balanced in Experiment B2.

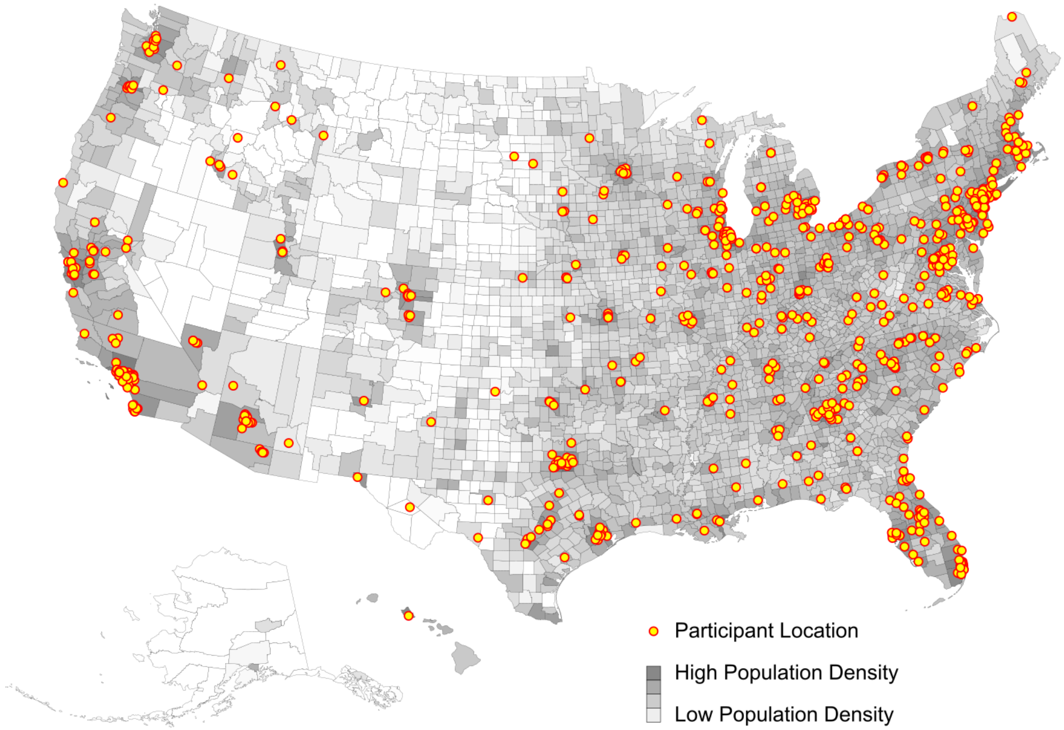
Experiment B3: HBS MBA, Incentivized

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

Table 1.1 Panel C shows that about 60% of participants are male, roughly 70% are from the US (and 30% are international students), and roughly 70% have primary educational background in social science or science and engineering. The MBA participants have a higher level of risk tolerance than MTurk participants, according to both lottery choice-based assessment and subjective assessment. More than 40% report having some or extensive investment experience. The vast majority, 80%, own stocks; a significant fraction, 40%, have worked in finance. Participant characteristics across the two treatment conditions are

their choices are implemented.

generally balanced in Experiment B3.



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

Figure 1.1: *Geographic Distribution of MTurk Participants*

Table 1.1: *Demographics of Benchmark Experiment Samples*

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

Panel A. Experiment B1: MTurk, Hypothetical

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

Table 1.1 (Continued)

Panel B. Experiment B2: MTurk, Incentivized

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

Panel C. Experiment B3: HBS MBA, Incentivized

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

1.2.2 Results

Table 1.2 reports results of the benchmark experiment. The first four columns in Panel A show mean allocations to the risky asset in the high and low interest rate conditions, the difference between the two conditions, and the *t*-stat that the difference is significantly different from zero. We find that the mean allocation to the risky asset is about 7 to 9 percentage points higher in the low interest rate condition. Specifically, the mean allocation to the risky asset increases from 48.15% in the high rate condition to 55.32% in the low rate condition in Experiment B1 (difference is 7.17%), from 58.58% to 66.64% in Experiment B2 (difference is 8.06%), and from 66.79% to 75.61% in Experiment B3 (difference is 8.83%). It is natural that the general level of risk tolerance can vary across these experiments depending on the subject pool and the setting (e.g. HBS MBAs are more risk tolerant than MTurk participants; MTurk participants are more risk tolerant investing experimental endowments than investing a significant amount of savings), so the *level* of mean allocations is different in Experiments B1 to B3. However, these differences in risk tolerance do not seem to affect the pattern of reaching for yield (i.e. the treatment effect).

Panel A columns (5) to (9) report additional tests. Column (5) shows *p*-values from non-parametric Mann-Whitney-Wilcoxon tests (all significant at the 5% level). The remaining columns report mean differences in allocations controlling for individual characteristics, through OLS regressions as well as propensity score matching (estimates of average treatment effects are reported). The covariates include gender, education, age, risk tolerance, wealth, investment experience in the MTurk samples; and gender, risk tolerance, investment experience, and work experience in finance in the HBS MBA sample. The treatment effect is very similar with controls.[6] Figure 1.2 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

[6]To check for robustness to extreme observations, in addition to the non-parametric test in Panel A column (5), we also run least absolute deviation regressions with controls (same specification as Panel A column (6) and Equation (1.1)). The coefficient on the low interest rate condition in Experiments B1, B2, B3 is 6.56, 12.70, 10.00 ($t-$stat 1.74, 3.80, 3.17) respectively. The results are similar to those with OLS.

high rate condition.

Table 1.2 Panel B presents the regression results for each sample, with coefficients on control variables:

$$Y_i = \alpha + \beta Low_i + X_i' \gamma + \epsilon_i \tag{1.1}$$

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

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

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

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

Our results on reaching for yield are consistent in different settings and subject pools. Some previous studies find the influence of psychological forces and certain biases may diminish with education and experience (List and Haigh, 2005; Cipriani and Guarino, 2009; Kuchler and Zafar, 2017), while others do not find such an effect or find the opposite (Haigh and List, 2005; Abbink and Rockenbach, 2006; Cohn et al., 2015). In our data, HBS MBAs and MTurks reach for yield by a similar degree. Nor do we find that reaching for yield declines with wealth, investment experience, or education among MTurks, or with investment and work experience in finance among MBAs, as shown in Internet Appendix Table A.1. Among the HBS MBAs who have worked in finance (42% of the sample), for example, the difference in mean allocations to the risky asset between the high and low interest rate conditions is 10 percentage points (t-stat 2.47).

Stake Size in Incentivized Experiments

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

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consumption and savings to interest rates (Mankiw et al., 1985; Hall, 1988; Campbell and Mankiw, 1989). In Section 1.5, we also present suggestive evidence that lower interest rates appear to be associated with both higher portfolio shares and higher dollar amounts invested in risky assets.

Table 1.2: *Low Interest Rates and Risk Taking: Benchmark Experiment Results*

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

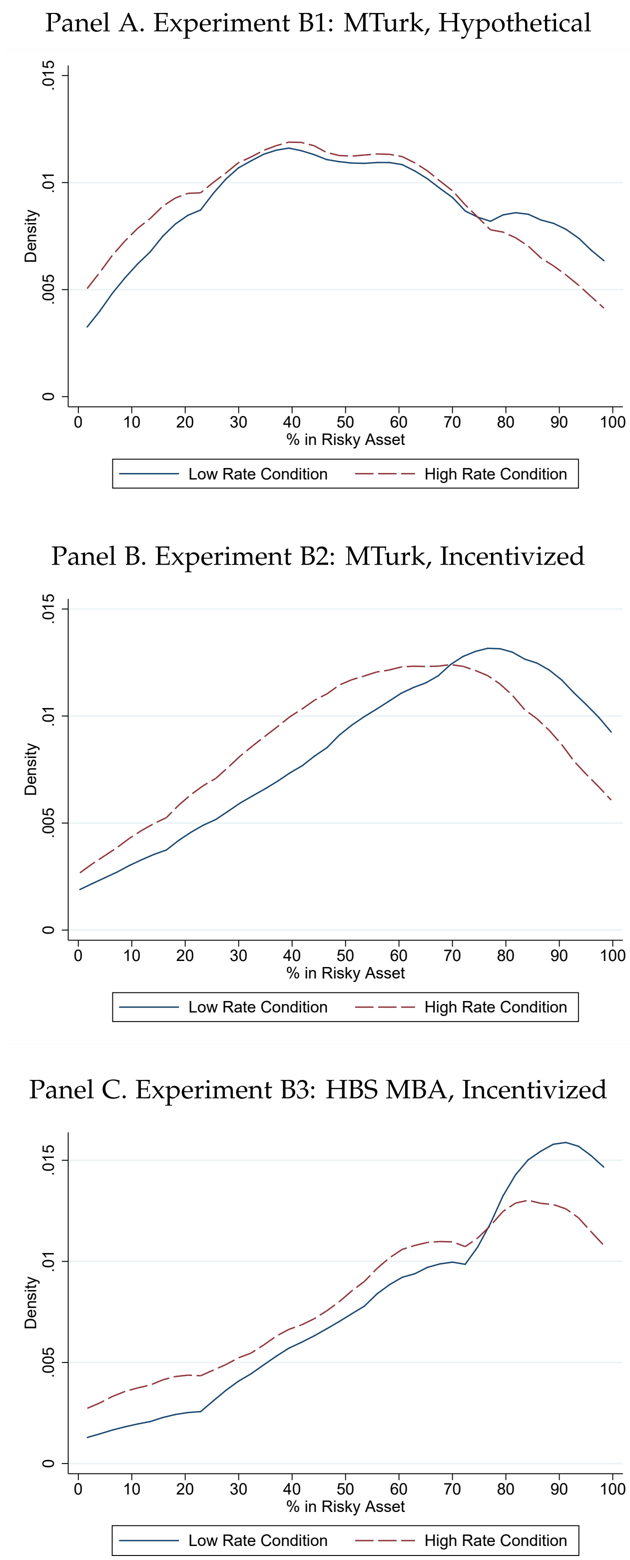
Panel A. Allocations to Risky Asset (%)

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

Panel B. Regressions with Individual Characteristics

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

Robust t-statistics in brackets



Note: 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.

Figure 1.2: *Distribution of Allocations to the Risky Asset in Benchmark Experiments*

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 et al., 2013; Bossaerts et al., 2007; Cohn et al., 2015), and we use stake size in line with prior work. We also find that participants' risk tolerance in the incentivized experiments is significantly correlated with allocations of their household financial wealth, as shown in Internet Appendix Table A.3.

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.

1.3 Potential Mechanisms

In this section, we discuss potential explanations of our findings in Section 1.2. We first show that conventional portfolio choice theories may not easily explain the reaching for yield behavior we document. We then suggest two categories of possible explanations, reference dependence and salience, which we test in Section 1.4.

1.3.1 Conventional Portfolio Choice Theory

The investment decision in our benchmark experiment corresponds to a standard static portfolio choice problem with one risk-free asset and one risky asset. An investor considers allocating wealth w between a safe asset with returns r_f, and a risky asset with returns

$r_f + x$, where x is the excess returns with mean $\mu = \mathbb{E}x > 0$. Let ϕ denote the proportion of wealth allocated to the risky asset, and $1 + r_p = 1 + r_f + \phi x$ the portfolio returns. The investor chooses optimal $\phi^* \in [0, 1]$ to maximize expected utility:

$$\phi^* = \arg\max_{\phi \in [0,1]} \mathbb{E}u\left(w\left(1 + r_p\right)\right) \tag{1.2}$$

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

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

$$\phi^*_{mv} \triangleq \arg\max_{\phi \in [0,1]} \ \mathbb{E}r_p - \frac{\gamma}{2} Var\left(r_p\right) = \min\left(\frac{\mathbb{E}x}{\gamma Var\left(x\right)}, 1\right), \tag{1.3}$$

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.[9]

General Case. The optimal mean-variance portfolio allocation ϕ^*_{mv} in Equation (1.3) is a second-order approximation to the optimal allocation to the risky asset ϕ^* defined in Equation (1.2). 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*

[9] For our incentivized experiments, would wealth outside the experiment affect predictions of the conventional portfolio choice analysis? We make three observations. First, if the investor's outside wealth w_o has a non-stochastic return r_o, we can just redefine the utility function $\tilde{u}\left(w\left(1 + r_p\right)\right) = u\left(w_o\left(1 + r_o\right) + w\left(1 + r_p\right)\right)$ 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 (1.2)) still should not change with respect to the interest rate. Finally, as Barberis et al. (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.

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.[10]

The intuition for this result is that, for a given distribution of x, when r_f increases the investor effectively becomes wealthier. If absolute risk aversion is decreasing in wealth, the investor would be less risk averse and more willing to invest in the risky asset. In other words, the investor would "reach against yield," which is the opposite of what we document in Section 1.2. This wealth effect, however, is not first order and it drops out in the mean-variance approximation.[11]

Proposition 1 assumes weakly decreasing absolute risk aversion, a property shared by commonly used utility functions (e.g. CRRA). The prediction of Proposition 1 would be reversed if investors instead have increasing absolute risk aversion. Is this a possible explanation for the reaching for yield phenomenon we document? In studies of choice under uncertainty, increasing relative risk aversion is sometimes observed, but (weakly) decreasing absolute risk aversion appears to be a consensus (Holt and Laury, 2002). Moreover, increasing absolute risk aversion is hard to square with additional experimental results we present in Section 1.4 to test mechanisms.

In the above we follow the experiment in Section 1.2 and study a static portfolio choice problem in (1.2). The static design helps us cleanly tease out the behavioral mechanisms that may generate reaching for yield behavior. In Internet Appendix A.2.1, we discuss the impact of interest rates on portfolio allocations more generally, such as in dynamic portfolio choice problems with hedging or life-cycle motives. These explanations do not seem to explain the experimental results.

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[10]In Section 1.3, we focus on the partial derivative of investment allocations with respect to the risk-free rate, holding inflation and inflation expectations constant, as in our randomized experiment. We discuss other issues related to inflation outside of the experiment in Internet Appendix A.2.7.

[11]Why do we only need decreasing *absolute* risk aversion, instead of decreasing *relative* risk aversion, for ϕ^* to be increasing in r_f? Note that the investor's final wealth is given by $w\left(1 + r_f + \phi x\right)$. 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).

1.3.2 Reference Dependence

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

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

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

We use the same set-up as in (1.2), but now we assume the utility function u features loss aversion captured by a kink around the reference point:

Assumption 1.

$$u\left(w\left(1+r_p\right)\right)=\begin{cases} w\left(r_p-r_r\right) & r_p \geq r_r \\ -\lambda w\left(r_r-r_p\right) & r_p < r_r \end{cases} \tag{1.4}$$

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

Here we only include the reference point component, without additional features of the Prospect Theory such as diminishing sensitivity and probability reweighting, as the gist of our observation relates to the reference point and loss aversion around the reference point. We discuss the case with diminishing sensitivity in Internet Appendix A.2.2.[12] Probability

[12] As Internet Appendix A.2.2 explains in detail, the theoretical prediction of whether diminishing sensitivity contributes to reaching for yield is ambiguous We then evaluate the results numerically based on standard

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 A.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 asset. This result suggests a potential explanation for the findings in Section 1.2 that participants in the low interest rate condition invest more in the risky asset.

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

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

Prospect Theory parameter values (Tversky and Kahneman, 1992). We find it seems hard for diminishing sensitivity *alone* to account for the evidence in Section 1.2 without the loss aversion component. Some recent research also questions diminishing sensitivity, especially the convexity of the utility function in the loss domain, in the investment context (Bracha, 2016).

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

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

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

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

Reference Point Formation

A natural question is where investors' reference points come from. In the following, we discuss the leading theories of reference points, and explain why people's past experiences may be the main contributor to the type of reference dependence that generates reaching for yield. We provide proofs and more discussions in Internet Appendix Section A.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 non-negative, it would be higher than the status quo $r_f \geq r_r = 0$. This falls into the second case of Proposition 2, and does not explain the reaching for yield behavior in our benchmark experiment.[13]

Later work introduces reference points that are equal to the risk-free rate (Barberis et al., 2001), as well as reference points that are rational expectations of outcomes in people's choice set (Kőszegi and Rabin, 2006; Pagel, 2017). In both cases, when the risk-free rate changes while excess returns are held fixed, returns on the safe asset, returns on the risky asset, and the reference point move in parallel. Accordingly, the trade-offs in the investment decision remain unchanged, and allocations should not be different across the treatment conditions in our benchmark experiment.[14]

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

[14]For expectations-based reference points, this result applies when the reference point is entirely determined

Another form of reference point that can be important in our setting highlights the impact of past experiences (Simonsohn and Loewenstein, 2006; Bordalo et al., 2017b; 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.[15] 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."[16]

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.

1.3.3 Salience and Proportional Thinking

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

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

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

[16]In the incentivized experiments, if participants mingle the experimental returns with other returns and monetary payoffs in their lives, one question is whether they compare the experimental returns or the sum of all monetary payoffs with respect to their reference points. As Barberis et al. (2006) highlight, narrow framing—the tendency to consider an investment problem in isolation as opposed to mingling it with other risks (e.g. labor income risks, other investments)—appears to be a robust element of investor behavior. To the extent that participants are inclined to frame narrowly and evaluate the investment problem on its own, we can directly apply the predictions of the reference dependence mechanisms studied in this section. The same holds for the salience and proportional thinking mechanism in Section 1.3.3.

This intuition can be formalized by a version of the Salience Theory of Bordalo et al. (2013b). It also connects to the well documented phenomenon that people tend to evaluate stimuli by proportions (i.e. 6/1 is much larger than 10/5) rather than by differences (Weber's law; Tversky and Kahneman (1981); Kőszegi and Szeidl (2013); Cunningham (2013); Bushong et al. (2016)).

Equation (1.5) outlines a representation of this idea, which uses a variant of the mean-variance analysis in Equation (1.3). 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:

$$\phi_s^* \triangleq \arg\max_{\phi \in [0,1]} \; \delta \mathbb{E} r_p - \frac{\gamma}{2} Var\left(r_p\right), \tag{1.5}$$

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 (1.5) embeds the idea that investors' perception of the risky asset's compensation for risk is not exactly the *difference* between the average returns on the risky asset and the risk-free rate (as in the conventional mean-variance analysis). Instead, it is also affected by the *proportion* of the average returns of the two assets. When the proportion is large, investors perceive compensation for risk taking to be better, and behave as if the return dimension in Equation (1.5) gets a higher weight.

In the language of the Salience Theory of Bordalo et al. (2013b), δ captures the salience of the expected return dimension relative to the risk dimension. When the proportion of the average returns of the two assets is larger, the expected return dimension becomes more salient, and gets a higher weight in portfolio decisions.[17] We adopt a specification of δ following Bordalo et al. (2013b).

Assumption 2. *We require the risk-free rate $r_f > 0$ throughout this subsection. Following Bordalo*

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

et al. (2013b), define

$$\delta(r_f + \mathbb{E}x, r_f, Var\left(x\right), 0) = f\left(\left|\frac{(r_f + \mathbb{E}x) - r_f}{(r_f + \mathbb{E}x) + r_f}\right| - \left|\frac{Var\left(x\right) - 0}{Var\left(x\right) + 0}\right|\right), \tag{1.6}$$

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

This definition is a generalization of the formulation in Bordalo et al. (2013b) and Bordalo et al. (2016).[18] δ is increasing in the ratio of the average returns between the two assets (through the first term in the parenthesis), and decreasing in the ratio of their variance (through the second term in the parenthesis). Our focus here is how changes in the average returns of the assets affect investment decisions; we hold fixed the risk properties (the second term in the parenthesis is always one).

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

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

1.4 Testing Mechanisms

In this section, we perform three additional experiments to test explanations for the reaching for yield behavior discussed in Section 1.3. We find evidence supportive of both reference dependence and salience.

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[18]In the original set-up, either the risk dimension is more salient or the return dimension is more salient, and the more salient dimension receives a fixed weight. When there is a risk-free asset, the risk dimension is always more salient, by a fixed amount. Accordingly, returns of the risk-free asset do not change the salience of the return dimension relative to the risk dimension. We generalize Bordalo et al. (2013b) to a continuous salience function that allows salience to move even when there is a risk-free asset. Our formulation nests the original salience function as a special case $f\left(t\right) = \begin{cases} \beta & t > 0 \\ \frac{1}{\beta} & t < 0 \end{cases}$, where $\beta > 1$. In addition, the decision problem in Bordalo et al. (2013b) and Bordalo et al. (2016) is a discrete choice problem. We generalize it to continuous decisions. See Internet Appendix Section A.2.6 for more discussions.

1.4.1 Experiment T1 (Non-Linearity)

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

Through this experiment, we would like to examine two main questions. The first is whether reaching for yield exhibits non-linearity, and is most pronounced when interest rates are low. Both reference dependence and salience/proportional thinking predict such non-linearity. In the model of reference point and loss aversion in Section 1.3.2, reaching for yield occurs when interest rates are below the reference point. In the model of salience/proportional thinking in Section 1.3.3, allocations to the risky asset would be more sensitive to interest rates when interest rates are low, where the ratio of the average returns $(r_f + \mathbb{E}x)/r_f$ changes more with the risk-free rate. On the other hand, conventional portfolio choice theory with increasing absolute risk aversion, for instance, does not predict strong non-linearity. The second question is whether we observe "reaching against yield" (i.e. allocations to the risky asset increasing in the risk-free rate) when interest rates are sufficiently high, as predicted by the traditional Prospect Theory formulation in Proposition 2.

We conduct Experiment T1 in June 2016. Participants are recruited on MTurk. As in the benchmark experiments, each interest rate condition has 200 participants. Similar to Experiment B2 (Benchmark Incentivized, MTurk), participants consider allocating experimental endowment of 100,000 Francs to the risk-free asset and the risky asset. The payment structure follows Experiment B2. The participation payment is $0.7. Participants may also receive a bonus payment proportional to their investment outcomes, with every 8,950 Francs converted to one dollar (so the bonus payment is on the scale of $12). We implement the decision of 10% randomly chosen participants and they receive the bonus payment. Table A.6 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.[19]

Table 1.3 presents the results of Experiment T1. The mean allocation to the risky asset is 78% when the risk-free rate is -1%, 70% when the risk-free rate is 0%, 65% when the risk-free rate is 1%, and 58% when the risk-free rate is 3%. As interest rates rise further, allocations change more slowly. The mean allocation to the risky asset is 57% when the risk-free rate is 5%, which is roughly the same as when the risk-free rate is 3%. It declines to 50% when the risk-free rate is 10%, and stays about the same when the risk-free rate is 15%. Mean allocations across different interest rate conditions are also plotted in Figure 1.3.

Table 1.3: *Allocations in Various Interest Rate Conditions*

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

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

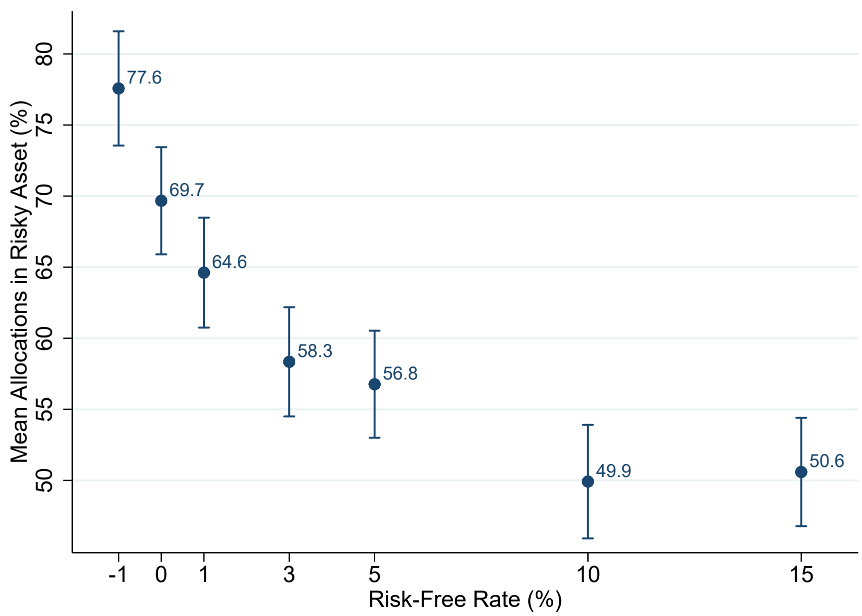
Risk-Free Rate	5%	10%	15%
Mean Returns of Risky Asset	10%	15%	20%
Mean Allocations to Risky Asset (%)	56.77	49.92	50.59
95% CI	(52.98, 60.55)	(45.90, 53.93)	(46.76, 54.43)

Results in Experiment T1 suggest notable non-linearity in how investment decisions respond to interest rates. Reaching for yield is particularly pronounced when interest rates are low, roughly below 3%. Statistical tests can reject linearity with high significance.[20] The

[19]For incentivized experiments in Section 1.4, participants receive their bonus payments shortly after participation. Delaying the bonus by one year requires us to collect MTurk participants' contact information, in case they no longer work on MTurk in one year's time. In Section 1.2 and Internet Appendix Table A.2, we have tested that the results are robust to payment timing. Therefore, in the additional experiments we pay the bonus within one week to simplify the logistics.

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

shape of the non-linear response is in line with reasonable reference points based on the average level of interest rates and investment returns most participants were used to prior to the Great Recession. The pattern is also generally consistent with salience/proportional thinking, as the ratio of the average returns $(r_f + \mathbb{E}x)/r_f$ becomes significantly less sensitive to r_f when r_f is high. On the other hand, conventional portfolio choice theory with increasing absolute risk aversion does not easily square with the strong non-linearity.



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

Figure 1.3: *Mean Allocations Across Interest Rate Conditions*

In addition, while we see clear patterns of reaching for yield when interest rates get into the low range, we do not observe reaching against yield when interest rates approach the high end. In Section 1.3 Proposition 2, we show the baseline Prospect Theory formulation does predict reaching against yield when the risk-free rate is higher than the reference point. One possibility is that reaching against yield is modest in magnitude, and our sample size of 200 per condition does not have enough power to detect it; this effect could be further dampened by salience/proportional thinking. Another possibility is that the reaching against yield prediction is not very robust, and is specific to the functional form in the traditional Prospect Theory formulation. For example, an alternative formulation of reference dependence is that people experience discomfort/loss aversion when the average return of the portfolio is below the reference point (as opposed to experiencing loss aversion for each state where the realized return is below the reference point, as in the traditional formulation in Section 1.3.2). This alternative formulation predicts reaching for yield when interest rates are low, but does not predict reaching against yield when interest rates are high. We present this alternative formulation in Internet Appendix A.2.3.[21]

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

1.4.2 Experiment T2 (History Dependence)

In Experiment T2, we examine how investment history and reference dependence affect investment decisions. Specifically, participants in this experiment make two rounds of investment decisions: half of the participants (Group 1) first make decisions in the high interest rate condition (5% safe returns and 10% average risky returns, same as the benchmark experiment), and then make decisions in the low interest rate condition (1% safe returns and 6% average risky returns); the other half of the participants (Group 2) 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

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

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 1.3.2 suggests, allocations to the risky asset in a low rate environment would increase when people have higher reference points. Accordingly, participants in Group 1 may invest more aggressively in the risky asset in the low interest rate condition.

We conduct two versions of Experiment T2. In the incentivized version, in each round participants consider allocating experimental endowment of 100,000 Francs to the safe asset and the risky asset (the outcomes of the risky asset in the two rounds are uncorrelated). Participants are recruited on MTurk in June 2016. They receive a participation payment of \$1.2. They may also receive a bonus payment proportional to their investment outcome in one randomly chosen round, with every 8,950 Francs converted to one dollar (so the bonus payment is on the sale of \$12). Investment outcomes for both rounds are displayed after the entire experiment is completed. Participants are then informed which round the bonus payment would depend on, and whether they are among the 10% randomly selected participants to receive the bonus payment. Making payments based on randomly chosen outcomes is standard in prior experimental work (e.g. Holt and Laury (2002); Frydman and Mormann (2016)).[22] To check the robustness of this result, we also report results from a hypothetical version. In the hypothetical version, in each round participants consider hypothetical questions about investing total savings of \$10,000 between the safe asset and the risky asset. Participants are recruited from MTurk in August 2015. They receive \$0.5 for participation. In both versions, there are 200 participants in Group 1 and 200 participants in Group 2. Internet Appendix Table A.7 shows the demographics in Experiment T2.

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

Table 1.4: *Path Dependence of Investment Decisions*

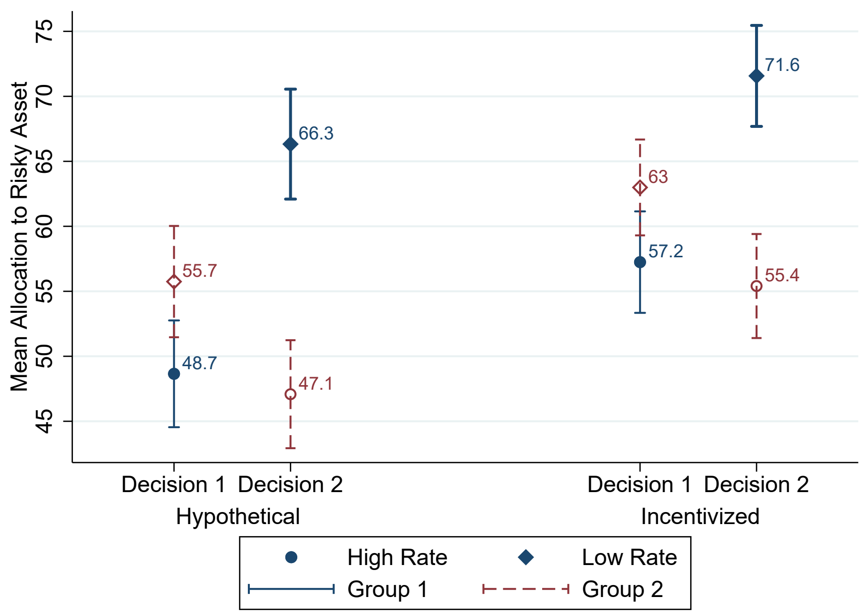
This table presents results of Experiment T2. Half of the participants are randomly assigned to Group 1, and they first make investment decisions in the high interest rate condition (5% risk-free rate and 10% average risky returns), and then make decisions in the low interest rate condition (1% risk-free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

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

(a) *Hypothetical*

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

(b) *Incentivized*



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

Figure 1.4: *Path Dependence of Investment Decisions*

Table 1.4 and Figure 1.4 present the results, which show several findings. First, there is reaching for yield both within group and across groups. Within each of Group 1 and Group 2, allocations to the risky asset are higher in the low rate condition than in the high rate condition. Across Group 1 and Group 2, when making the first decision, the group facing the low rate condition (Group 2) has significantly higher allocations to the risky asset. This is analogous to the benchmark experiment.

Second and importantly, participants in Group 1—who consider the high rate condition first—have particularly high allocations to the risky asset in the low rate condition. On average, they invest roughly 10 percentage points more in the low rate condition than participants in Group 2. These results are in line with predictions of reference dependence in Section 1.3.2 Corollary 1 and history-dependent reference points.[23]

Internet Appendix Section A.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 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

[23]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 1.4.1.

the previous economic environment. It could be more pronounced if the prior environment had relatively high interest rates. This observation connects to recent research that highlights the importance of past experiences in economic decision making (Malmendier and Nagel, 2011, 2016; Bordalo et al., 2017b).

History-dependent reference points could be affected by both short-term and long-term experiences.[24] 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 1.4.1, the non-linearity in Experiment T1 is in line with reference points from prior life experiences. Second, we also test whether heterogeneity in lifetime experiences, which may result in different reference points, can help explain differences in investment decisions. In our experiments, due to relative homogeneity in age, variations in lifetime experiences are limited (the interquartile difference is average experienced interest rates, for example, is about 1%). Moreover, given we only have one cross-section, we cannot separate experience effects from age effects. To shed further light on this issue, in Internet Appendix Section A.3.3 we use panel data from the Survey of Consumer Finances and apply the empirical strategy of Malmendier and Nagel (2011). We present suggestive evidence that, at each point in time, individuals who experienced higher interest rates over their lifetime appear less satisfied with safe assets and exhibit a higher propensity to invest in risky assets like stocks. While there are several caveats in the observational data (e.g. hard to fully control for potential differences in perceived risks and returns of risky assets), the overall pattern seems consistent with history-dependent reference points.

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

1.4.3 Experiment T3 (Salience and Proportional Thinking)

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

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

> **Investment A**: Investment A's return is **5%** for sure.
>
> For example, suppose you put 100 Francs into this investment, you will get 105 Francs. ...
>
> **Investment B**: Investment B has nine possible outcomes. Its average return is **10%**. The volatility of the investment returns is 18%. The nine possible outcomes are shown 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 1). 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.[25] Additionally, the test helps further differentiate our findings from conventional portfolio choice theory with increasing absolute risk aversion, which does not predict variations based on framing.

In Experiment T3, we randomly assign participants to different framing conditions and different return conditions (i.e. baseline high, baseline low, gross high, gross low), with 200 participants in each condition. Participants are recruited on MTurk in June 2015. Experiment T3 and Experiment T1 are run together; all procedures and payment structures are the same. Internet Appendix Table A.8 shows the demographics in Experiment T3.

Table 1.5 and Figure 1.5 present results of Experiment T3. With baseline framing, the mean allocation to the risky asset is 57.13% in the high interest rate condition, and 64.51% in the low interest rate condition. With gross framing, the mean allocation to the risky assets is 52.65% and 54.44% in the high and low interest rate conditions respectively. Allocations to the risky asset are lower with gross framing than with baseline framing, especially in the low rate condition. The mean allocation in the risky asset decreases by 4.47% from baseline framing to gross framing in the high interest rate condition, and by 10.06% in the low

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

interest rate condition. This result is consistent with predictions of salience and proportional thinking. Correspondingly, reaching for yield is dampened with gross framing.[26]

Table 1.5: *Baseline and Gross Framing*

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

Panel A. Mean Allocations to Risky Asset (%)

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

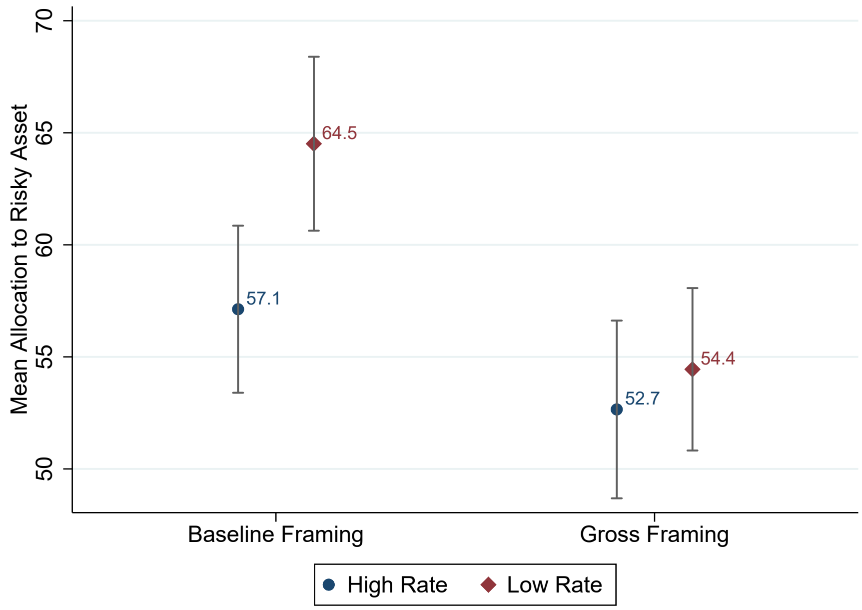
Panel B. Differences Controlling for Individual Characteristics

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

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

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

investment decisions; the explanations also echo both categories of mechanisms.



Note: 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.

Figure 1.5: *Mean Allocations with Baseline and Gross Framing*

1.5 Suggestive Evidence from Observational Data

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

There are two important challenges in the analysis using observational data. First, it is hard to assess investors' beliefs about the returns and risks of risky assets. Ideally, we would like to control for investors' expectations of excess returns and risks of the risky asset, and isolate the impact of shifts in the risk-free rate. Even if investors have rational expectations, it could be hard to find exact measures of asset properties. Moreover, recent research documents that households' subjective expectations of stock returns differ from model-based expected returns (Greenwood and Shleifer, 2014a; Amromin and Sharpe, 2013). In light of this issue, we control for both model-based measures and subjective expectations from investor surveys. Second, interest rate variations can be correlated with other drivers of investment decisions, such as general economic conditions and investors' risk tolerance. To the extent that investors are more risk averse in recessions, this bias would work against us. We include controls of economic conditions (e.g. GDP growth, credit spreads (Gilchrist and Zakrajšek, 2012)). In the data, these controls strengthen our results.[27]

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

We use the three-month Treasury rate for the risk-free rate. For control variables, we

[27] 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 A.12. A caveat is, to the extent that monetary policy shocks may affect stock market conditions, they are not perfect instruments unless we can find precise measures of expectations of stock returns and risks. In addition, it could also be hard to rule out that monetary policy shocks may affect investors' risk tolerance for other reasons (e.g. by influencing economic conditions).

use several model-based measures of expected stock returns, including the Campbell-Shiller price-earnings ratio (P/E10), the surplus consumption ratio ($Surp$) of Campbell and Cochrane (1999), as well as predicted next twelve-month excess stock returns (estimated using past twelve-month stock returns and surplus consumption).[28] In addition, we control for proxies of subjective expectations using investor sentiment measured in the AAII survey, as in Greenwood and Shleifer (2014a). 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 A.4 provides a summary of variable definitions and data sources. Table 1.6 presents summary statistics of the main variables used in this section.

Results. Table 1.7 presents results using portfolio allocations data from AAII. We find that lower interest rates are associated with higher allocations to stocks and lower allocations to "cash." A one percentage point decrease in interest rates is associated with a roughly 1.4 to 2 percentage points increase in allocations to stocks and a similar size fall in allocations to "cash." In our benchmark experiments, the treatment is a 4 percentage points difference in the level of interest rates, which is associated with a roughly 8 percentage points change in the mean allocation to the risky asset. The magnitude of investment allocations' response to interest rates appears similar in the experiment and in the observational data. In Internet Appendix Table A.11, 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.

[28] 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 1.6: *Summary Statistics of Observational Data*

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

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

Table 1.8 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.[29]

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 A.5 and Figure A.6. The sVAR analysis yields the same results. The impulse response suggests persistent impact in the medium run.

Who takes the other side of households' investment flows? In Internet Appendix Table A.13, 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 A.13 shows that following a fall in interest rates, the financial sector tends to have higher inflows to equities, although the increase is not statistically significant. The inflows from US households and institutions are partly accommodated by investors in the rest of the world, who reduce their holdings of US equities. The main player on the other side of the inflows appears to be US corporate issuers, whose net equity issuance increases. We also examine changes in asset prices to verify that the flows are driven by higher demand for equities (as opposed to higher supply). Internet Appendix Figure A.7 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 et al. (2017).

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

Table 1.7: *Interest Rates and AAII Portfolio Allocations*

Monthly time series regressions:

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

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

Panel A. Interest Rates and Mean Allocations to Stocks

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

Newey-West t-statistics in brackets

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

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

Newey-West t-statistics in brackets

Table 1.8: *Interest Rates and Household Investment Flows*

Time series regressions:

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

where r_f is 3-month Treasury rate. In Panel A, F is monthly flows into equity mutual funds (normalized by net asset value of equity mutual funds, i.e. F is flows as a percentage of net asset value) using data from ICI; X includes controls in Table 1.7. In Panel B, F is monthly flows into high yield corporate bond mutual funds (normalized by net asset value of high yield corporate bond mutual funds) using data from ICI; X includes past 12-month excess returns of high yield corporate bonds in column (2), past 12-month excess returns and high yield corporate default rates in column (3), and predicted next 12-month high yield corporate bond excess returns (estimated using past 12-month excess returns and corporate default rates) in column (4), as well as the credit spread and real GDP growth in the past four quarters. In Panel C, F is quarterly household sector flows into stocks (including both direct holdings and mutual fund holdings, normalized by household financial assets) using data from Flow of Funds; X includes controls in Table 1.7 (measured at the end of the previous quarter). In Panel D, F is quarterly household sector flows into interest-bearing safe assets (time and saving deposits, money market mutual funds, commercial papers, normalized by household financial assets, i.e. F is flows as a percentage of household financial wealth) using data from Flow of Funds; X includes controls in Table 1.7 (measured at the end of the previous quarter). All regressions include four lags of F. Standard errors are Newey-West, using the automatic bandwidth selection procedure of Newey and West (1994).

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

Newey-West t-statistics in brackets

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.

1.6 Conclusion

In this paper, we document intrinsic reaching for yield behavior at the individual level and analyze its drivers. Using simple randomized experiments of investment decision making, we show that allocations to the risky asset are significantly higher when interest rates are low, holding fixed the excess returns of the risky asset. We find consistent results in different settings, and in diverse subject pools including MTurk workers and HBS MBAs. 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). There has been less focus on savers. Our findings, along with other recent research (Hartzmark and Solomon, 2017), suggest there is also much to be understood about savers' behavior. Savers' reaching for yield behavior can also influence financial institutions' actions: institutions may invest in riskier assets to cater to clients' demand, or may design securities that highlight returns and shroud risks to further exploit these preferences (Célérier and Vallée, 2017).

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

Chapter 2

Anatomy of Corporate Borrowing Constraints[1]

2.1 Introduction

Borrowing constraints of firms play a critical role in macroeconomic analyses with financial frictions. What determines these borrowing constraints? In some work, firms' borrowing depends on cash flows from operations and investment (Townsend, 1979; Stiglitz and Weiss, 1981; Holmstrom and Tirole, 1997). More recently, the spotlight fell on the liquidation value of physical assets that firms can pledge as collateral (Hart and Moore, 1994; Shleifer and Vishny, 1992; Kiyotaki and Moore, 1997; Bernanke, Gertler and Gilchrist, 1999; Brunnermeier and Sannikov, 2014). As the Great Recession inspires growing interest in macro-finance modeling, a key question is what types of constraints apply and in what setting?

In this paper, we collect detailed data and empirically investigate borrowing by non-financial firms in the US. We show two features of corporate borrowing given the legal infrastructure in the US. First, US large non-financial firms primarily borrow based on cash flows from operations ("cash flow-based lending" in creditor parlance), rather than the liquidation value of physical assets ("asset-based lending"). Second, with cash flow-based

[1] Joint with Chen Lian

lending, a standard form of borrowing constraint restricts a firm's total debt as a multiple of a specific measure of cash flows, namely operating earnings.[2] We refer to this type of constraint as "earnings-based borrowing constraint" or EBC.

Building on the features of corporate borrowing, we then study how different financial variables affect firms' borrowing constraints and outcomes on the margin. First, with cash flow-base lending, cash flows in the form of operating earnings relax EBCs, and enable firms to borrow and invest more. This effect is only present when cash flow-based lending prevails and EBCs apply. The mechanism also points to a new channel for firms' investment sensitivity to cash flows, one that arises from cash flows' direct impact on borrowing constraints, rather than effects on internal funds. Second, as corporate borrowing does not rely heavily on physical assets, large US firms' sensitivity to collateral value, such as the value of real estate assets, could be diminished. This low sensitivity may dampen asset price feedback type of financial acceleration through firms' balance sheets (Kiyotaki and Moore, 1997; Bernanke, Gertler and Gilchrist, 1999). In the Great Recession, for instance, property price drops did not have a detectable impact on major non-financial firms' borrowing and investment through collateral damage. Finally, results in the US reverse in Japan, where corporate borrowing historically emphasizes physical assets (particularly real estate) given different legal environments and lending traditions.

We begin by assembling detailed data on corporate debt, which integrates information from a number of databases (e.g. CapitalIQ, FISD, SDC, DealScan, ABL Advisors, Compustat, Flow of Funds, SBA, Call Reports) and from hand collected data. The first part of our data focuses on the collateral structure of debt, which covers individual debt for the majority of public non-financial firms since 2002, as well as aggregate estimates for the non-financial corporate sector. The second part of our data focuses on debt limit requirements and sources of these restrictions. The data helps us establish two main facts that point to the central role of cash flows in corporate borrowing in the US.

[2]In particular, earnings before interest, taxes, depreciation, and amortization (EBITDA), over the past twelve months. In this paper, we use the term "operating earnings" to refer to EBITDA.

First, borrowing against cash flows accounts for the majority of US non-financial corporate debt. Specifically, 20% of corporate debt is collateralized by specific physical assets (e.g. real estate, inventory, equipment, receivables, what creditors usually refer to as "asset-based lending"), both in terms of aggregate dollar amount outstanding and for a typical large non-financial firm (assets above Compustat median). The remaining 80% is not tied to specific physical assets, and creditors' payoffs (in both ordinary course and bankruptcy) are driven by cash flows from continuing operations (what creditors refer to as "cash flow-based lending").[3] The composition of corporate debt suggests that the liquidation value of physical assets might not be the defining constraint for large US firms.

Second, borrowing constraints commonly rely on a specific measure of cash flows. They stipulate that a firm's total debt or debt payments cannot exceed a multiple of EBITDA (earnings before interest, taxes, depreciation and amortization) in the past twelve months. These EBCs restrict total debt at the firm level, rather than the size of a particular debt contract. A primary source of EBCs is financial covenants in cash flow-based loans and bonds. Those in loans monitor compliance on a quarterly basis, so the constraint is relevant not just for issuing new debt, but also for maintaining existing debt. Among large public non-financial firms, around 60% have earnings-based covenants explicitly written in their debt contracts. Given contracting constraints, creditors focus on current EBITDA as a principal metric of cash flow value, which is informative as well as observable and verifiable.

Corporate borrowing based on cash flows is not always the norm. Its feasibility and practicality rely on legal infrastructure (e.g. accounting, bankruptcy laws, court enforcement) and on firms generating sufficient cash flows. Once these conditions are met, cash flow-based lending can be more appealing than pledging specific assets, as most corporate assets are specialized, illiquid, or intangible. These factors shape several variations across firm groups, which we revisit later to examine firm behavior under different forms of corporate

[3]The physical assets in asset-based lending are analogous to "land" in Kiyotaki and Moore (1997). Cash flows from firms' operations in cash flow-base lending are analogous to "fruit" in Kiyotaki and Moore (1997). Bankruptcies for cash flow-based debt are primarily resolved through Chapter 11, which focuses on going concern cash flow value instead of liquidation value of specific physical assets.

borrowing. First, cash flow-based lending is less common among small firms, given their low profits (if not sustained losses) and higher likelihood of liquidation: for small public firms, the median share of cash flow-based lending is less than 10%; fewer than 15% of small firms are subject to earnings-based covenants. Second, cash flow-based lending and EBCs are similarly less prevalent among low profit margin firms. Third, while cash flow-based lending dominates in large firms across most industries, airlines and utilities are two exceptions, where firms have a substantial amount of standardized transferable assets (aircraft and power generators) and a significantly higher share of asset-based lending.[4] Finally, the predominant form of corporate borrowing may vary across countries given differences in institutional environments, which we illustrate using the example of Japan.

After documenting the key features of corporate borrowing based on debt contracts, we further investigate how these features shape the way different financial variables affect firms' borrowing constraints and outcomes on the margin. With cash flow-based lending and EBCs, cash flows in the form of operating earnings directly relax borrowing constraints, and enable firms to both *borrow* and invest more. On the other hand, these corporate borrowing features may diminish firms' sensitivity to the value of physical assets such as real estate. Taken together, major US non-financial firms do face borrowing constraints, but the primary constraint appears different from physical collateral constraints commonly used in the macro-finance literature.

We begin by analyzing how cash flows in the form of operating earnings relax borrowing constraints. We start with a baseline test following traditional investment regressions, with a few modifications. First, we study debt issuance as the outcome variable to investigate the response of borrowing, and then proceed to investment activities. Second, we focus on the role of operating earnings (EBITDA), which directly enter the borrowing constraints. Third, we start with firms where cash flow-based lending and EBCs are most important, specifically large firms with earnings-based covenants, and then analyze several firm groups

[4] The high share of asset-based lending in airlines is consistent with Benmelech and Bergman (2009) and Benmelech and Bergman (2011), who thoroughly analyze the collateral channel in this industry.

where EBCs are less relevant. We find that among large firms with EBCs, all else equal, a one dollar increase in EBITDA is on average associated with a 27 cents increase in net long-term debt issuance. Investment activities increase by about 15 cents. These patterns do not exist among other firm groups not bound by EBCs (e.g. unconstrained firms and firms that primarily use asset-based lending, such as small firms, low margin firms, airlines and utilities, Japanese firms, etc.). The set of results across different firm groups is not easy to account for based on standard empirical concerns, which we address in detail.

We supplement the baseline test with a natural experiment that contributes to exogenous variations in operating earnings (EBITDA), due to changes in an accounting rule (Financial Accounting Standards Board's rule SFAS 123(r)). Before the adoption of this rule, firms' option compensation expenses do not formally count towards earnings, while the new rule requires their inclusion. Thus the rule affects the calculation of operating earnings, but does not directly affect firms' cash positions or economic fundamentals. As prior research demonstrates, contracting frictions make it hard to neutralize changes in accounting rules, and they tend to have a significant impact on borrowers through debt covenants (Frankel, Lee and McLaughlin, 2010; Moser, Newberry and Puckett, 2011; Cohen, Katz and Sadka, 2012; Shroff, 2017). We instrument operating earnings after the adoption of SFAS 123(r), using average option compensation expenses in three years prior to the rule announcement. We find strong first-stage results among all firm groups, but only second stage results on debt issuance and investment for firms bound by EBCs. The findings attest to the influence of operating earnings on borrowing constraints and firm outcomes on the margin.

The analysis of earnings-based borrowing constraints also points to a new channel for investment sensitivity to cash flows. In the traditional corporate finance literature (Fazzari, Hubbard and Petersen, 1988; Froot, Scharfstein and Stein, 1993; Kaplan and Zingales, 1997), the main function of cash flows is to increase internal funds: following the pecking order idea (Myers and Majluf, 1984), more internal funds boost investment but *substitute out* external financing as long as investment has diminishing marginal returns. With cash flow-based lending and EBCs, however, cash flows in the form of operating earnings can raise investment by directly relaxing borrowing constraints and *crowding in* external borrowing.[5]

While lending practices in the US contribute to the sensitivity of corporate borrowing and investment to cash flows (especially operating earnings), they may diminish the sensitivity to the value of physical assets such as real estate (which accounts for only 7% of US non-financial corporate debt by value). Using both traditional estimates of firm real estate value and hand collected property-level data from company filings, we find that US large non-financial firms' borrowing has relatively small sensitivity to real estate value, concentrated in asset-based debt. For cash flow-based debt, the sensitivity is absent, if not negative and offsetting the response of asset-based debt. Overall, borrowing increases by three to four cents on average for a one dollar increase in property value, consistent with findings by Chaney, Sraer and Thesmar (2012). The magnitude is considerably smaller than the impact of operating earnings among US large firms.

This observation helps understand aspects of the Great Recession and the transmission of property value declines in this crisis. By exploiting firms' differential exposures to property price declines, we do not find that the drop in the value of real estate assets had a significant impact on borrowing and investment.[6] Such diminished sensitivity may decrease the scope of asset price feedback type of financial acceleration through firms' balance sheets. Meanwhile, the decline in corporate earnings did have a significant impact through EBCs, which accounts for roughly 10% of the drop in debt issuance and capital expenditures among public firms from 2007 to 2009. The magnitude is meaningful but not catastrophic, in line with the view that the US Great Recession is a crisis centered around households and banks rather than major non-financial firms.[7]

[5]This observation may also provide a new perspective for the debate about whether more constrained firms are more sensitive to cash flows (Kaplan and Zingales, 1997, 2000; Fazzari, Hubbard and Petersen, 2000): among plausibly more constrained small firms, cash flow-based lending and EBCs are uncommon, which removes one possible channel of cash flow sensitivity (if cash flows are measured based on earnings, which is typical in the literature).

[6]Our result is consistent with indirect evidence from Mian and Sufi (2014) and Giroud and Mueller (2017), and with their proposition that the main effect of the property price collapse was to impair household demand.

[7]In Section 2.4.5, we also study financial acceleration dynamics under different forms of borrowing constraints in a simple general equilibrium framework following Kiyotaki and Moore (1997). Under cash

The story in the US finds its antithesis in Japan. Unlike the US where cash flow-based lending prevails, Japan historically lacked legal infrastructure for such lending practices, and instead developed a corporate lending tradition focused on physical assets, especially real estate. We show that Japanese firms do not display sensitivity of debt issuance to operating earnings. Japanese firms are, however, very sensitive to declines in the value of real estate assets during the Japanese property price collapse in the early 1990s. Gan (2007) shows the drop in Japanese firms' property value had a substantial and long-lasting impact on their borrowing and investment. Using the specification of Gan (2007), we do not find similar results among US firms during the Great Recession. Recognizing the differences in institutional environments and corporate borrowing practices helps synthesize distinct evidence across different countries.

The domain of our study is *non-financial corporations*. Financial institutions' borrowing constraints may take different forms, and tie to the liquidation value of securities pledged as collateral. The ensuing fire-sale amplifications have been thoroughly analyzed (Shleifer and Vishny, 1997; Gromb and Vayanos, 2002; Coval and Stafford, 2007; Garleanu and Pedersen, 2011), and map closely to models of asset price feedback (Shleifer and Vishny, 1992; Kiyotaki and Moore, 1997; Aiyagari and Gertler, 1999; Bernanke, Gertler and Gilchrist, 1999; Brunnermeier and Sannikov, 2014). Small businesses' constraints may also be different and significantly dependent on real estate value, making them highly exposed to property price fluctuations due to collateral value (Adelino, Schoar and Severino, 2015; Schmalz, Sraer and Thesmar, 2017). For residential mortgages, Greenwald (2018) documents the role of "payment-to-income" constraints, a form of constraint similar to the earnings-based constraints we study among firms.[8]

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flow based-lending and EBCs, the resale/liquidation value of physical assets does not directly affect a firm's borrowing constraint, asset price feedback dissipates, and financial acceleration is indeed much more limited.

[8]As Greenwald (2018) shows, in residential mortgages the "payment-to-income" (PTI) constraints coexist with the "loan-to-value" (LTV) constraints. In this setting, creditors' claims are primarily tied to the property that serves as collateral, and LTV is the primary constraint. However, seizing and liquidating collateral is not frictionless, so PTI constraints may also be used as a secondary constraint to reduce foreclosure costs (in the cases where seizing collateral is close to costless, e.g. margin loans against financial securities, collateral/margin constraints are first-order and cash flow constraints are absent). In corporate cash flow-based lending, in

Related Literature. Our paper relates to several strands of research. First, an important macro-finance literature offers theoretical insights about firms' borrowing constraints and their economic significance (Hart and Moore, 1994, 1998; Shleifer and Vishny, 1992; Kiyotaki and Moore, 1997; Bernanke, Gertler and Gilchrist, 1999; Holmstrom and Tirole, 1997; Buera and Moll, 2015; Di Tella, 2017; Dávila and Korinek, 2017; Diamond, Hu and Rajan, 2017).[9] These analyses motivate our empirical investigation. We show the prevalence of cash flow-based versus asset-based lending, the pervasiveness of earnings-based borrowing constraints, and variations across firms and countries. We also document that different forms of corporate borrowing can have distinct empirical implications. Macro-finance mechanisms may not apply uniformly across the board; it is important to adapt based on the setting of interest.

Second, our work builds on research on corporate debt to better understand questions in macro-finance. Rauh and Sufi (2010) highlight the importance of studying debt composition and heterogeneity. We perform a systematic analysis of asset-based and cash flow-based lending, and investigate their macro-finance implications. We also draw on studies of financial covenants (Chava and Roberts, 2008; Roberts and Sufi, 2009; Nini, Smith and Sufi, 2009, 2012; Ivashina, 2009; Murfin, 2012; Becker and Ivashina, 2016) to examine the enforcement of earnings-based borrowing constraints and connect to macro-finance mechanisms.

Third, our investigation of borrowing constraints sheds new light on how cash flows affect corporate borrowing and investment. With earnings-based borrowing constraints, cash flows in the form of operating earnings could directly relax borrowing constraints, and help crowd in borrowing and investment. This observation also suggests a distinct channel for the widely studied issue of investment sensitivity to cash flows (Fazzari, Hubbard and

comparison, creditors' claims are tied predominantly to the firm's cash flow value, cash flows have higher verifiability, and creditors often exert contingent transfers of control rights, so the primary constraints are based on cash flows/earnings, with no substantive constraints on physical collateral value.

[9]For more theoretical analyses of the impact of borrowing constraints, see also Mendoza (2010), Bianchi (2011) in international macro; Midrigan and Xu (2014), Catherine, Chaney, Huang, Sraer and Thesmar (2017) in studies of productivity and misallocation; Bernanke and Gertler (1989), Carlstrom and Fuerst (1997), Gertler and Kiyotaki (2010), Jermann and Quadrini (2012) in business cycle analyses; Rampini and Viswanathan (2010, 2013) in corporate finance, among many others.

Petersen, 1988; Froot, Scharfstein and Stein, 1993; Kaplan and Zingales, 1997; Rauh, 2006). Sufi (2009) studies how earnings-based covenants (cash flow-based financial covenants in his paper) affect firms' access to bank lines of credit and precautionary saving behavior.

Fourth, our investigation helps understand firms' vulnerability to property value shocks and features of the Great Recession. Building on previous research (Chaney, Sraer and Thesmar, 2012), we find US firms' borrowing and investment exhibit some sensitivity to real estate value. However, the sensitivity is concentrated in asset-based debt, is less pronounced than the sensitivity to earnings, and appears sufficiently modest to avert severe impact of collateral damage. We also connect to studies of the Great Recession, and use firm property holdings data to further unpack the transmission of property price declines. Our findings suggest non-financial firms' collateral damage does not play a significant role in this crisis, and support the centrality of households' and financial institutions' balance sheet impairment in the US experience (Mian and Sufi, 2014; Giroud and Mueller, 2017; Berger, Guerrieri, Lorenzoni and Vavra, 2017; Kaplan, Mitman and Violante, 2017; Chodorow-Reich and Falato, 2017; Gertler and Gilchrist, 2017).

Finally, corporate lending practices develop based on legal infrastructure (La Porta, Lopez-de Silanes, Shleifer and Vishny, 1997, 1998; Djankov, Hart, McLiesh and Shleifer, 2008). We suggest that legal institutions could have a significant impact on the applicability of macro-finance mechanisms.

The rest of the paper is organized as follows. Section 2.2 documents the features of corporate borrowing in the US. Section 2.3 studies the impact of cash flows on corporate borrowing and investment; Section 2.4 studies the impact of property collateral value and implications for the transmission of shocks in the Great Recession. Section 2.5 concludes.

2.2 Corporate Borrowing in the US

In this section, we document two main facts about corporate borrowing in the US. First, in the aggregate and among large firms, the majority of corporate debt is based on cash flows from operations ("cash flow-based lending"), as opposed to the liquidation value of physical assets ("asset-based lending"). Second, in this setting, a standard form of borrowing constraint is tied to a specific measure of cash flows, namely operating earnings, which we refer to as earnings-based borrowing constraints (EBCs). Then we also discuss determinants of these practices and variations across firms. Finally, we overview the implications of these facts, which we explore in Sections 2.3 and 2.4.

To study these facts, we collect and integrate data from a number of sources. We utilize many sources because corporate debt information is often scattered: each dataset covers some specific types of debt, or some specific debt attributes. Combining many sources also allows us to cross check results using different datasets and enhance accuracy. The first part of our data focuses on debt composition, and uses key features such as collateral structure to categorize debt into asset-based and cash flow-based lending. We provide aggregate estimates for the non-financial corporate sector (using Flow of Funds, bond aggregates from FISD, large commercial loan aggregates from SNC, DealScan, and ABL Advisors, small business loan aggregates from SBA and Call Reports, capital lease estimates from Compustat, among others). We also perform firm-level analyses for most public firms since 2002 (using primarily debt-level descriptions from CapitalIQ, supplemented with bond data from FISD, loan data from DealScan, and additional debt information from SDC). The second part of our data focuses on EBCs. We record legally binding constraints specified in firms' debt contracts, including loans (DealScan) and bonds (FISD); we also document indications of such constraints imposed by market norms. We verify that we accurately capture the sources of these constraints by additionally scraping firms' annual report filings, and manually reading firms' disclosures in filings for a sample year of 2005.

2.2.1 Fact 1: Prevalence of Cash Flow-Based Lending

We first study the composition of corporate borrowing, and document the prevalence of cash flow-based lending among US non-financial firms.

Asset-Based Lending vs. Cash Flow-Based Lending

In asset-based lending, the debt is collateralized by specific assets (e.g. real estate).

Creditors have claims against the specific assets pledged as collateral, and their payoffs in default depend on the liquidation value of the collateral. This maps closely to borrowing against "land" in Kiyotaki and Moore (1997). Examples of asset-based lending include commercial mortgages (backed by commercial real estate) and other asset-based loans (backed by inventory, receivable, certain types of machinery and equipment, oil and gas reserves, etc.). Each debt typically has a size limit based on the liquidation value of the particular assets pledged as collateral for that debt.[10]

In cash flow-based lending, the debt is not tied to specific physical assets. Creditors' payoffs (in ordinary course and in bankruptcy) are based predominantly on cash flows from continuing operations, as opposed to the liquidation value of physical assets; Chapter 11 in the US enforces these cash flow-based claims.[11] This is analogous to borrowing against "fruits" in Kiyotaki and Moore (1997). Examples of cash flow-based lending include the majority of corporate bonds and a significant share of corporate loans such as most syndicated loans. The debt is often unsecured; the ones that are secured are secured by a lien on the entire corporate entity or by equity of the borrower (rather than specific physical assets), and the value of this form of collateral in bankruptcy is calculated based on the cash flow value from continuing operations (Gilson, 2010). The key function of having security is to establish priority in bankruptcy and restructuring (US bankruptcy laws treat secured creditors as one class with priority over unsecured creditors), not to liquidate the collateral. For debt limits, creditors do not focus on the liquidation value of physical assets; they focus instead on assessing and monitoring firms' cash flows from operations, which we discuss further in Section 2.2.2.

Classification Procedures

[10]The limit is enforced throughout the duration of the debt in some cases (e.g. revolving credit lines based on working capital), and enforced only at issuance in others (e.g. commercial mortgages).

[11]In Chapter 11, which is typical for firms using cash flow-based lending, the payoffs are determined by the cash flow value from continuing operations ("going-concern" value). In the rare cases of ending up in Chapter 7, cash flow-based debt generally has minimal recovery. Thus creditors' payoffs overall are not tied to the liquidation value of physical assets. Using bankruptcy filing data from CapitalIQ (see Iverson (2017) for a detailed description), about 90% of large public firms' bankruptcies are resolved through Chapter 11.

We perform the classification both in the aggregate (for non-financial corporate sector overall), and at the firm-level (for the majority of public non-financial firms). We summarize the classification procedures below, and explain the details in Appendix B.1.1 and B.1.2.

Aggregate Composition. For the aggregate estimates, we first analyze the composition of each of the major debt classes, e.g. mortgages (all asset-based), corporate bonds (primarily cash flow-based), commercial loans (combination of asset-based and cash flow-based), etc. The data we use include Flow of Funds, bond aggregates from FISD, large commercial loan aggregates from SNC, DealScan, ABL Advisors, small business loan aggregates from SBA and Call Reports, capital lease estimates from Compustat, etc. We then sum up asset-based lending and cash flow-based lending across the major debt classes to get the total estimates.

Firm-Level Composition. For firm-level composition, we first collect debt-level data on debt attributes and collateral structure. The primary source is debt descriptions from CapitalIQ, supplemented with bond data from FISD, loan daa from DealScan, and additional information from SDC.

For each debt, we classify it as asset-based if one of the following criteria is met: a) we directly observe the key features of asset-based lending (e.g. collateralized by specific assets or have borrowing limits tied to them); b) the debt belongs to a debt class that is usually asset-based (e.g. secured revolving line of credit, finance company loans, capital leases, small business loans, etc.), or it is labeled as asset-based; c) all other secured debt that does not have features of cash flow-based lending (discussed below) to be conservative (i.e. we may over-estimate rather than under-estimate the amount of asset-based lending). We leave personal loans (from individuals, directors, related parties, etc.), government loans, and miscellaneous loans from vendors and landlords unclassified (neither asset-based nor cash flow-based); their share is less than one percent in the aggregate, but can be more significant among certain small firms.

We classify a debt as cash flow-based if one of the following criteria is met: a) it is unsecured, or secured by substantially all assets/pledge of stock and does not have any features of asset-based lending; b) the debt belongs to a debt class that is primarily cash flow-based (e.g. corporate bonds other than asset-backed bonds and industrial revenue bonds, term loans in syndicated loans), or it is labeled as cash flow-based.

Results

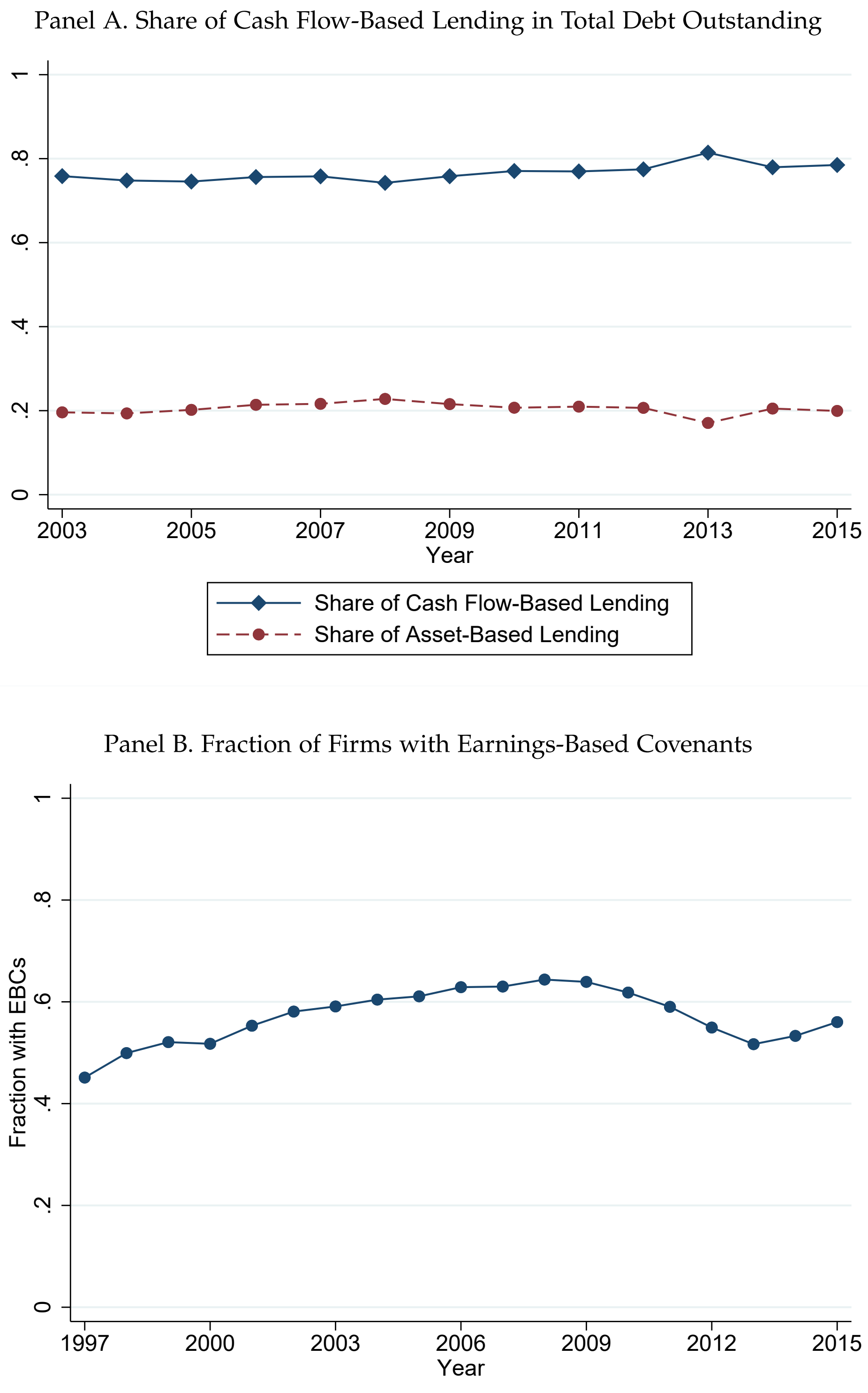
In the aggregate, among total US non-financial corporate debt outstanding, we find that asset-based lending accounts for roughly 20% of debt by value, of which around 7% are mortgages (secured by real estate) and the rest are other asset-based loans (secured by receivable, inventory, equipment, etc.). Meanwhile, cash flow-based lending accounts for about 80% of debt by value, of which 50% are corporate bonds and 30% are cash flow loans.

For individual firms, results are similar in large non-financial firms. Among the larger half of public firms (by assets), the median share of asset-based lending is 12%, while the median share of cash flow-based lending is 83%. Among rated firms, the median share of asset-based lending 8%, while that of cash flow-based lending is 89%.[12] In Figure 2.1 Panel A, we also aggregate up firm-level data and plot the share of cash flow-based and asset-based lending by year among large public non-financial firms: the share of cash flow-based lending is consistently 80% and that of asset-based lending is consistently 20%.

One question is whether firms' ability to borrow cash flow-based debt may have indirect positive dependence on the value of specific physical assets. We perform further checks in Appendix B.1 Table B.3. Results in Table B.3 show that the amount of asset-based debt a firm has is positively correlated with the amount of physical assets, whereas the amount of cash flow-based debt is not (if anything the correlation is typically negative).

Taken together, we find that cash flow-based lending accounts for the majority of US corporate debt, in the aggregate and among large firms. In the following, we document a prevalent form of borrowing constraints in this setting.

[12] Rauh and Sufi (2010) study debt structure of 305 rated firms, and provide firm-level data for debt outstanding by debt class (e.g. public bonds, revolvers, mortgages). With assumptions about whether each debt class is asset-based or cash flow-based (e.g. public bonds are cash flow-based, mortgages are asset-based, revolvers are a mix), we can get another estimate of debt composition. This alternative estimate and our firm-level calculations match closely; the median level matches one for one for firm-years in both samples.



Note: This figure shows the prevalence of cash flow-based lending and EBCs among large US public non-financial firms. In Panel A, we sum up firm-level estimates of asset-based and cash flow-based lending across all large firms (assets above Compustat median), and plot the share of each type among total debt of these firms in each year. Large public firms account for more than 95% of debt, sales, investment, and employment among all public firms. The solid line with diamond represents the share of cash flow-based lending; the dashed line with circle represents the share of asset-based lending. In Panel B, we merge covenant data from DealScan and FISD with Compustat, and plot the fraction of large firms with earnings-based covenants each year.

Figure 2.1: *Prevalence of Cash Flow-Based Lending and EBCs: Large Public Firms*

Table 2.1: *Composition of Corporate Borrowing*

This table summarizes the composition of corporate debt. Panel A shows aggregate estimates by debt type. Panel B shows median share by firm group (among public non-financial firms). Procedures for aggregate estimates and firm-level analyses are explained in detail in Appendix B.1.

Panel A. Aggregate Corporate Debt Share by Type:

Category	Debt Type	Share
Asset-based lending (20%)	Mortgage	6.5%
	Asset-based loans	13.5%
Cash flow-based lending (80%)	Corporate bond	48.0%
	Cash flow-based loans	32.0%

Panel B. Firm-Level Median Share by Group (Public Firms)

	Large Firms	Rated Firms	Small Firms
Asset-based lending	12.4%	8.0%	61.0%
Cash flow-based lending	83.0%	89.0%	7.2%

2.2.2 Fact 2: Prevalence of Earnings-Based Borrowing Constraints

The second stylized fact shows that, in the context of cash flow-based lending, a common form of borrowing constraint stipulates debt limits based on a specific measure of cash flows, operating earnings. We refer to this type of constraints as earnings-based borrowing constraints (EBCs). EBCs follow two main specifications. The first is a limit on the ratio of a firm's debt to its operating earnings:

$$b_t \leq \phi \pi_t \tag{2.1}$$

where π_t is the firm's annual operating earnings, b_t is the firm's debt, and ϕ is the maximum ratio.[13] The second is a limit on the minimum amount of earnings relative to debt payments:

$$b_t \leq \frac{\theta \pi_t}{r_t} \tag{2.2}$$

where $r_t b_t$ is interest payments, and θ is the minimum coverage ratio.

[13]The debt-to-earnings ratio is a central concept to creditors: in credit agreements, lenders typically use the term "leverage ratio" to refer to the debt-to-earnings ratio (rather than the debt-to-assets ratio).

EBCs have several features. First, the constraint applies at the firm level: both earnings π_t and the amount of debt b_t (or debt payments $r_t b_t$) are those of the borrowing firm. This is different from, for instance, the "loan-to-value" constraint of a mortgage that applies only to the size of that particular loan. At a given point in time, a firm may face earnings-based borrowing constraints from different sources, as we discuss shortly. Each of these constraints has a parameter ϕ or θ, and the tightest one binds first.[14] Second, the commonly used measure for π_t is EBITDA (earnings before interest, tax, depreciation, and amortization), over the past twelve months. As the name indicates, EBITDA excludes taxes and interest expenses. It also excludes non-operating income and special items (e.g. windfalls, natural disaster losses, earnings from discontinued operations). Third, EBCs apply not just when firms issue new debt; they can also affect the maintenance of existing debt. Even if a firm is not issuing new debt, if its earnings decline significantly, it may need to reduce debt to comply with these constraints imposed by existing debt.

Below we discuss the sources and enforcement of EBCs.

Earnings-Based Debt Covenants

An important source of EBCs is financial covenants in debt contracts. Covenants are legally binding provisions in debt contracts that specify restrictions on borrowers; financial covenants are one type of covenants limiting borrowers' financial conditions, assessed based on financial statements. Violations of covenants trigger "technical defaults," in which case creditors have legal power to accelerate payments or terminate the credit agreement. While such actions are infrequent, creditors use the bargaining power to request fees, increase borrowing costs, restrict borrowers' financial decisions, and replace management teams (Roberts and Sufi, 2009; Nini, Smith and Sufi, 2009, 2012). Covenant violations prompt transfers of control rights to creditors, and incur significant costs to borrowers.

A common type of financial covenants specify debt limits as a function of EBITDA, which we refer to as earnings-based covenants. They follow the forms in Equations (2.1)

[14] In Equations (2.1) and (2.2), we do not specify a time subscript t for the parameters ϕ or θ. At the firm level, the overall tightness of EBCs may vary over time (as old constraints get replaced by new ones, etc.).

and (2.2), and share the feature discussed above that the debt limits are at the firm level (so a firm is subject to constraint as long as one of its debt contracts contains such covenants). Earnings-based covenants can be found in both corporate loans and bonds. Those in loans generally monitor compliance on a quarterly basis (“maintenance tests"); thus continuous compliance is relevant for the maintenance of existing loans as well as the issuance of new debt, connected to the third feature discussed above. Those in bonds monitor compliance only when borrowers take certain actions such as issuing debt (“incurrence tests"), and are relevant for new debt issuance.

We study earnings-based covenants using three datasets: DealScan for commercial loans, FISD for corporate bonds, and scraped and hand collected data from annual reports. DealScan is the most widely used dataset for corporate loans, with comprehensive coverage (Strahan, 1999; Bradley and Roberts, 2015), especially for large syndicated loans (it may not cover small bilateral loans, personal loans, mortgage loans, finance company loans). As we verify below, commercial loans are the primary type of loans with earnings-based covenants. DealScan provides data on covenant specifications and thresholds; Table B.5 in Appendix B.2.1 lists the main specifications and the corresponding accounting variables compiled by Demerjian and Owens (2016). FISD is a comprehensive dataset for corporate bonds, with information on the type of covenant but not the covenant threshold. Finally, to check the comprehensiveness of data from DealScan and FISD and better understand the sources of earnings-based covenants, we scrape firms’ annual report filings, and manually read covenant-related discussions for the sample year of 2005. Our sample covers US public non-financial firms from 1996 to 2015, as covenant data is relatively sparse prior to 1996.

Earnings-based covenants primarily come from debt that belongs to cash flow-based lending. To get a comprehensive picture of the sources of earnings-based covenants, we read firms’ filings for the sample year of 2005. Among mentions of earnings-based covenants in filings, 90% come from debt that belongs to cash flow-based lending (or is packaged with cash flow-based debt[15]), such as cash flow-based commercial loans and corporate bonds.

[15]Commercial loans are typically organized in a package that shares the same covenants: the package

Less than 10% come from other types of loans (e.g. mortgage loans, equipment loans, capital leases, etc.). These results also verify the validity of using DealScan and FISD data for systematic analyses of earnings-based covenants.

Prevalence. Figure 2.1 Panel B merges data from DealScan and FISD with Compustat, and shows that earnings-based covenants are prevalent among large firms. Of all large public firms, about 50% to 60% have earnings-based covenants in their debt contracts.[16] To make sure DealScan data does not miss covenant information, we also scrape mentions of financial covenants from firms' 10-K filings. If we add mentions of earnings-based covenants from scraped data, the share of large non-financial firms with EBCs increases by another 5% per year (but the scraped data could contain false positives[17]). Large firms as a whole account for more than 90% of the sales, investment, and employment of all public firms. Those with earnings-based covenants account for about 60%. Some large firms do not have earnings-based covenants written in their debt contracts because they currently have little debt and are far from the constraints (e.g. Apple nowadays). Nonetheless, the constraint still exists and they are likely to have explicit debt covenants if the debt level is higher (e.g. Apple fifteen years ago).

In addition to earnings-based covenants, there are a few other types of financial covenants, mostly in corporate loans. These covenants are less prevalent in comparison, as we show in Internet Appendix Section IA1Other Types of Financial Covenantssection.1.[18]

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commonly contains a revolving credit line, which can be asset-based (secured by inventory and receivable, with borrowing limits based on eligible collateral), and cash flow-based term loans. Thus the revolving lines are also subject to earnings-based covenants although we categorize them into asset-based lending.

[16]Examples include AAR Corp, AT&T, Barnes & Noble, Best Buy, Caterpillar, CBS Corp, Comcast, Costco, Disney, FedEx, GE, General Mills, Hershey's, HP, IBM, Kohl's, Lear Corp, Macy's, Marriott, Merck, Northrop Grumman, Pfizer, Qualcomm, Rite Aid, Safeway, Sears, Sprint, Staples, Starbucks, Starwood Hotels, Target, Time Warner, US Steel, Verizon, Whole Foods, Yum Brands, among many others.

[17]For instance, the covenant mentioned in the filing may be about a loan that is already paid off. Firms may also discuss, for example, "interest coverage ratio" and "leverage ratio" in general, not in relations to covenant requirements. These cases are hard to cleanly tease out in the scraping process.

[18]Other financial covenants have two main forms. One type specifies an upper bound on book leverage, or relatedly a lower bound on book equity (book net worth). Since book equity is closely related to the accumulation of past earnings, this can be broadly viewed as a variant of EBC. The popularity of this type of covenant has declined in the past twenty years for several reasons that we discuss in the Internet Appendix Section IA1Other Types of Financial Covenantssection.1. Currently the prevalence of the book leverage/net

Violations and Tightness. We also examine consequences of covenant violations and covenant tightness. Here we focus on loan covenants, for which we have some information about covenant specifications and thresholds. Figure 2.2 plots firm-level debt growth in year $t+1$ against distance to the covenant threshold at the end of year t.[19] It shows that debt growth is on average positive when firms are in compliance (to the right of the dashed line), but becomes negative once firms break the covenants.[20] The evidence suggests that earnings-based covenants serve as effective borrowing constraints. It is consistent with previous research that provides in-depth analyses of covenant violations and how they restrict corporate borrowing (Chava and Roberts, 2008; Roberts and Sufi, 2009). Figure 2.3 shows that firms bunch near the constraint, indicating violations are costly and borrowers try to avoid them. For tightness, every year around 10% of large firms with DealScan loans break the thresholds set by earnings-based covenants; another 10% to 15% are within 0.5 standard deviations of the thresholds. The statistics are consistent with prior work (Nini, Smith and Sufi, 2012). The constraints are tight and relevant.[21]

Other Earnings-Based Borrowing Constraints

The earnings-based borrowing constraints a firm faces are not limited to financial covenants. The corporate credit market has important norms about debt relative to earnings:

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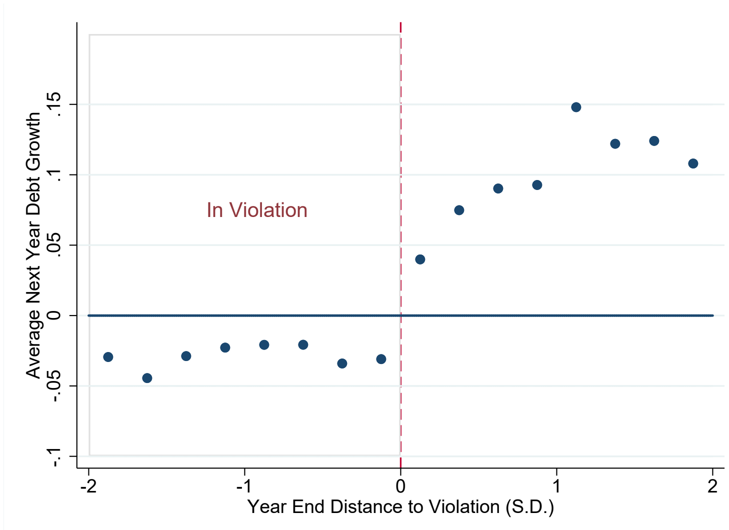
worth covenants is less than a third of the prevalence of earnings-based covenants, and violations are uncommon. The other type of financial covenant specifies limits on the ratio of current assets to current liabilities. These covenants are distinct from EBCs.

[19] As shown in Table B.5, earnings-based covenants have several variants. Firms sometimes have more than one type of these covenants; different firms may also have different types. For a uniform measure of distance, we first compute the minimum amount of earnings ($\underline{\pi}_{it}$) required such that the firm is in compliance with all of its earnings-based covenants (given the current level of debt). We then compute the difference between the minimum earnings required ($\underline{\pi}_{it}$) and the actual earnings (π_{it}), scaled by lagged assets. We normalize this distance by the standard deviation of ROA in the firm's 2-digit SIC industry.

[20] DealScan's data allows us to observe the threshold set by the initial credit agreement (at loan issuance). Firms may subsequently renegotiate with lenders to amend credit agreements and relax covenants, and these amendments may not be fully captured by DealScan's data. Thus the actual threshold may end up being slightly looser than the ones in our data. Nevertheless, we already observe a pause in debt growth once the initial threshold is reached.

[21] The fraction of firms violating covenants or close to violation does not show strong cyclical patterns. This suggests that firms are not passive; they appear to actively adjust debt level and control their distance to violation.

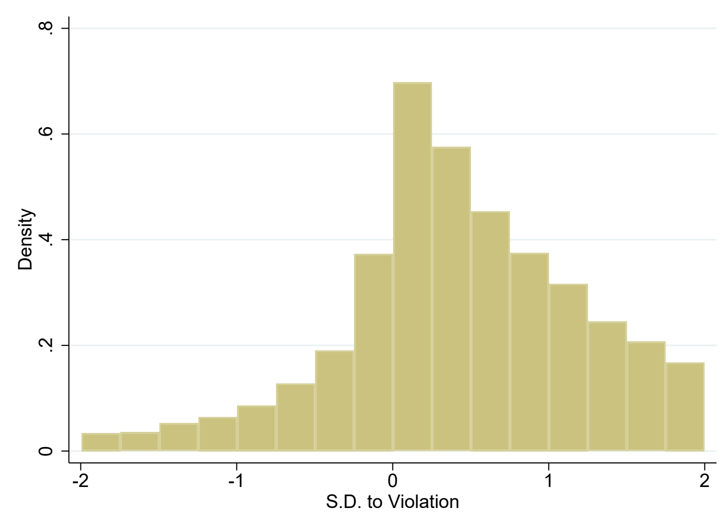
when a firm wants to issue debt, it can be hard to surpass a reference level of debt to EBITDA ratio lenders are accustomed to. This limit can be tighter than covenants in existing debt or in the new debt (the covenants of the new debt, if there are any, are typically set in a way that they will not be violated immediately). These earnings-based constraints at issuance are especially relevant for non-investment grade firms, which are closer to the limit. Such firms also commonly borrow from the leveraged loan market, where the reference debt to EBITDA ratio is emphasized the most. We document the impact of these additional constraints in Appendix B.2.2 using measures of the reference level in the leveraged loan market.



Note: This plot shows the relationship between debt growth and compliance with earnings-based covenants in DealScan loans. The x-axis is 20 bins based on distance to violation by year end, and the y-axis is the average debt growth in the next year in each bin. As shown in Table B.5, there are several variants of earnings-based covenants. Firms sometimes have more than one type, and different firms can also use different types. To find a uniform measure of distance, we first compute the minimum amount of earnings ($\underline{\pi}_{it}$) required such that the firm is in compliance with all of its earnings-based covenants (given the current level of debt and debt payments). We then compute the difference between the minimum earnings required ($\underline{\pi}_{it}$) and the actual earnings (π_{it}), scaled by lagged assets. We normalize this distance by the standard deviation of ROA in the firm's 2-digit SIC industry. We take the firm-year observations that are within +/- 2 standard deviations, and group them into 20 equally spaced bins. The first bin on the right on the dashed line at zero includes firms within 0 to 0.2 standard deviations, so on so forth. Firms in the shaded region to the left of zero are those that are not in compliance with at least one earnings-based covenant based on DealScan data; those to the right of zero are in compliance with all such covenants.

Figure 2.2: *Debt Growth and Earnings-Based Covenants*

In sum, earnings-based borrowing constraints play an important role in US corporate credit markets, and tie closely to the prevalence of cash flow-based lending. In Internet Appendix Section IA2Contracting Bases of Earnings-Based Covenantssection.2, we provide formal models to analyze the contracting functions of earnings-based covenants in cash flow-based lending, including incentive provision (Innes, 1990) and contingent transfer of control rights (Aghion and Bolton, 1992). We also discuss why creditors focus on current EBITDA: within contracting constraints, creditors use current EBITDA as a key metric; this strikes a balance between being informative about firm performance and cash flow value, and importantly being observable and verifiable. For instance, EBITDA excludes windfalls to focus on cash flow generation by core businesses; it excludes interest expenses and taxes to exclude mechanical influence due to capital structure (e.g. tax advantages of debt). It is available on a regular basis based on financial statements.



Note: This plot shows the histogram of firm-year observations across the same bins as in Figures 2.2. The bins measure the distance to violating earnings-based loan covenants in DealScan data. Firms to the right of zero are in compliance with all earnings-based covenants.

Figure 2.3: *Bunching around Earnings-Based Covenant Threshold*

2.2.3 Heterogeneity in Corporate Borrowing

Our previous discussions focus on large US non-financial firms. Corporate borrowing based on cash flows is not always the norm. The primary form of borrowing varies across large and small firms, in certain industries, and across countries, which we summarize below. These variations are driven by three main factors that affect the feasibility and utilization of cash flow-based lending: legal foundations, firms' cash flow generating ability, and asset specificity. First, the feasibility of lending and contracting based on cash flows relies on legal infrastructure, including reliable financial accounting and auditing, as well as statues (especially bankruptcy laws) and court enforcement that ensure lending based on cash flows can get paid back on average. With weak accounting, weak courts, or bankruptcy regimes that tie creditors' payoffs to the liquidation value of physical assets, cash flow-based lending could be harder to pursue. Second, firms also need to be able to generate sufficient cash flows for cash flow-based lending to be practical. Third, among firms that can access both asset-based and cash flow-based lending, the relative utilization can depend on asset attributes. Most large US firms have a small amount of standardized transferable assets that support low-cost asset-based lending. The majority of assets, however, are specialized, illiquid, or intangible,[22] and the US institutional environment makes cash flow-based lending more appealing.[23] In certain industries, particularly airlines and utilities, firms have a large share of standardized transferable assets, which facilitate asset-based lending.

Variations in the US

Small Firms. Cash flow-based lending and EBCs are much less common among small firms. The median share of cash flow-based lending is about 7% (while the median share of asset-based lending for these firms is 61%; the rest are personal loans from individuals

[22]This is consistent with the observation of Catherine, Chaney, Huang, Sraer and Thesmar (2017) that the pledgeability of physical assets is low on average.

[23]For instance, Boeing's aircraft production facilities generate high cash flows when producing Boeing aircraft, but the liquidation value of these assets could be very low. In such cases, borrowing against cash flows would be more appealing than borrowing against specific physical assets in the US environment. Correspondingly, the debt is structured to focus on cash flows (e.g. extensive use of financial covenants), rather than enforcing creditors' rights over specific physical assets.

and other miscellaneous borrowing). EBCs are found in only 12% of small firms (assets less than Compustat median). The majority of small firms have little profits if not sustained losses (Denis and McKeon, 2016).[24] In addition, financial distress of small firms is more likely to be resolved through liquidations (Bris, Welch and Zhu, 2006; Bernstein, Colonnelli and Iverson, 2017), given the fixed costs of restructuring (e.g. legal and financial personnel) and the uncertain prospects of small firms. This makes it harder for creditors to count on cash flow value from continuing operations. With limited access to cash flow-based lending, small firms rely significantly on physical assets to obtain credit.

Low Profitability Firms. Similar to the case of small firms, firms with low profitability and low margins also have substantially lower shares of cash flow-based lending (higher shares of asset-based lending), and lower prevalence of EBCs. Among low margin firms (profit margin in the bottom half of all Compustat firms), the median shares of cash flow-based lending and asset-based lending are 41% and 39% respectively, while among high margin firms the median shares are 74% and 19% respectively.

Airlines and Utilities. Figures 2.4 shows corporate borrowing in different industries, focusing on rated firms so that firms in different industry groups are comparable in size and capital market access. Most industries display similar patterns, with the exception of airlines and utilities. In these two industries, even rated firms have a significant share of asset-based lending and a relatively small share of cash flow-based lending. The prevalence of EBCs is also lower. Airlines and utilities are special cases where firms have a large amount of standardized transferable assets (aircraft and power generators) that facilitate asset-based lending.

Cross-Country Variations

Across countries, lending practices may vary given different legal infrastructure (La Porta, Lopez-de Silanes, Shleifer and Vishny, 1997, 1998). In most developing countries, high quality accounting information can be a major hurdle. Among developed countries, differences

[24]For instance, the median EBITDA to asset ratio among small Compustat firms is -0.01 (while that among large Compustat firms is 0.13).

in accounting quality still exist but may not be large enough (especially among established firms) to account for most of the variations. Differences in laws and practices regarding financial distress seem more important. In the US, the tenet of Chapter 11 is to prevent liquidations and preserve cash flow value from continuing operations (i.e. "going-concern value").[25] In Chapter 11, creditors' payoffs are determined by the cash flow value of the firm, distributed according to priority (Gilson, Hotchkiss and Ruback, 2000; Gilson, 2010). Chapter 11 also has multiple provisions to facilitate the process (e.g. automatic stay, debtor-in-possession, DIP financing[26]), which together make cash flow value central to creditors and attenuate the role of physical collateral. In continental Europe, liquidations are more common and bankruptcy procedures give more power to secured creditors (Djankov, Hart, McLiesh and Shleifer, 2008; Smith and Stromberg, 2004).[27]

In major developed countries, legal infrastructure and lending practices in Japan traditionally lie at the other end of the spectrum from the US. Prior to 2000, bankruptcy courts in Japan were largely dysfunctional, due to limited court capacity and provisions that discouraged companies from filing for bankruptcy protection. Without court supervision, it is harder to contract on cash flow value and enforce corresponding payouts. In addition, there are no stays that prevent creditors from seizing collateral and disrupting efforts for reorganization. Thus, physical collateral that can be seized tends to be central. It is well known that corporate lending in Japan historically focused on hard assets, and real estate is especially popular (Gan, 2007; Peek and Rosengren, 2000; Tan, 2004). Rajan and Zingales (1995) also find that tangible assets have a significantly higher impact on firm leverage in Japan compared to other G-7 countries. In Sections 2.3 and 2.4, we contrast our findings

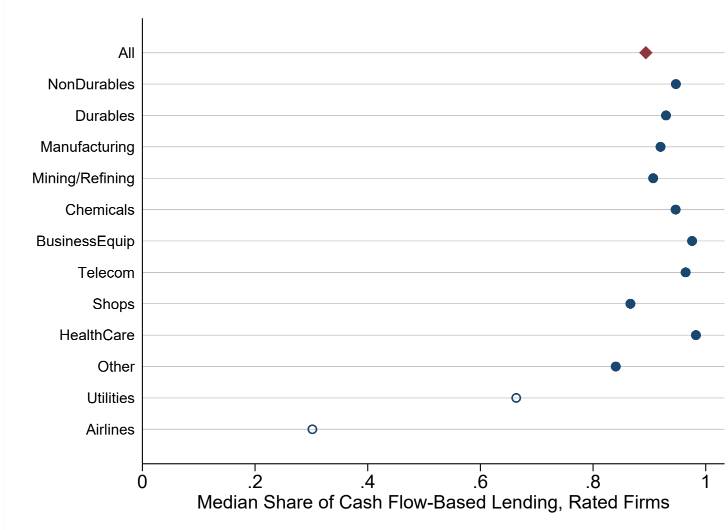
[25] Bernstein, Colonnelli and Iverson (2017) provide detailed empirical evidence that the Chapter 11 restructuring procedure prevents loss of value relative to the Chapter 7 liquidation procedure.

[26] The automatic stay prevents creditors from seizing collateral and other debt collection activities after bankruptcy filing. Chapter 11 allows existing management teams to stay (debtor-in-possession) to increase incentives for firms to file and conduct timely restructuring. Firms can also obtain additional high priority debt (DIP financing) to support continued operations and ameliorate debt overhang problems.

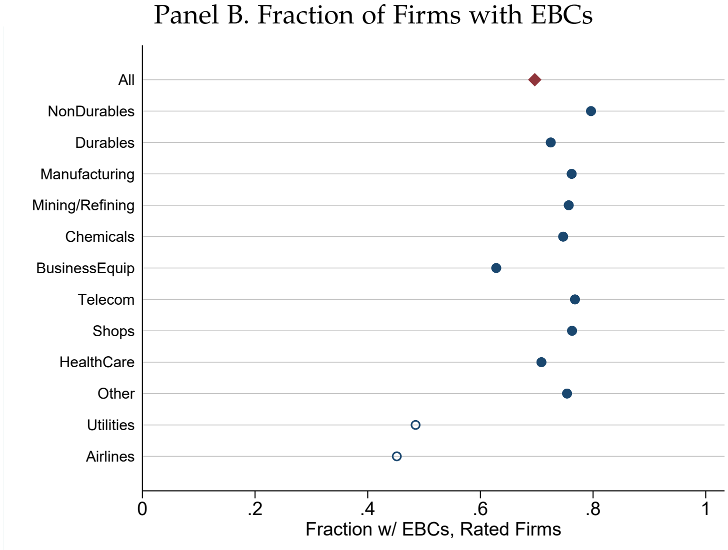
[27] In the US, the share of unsecured corporate debt, as one indicator for the prevalence of cash flow-based lending, is fairly high, at around 50%. The figure is about 30% in the UK. It is less than 20% for Germany, France, and EU average, and similarly low for Japan.

in the US with results in Japan, which further illustrates the impact of different forms of corporate borrowing constraints.

Panel A. Median Share of Cash Flow-Based Lending



Panel B. Fraction of Firms with EBCs



Note: This figure shows the prevalence of cash flow-based lending and EBCs across major industry groups. We focus on rated firms to make firm size and capital market access more comparable across industries. The industry groups are Fama-French 12 industries plus airlines (two digit SIC is 45). Panel A shows the median share of cash flow-based lending in all rated firms and in rated firms of each industry group. Panel B shows the fraction of firms with earnings-based covenants in each group.

Figure 2.4: *Prevalence of Cash Flow-Based Lending and EBCs: Rated Firms by Industry*

2.2.4 Implications

In the above, we document key features of corporate borrowing based on debt contracts. The findings highlight the prevalence of cash flow-based lending and EBCs among US large non-financial firms. In the following, we further examine how such practices shape the way financial variables affect borrowing constraints and firm outcomes on the margin. In Section 2.3, we study how they affect the role of cash flows in corporate borrowing and investment. In Section 2.4, we study the mirror image: how they affect the sensitivity of corporate borrowing and investment to the value of physical assets, specifically real estate, and implications for the transmission of shocks in the Great Recession. The results attest to the contract-level features. With the prevalence of cash flow-based lending, cash flows in the form of operating earnings can have an important impact on borrowing constraints and firm outcomes, while the value of physical assets has a mild influence. Taken together, major US non-financial firms do face borrowing constraints, but the primary constraint can take a different form.

2.3 Cash Flows, Corporate Borrowing, and Investment

In this section, we study how cash flow-based lending and EBCs shape the way cash flows affect corporate borrowing and investment on the margin.

In the presence of EBCs, cash flow in the form of operating earnings (EBITDA) can directly relax borrowing constraints, and enable firms to both borrow and invest more, as further discussed in Section 2.3.1. We document this mechanism using both traditional investment regression specifications as well as an accounting natural experiment that generates exogenous shocks to EBITDA. This mechanism is not present among firms not bound by EBCs, such as unconstrained firms and various firm groups with low presence of cash flow-based lending (e.g. small firms, low margin firms, airlines and utilities, Japan firms).[28]

[28]As a concrete example, US non-financial firms routinely discuss their primary financing constraints in

By studying borrowing constraints, our observation also suggests a new channel for the widely studied issue of investment sensitivity to cash flows (Fazzari, Hubbard and Petersen, 1988; Froot, Scharfstein and Stein, 1993; Kaplan and Zingales, 1997; Blanchard, Lopez-de Silanes and Shleifer, 1994; Rauh, 2006). In the traditional corporate finance framework, the main function of cash flows is to increase internal funds. Following the pecking order idea (Myers and Majluf, 1984), higher internal funds help firms invest more, while *substituting out* external financing as long as investment has diminishing marginal returns. With EBCs, cash flows in the form of operating earnings (EBITDA) also facilitate investment by *crowding in* external borrowing. Meanwhile, holding EBITDA fixed, higher cash receipts boost internal funds but do not relax EBCs, and are associated with higher investment but reductions in borrowing as the conventional pecking order framework would predict.

2.3.1 Mechanisms

We first provide a simple framework to illustrate the potential channels through which cash flows can affect firms' borrowing constraints and outcomes, in the case with cash flow-based lending and EBCs. The framework is adapted from Froot, Scharfstein and Stein (1993) and Kaplan and Zingales (1997). Consider a firm that makes investment decisions I and maximizes profits. The investment payoff is $F(I)$, with $F' > 0$ and $F'' \leq 0$. Investment can be financed with internal funds w or external borrowing b. The discount rate on investment is 1 for simplicity.

External borrowing incurs additional costs, due to frictions in capital markets. With EBCs a key feature is that a firm's capacity and effective costs of borrowing depends on cash flows in the form of EBITDA, denoted by π. We can summarize the additional costs of borrowing as a function b and π: $C(b, \pi)$. We assume $C_{b\pi}(b, \pi) \leq 0, \forall b, \pi$, which means

annual reports. These discussions indicate that major US non-financial firms still face borrowing constraints, but the primary constraint could be different from the commonly studied collateral constraint and instead focus on earnings. For instance, in its 2012 report, Coty Inc (one of the largest global beauty product producers) writes: *"We remain dependent upon others for our financing needs, and our debt agreements contain restrictive covenants...[F]inancial covenants may restrict our current and future operations and limit our flexibility and ability to respond to changes or take certain actions...Financial covenants...require us to maintain, at the end of each fiscal quarter, a consolidated leverage ratio of consolidated total debt to consolidated EBITDA."*

that an increase in EBITDA decreases the marginal cost of borrowing for any given level of b. One specific form of $C(b,\pi)$ corresponding to earnings-based covenant $b \leq \theta\pi$ is $C(b,\pi) = 0$ when $b \leq \theta\pi$ and $C(b,\pi) = +\infty$ when $b > \theta\pi$. We use a more general specification of C to capture that the costs of external borrowing could increase as the firm approaches the constraint.[29]

The firm's optimization problem is

$$(I^*, b^*) = \arg\max_{I,b\geq 0} F(I) - C(b;\pi) - I \quad (2.3)$$
$$s.t.\ I = w + b.$$

In this case, we get two predictions about the influence of cash flow variables on corporate borrowing and investment.

Proposition 4. *Suppose $F'(w) > C_b(0,\pi)$, that is, the optimal external borrowing $b^* > 0$ (an internal solution).*

Prediction 1: *All else equal, EBITDA relaxes EBCs and crowds in borrowing and investment.*

For a given amount of internal funds w, borrowing and investment are weakly increasing in EBITDA $\frac{\partial b^*}{\partial \pi}|_w \geq 0$ and $\frac{\partial I^*}{\partial \pi}|_w \geq 0$.

Prediction 2: *Holding EBITDA constant, higher internal funds crowd in investment but substitute out borrowing.*

For a given amount of EBITDA π, investment is strictly increasing in internal funds $\frac{\partial I^*}{\partial w}|_\pi > 0$, but borrowing is weakly decreasing in internal funds: $\frac{\partial b^*}{\partial w}|_\pi \leq 0$ (the inequality holds strictly if the production function F is strictly concave).

In the presence of EBCs, all else equal, an increase in EBITDA π relaxes borrowing constraints and decreases the effective costs of borrowing. Thus this type of cash flows helps *crowd in* corporate borrowing. Meanwhile, holding EBITDA constant, higher internal

[29] For example, in a dynamic setting, even if EBCs do not bind in the current period, more borrowing may increase the probability of violating EBCs in the next period, which adds to the effective cost of external borrowing C.

funds substitutes out borrowing.[30] This substitution between internal funds and external financing holds in the pecking order framework (Myers and Majluf, 1984; Froot, Scharfstein and Stein, 1993; Kaplan and Zingales, 1997).[31] Without controlling for internal funds, the total impact of an increase in EBITDA π would have two components: the effect on external borrowing and the effect on internal funds:

$$\frac{db^*}{d\pi} = \underbrace{\frac{\partial b^*}{\partial \pi}}_{+} + \underbrace{\frac{\partial b^*}{\partial w}}_{-} \frac{\partial w}{\partial \pi} \quad \text{and} \quad \frac{dI^*}{d\pi} = \underbrace{\frac{\partial I^*}{\partial \pi}}_{+} + \underbrace{\frac{\partial I^*}{\partial w}}_{+} \frac{\partial w}{\partial \pi}. \tag{2.4}$$

To the extent that π and w are positively correlated, the two effects work in different directions for borrowing, and work in the same direction for investment.[32]

In the above, we use a simple one-period setting for illustration. In a multi-period setting, we can specify b in Equation (2.3) as net debt issuance in a particular period. We can then write the cost of external borrowing as $C\left(b + b^{old}, \pi\right)$, where b^{old} is the firm's existing debt, b is (net) debt issuance, and $b + b^{old}$ is total debt. Then the results in Proposition 4 apply to b conditioning on b^{old}. In the empirical tests below, we thus focus on outcome variables in flows (i.e. debt issuance and investment, always controlling for lagged debt in levels b^{old}),

[30]EBITDA and net cash receipts can be different for several reasons, which we discuss in detail in Section 2.3.2 and Appendix B.4.

[31]In the corporate finance literature on investment cash flow sensitivity, the traditional framework (Froot, Scharfstein and Stein, 1993) specifies the cost of external financing as $C(b)$, a convex function of the amount of borrowing. For a given amount of borrowing, financial variables, e.g. cash flows and physical collateral, do not have an independent impact on C. In this case, the role of cash flows is to increase internal funds (but do not relax borrowing constraints). Accordingly, they boost investment but *decrease* external borrowing. As the firm expands investment using cheaper internal funds, the marginal product of investment drops as long as $F(I)$ is concave, and the firm would reduce costly external financing so the marginal cost of investment decreases accordingly. Here controlling for internal funds, EBITDA does not have an independent role. Without controlling for internal funds, EBITDA would be negatively correlated with borrowing.

[32]In the macro-finance literature that focuses on the general equilibrium feedback between firms' borrowing capacity and economic output (Kiyotaki and Moore, 1997; Bernanke, Gertler and Gilchrist, 1999), models link a firm's borrowing capacity directly to the liquidation value of physical assets. In this case, the cost of external borrowing does not depend on cash flows directly. It is possible that higher cash flows may increase borrowing indirectly as they increase firms' internal funds ("net worth"), allow firms to acquire more physical assets, and relax borrowing constraints. However, here all components of *internal funds* have the same positive impact on borrowing; EBITDA does not play an independent role after controlling for internal funds. In addition, this channel only applies to debt that is tied to physical collateral. We provide a more detailed discussion in Appendix B.3 about how financial variables affect corporate borrowing and investment in classic models including Kiyotaki and Moore (1997), Bernanke, Gertler and Gilchrist (1999) and Holmstrom and Tirole (1997) and Tirole (2006).

which also lines up most closely with prior research.

In the rest of this section, we empirically investigate how cash flows in the form of operating earnings affect firms' borrowing and investment on the margin. We focus on the borrowing constraint channel, and differentiate it from the internal funds channel.

2.3.2 Baseline Test

We begin with standard OLS regressions, following the traditional investment regression specifications since Fazzari, Hubbard and Petersen (1988). We explain the set-up, lay out the findings, and address possible concerns. In Section 2.3.3, we further study exogenous variations in operating earnings due to an accounting natural experiment.

Empirical Specification

The baseline test follows standard investment regressions (Fazzari, Hubbard and Petersen, 1988; Hoshi, Kashyap and Scharfstein, 1991; Kaplan and Zingales, 1997), and performs annual regressions:

$$\begin{aligned} Y_{it} &= \alpha_i + \eta_t + \lambda \text{EBITDA}_{it} + X_{it}'\zeta + \epsilon_{it} \\ Y_{it} &= \alpha_i + \eta_t + \beta \text{EBITDA}_{it} + \kappa \text{OCF}_{it} + X_{it}'\gamma + \epsilon_{it} \end{aligned} \tag{2.5}$$

We make several modifications to the traditional set-up, as we explain below.

Outcome variables. For the outcome variables, prior research typically focuses on investment. We start instead with borrowing, which is key to understanding the mechanisms; we then proceed to the impact on investment activities. The main debt issuance variable we use is net long-term debt issuance from the statement of cash flows, defined as issuance minus reduction of long-term debt (Compustat item DLTIS - DLTR), normalized by lagged assets. We focus on long-term debt because it is most closely tied to investment activities. We also present results for several other debt issuance variables, including changes in total book debt, and changes in both secured debt and unsecured debt (using additional data from CapitalIQ). Since EBCs apply at the firm level, all types of debt may be affected. For investment activities, we examine capital expenditures (spending on plant, property, and equipment) as well as R&D spending, normalized by lagged assets.

Independent variables. The main independent variable of interest is operating earnings (EBITDA), which directly affect EBCs. We use the Compustat variable EBITDA,[33] normalized by lagged assets. We start with the first line in Equation (2.5), which includes EBITDA and controls. This specification mimics traditional investment regressions which have one central cash flow variable, usually measured using earnings (e.g. income before extraordinary items plus depreciation and amortization or EBITDA). Here the EBITDA coefficient λ picks up both the impact through relaxing EBCs, and the impact through increasing cash receipts/internal funds.

To isolate the impact of EBITDA through borrowing constraints, we then control for measures of internal funds. We control for net cash receipts OCF, measured using Compustat variable OANCF (adding back interest expenses XINT to prevent mechanical correlation with debt issuance) normalized by lagged assets. Net cash receipts OCF captures the actual amount of cash a firm gets from its operations (it does not include cash receipts/outlays due to financing or investment activities). For a firm over time, EBITDA and OCF are about 0.6 correlated. These two variables are different for several reasons. First, there are timing differences between earnings recognition (when goods/services are provided to customers) and cash payments (which can be before, during, or after earnings recognition). Second, OCF includes net cash receipts due to non-operating income, special items, and taxes, which may not count towards EBITDA. Third, accounting rules may stipulate additional exclusions or inclusions to earnings. Appendix B.4 provides a detailed discussion of the definitions of EBITDA and OCF and their relationships. We also control for cash holdings (Compustat CHE, which includes holdings of cash and short-term/liquid financial securities, normalized by assets) at the beginning of period t.

Other control variables include average Q (market value over book value of assets,

[33]The Compustat EBITDA variable is defined as sales minus operating expenses (Cost of Goods Sold plus Selling, General & Administrative Expense). The specific definitions of EBITDA may vary slightly in different debt contracts, but share the core component captured by the Compustat variable.

Compustat DLC + DLTT + stock price times shares outstanding from CRSP over Compustat AT) and past 12 months stock returns that some work found to be a useful empirical proxy for Q (Barro, 1990; Lamont, 2000). We also control book leverage (total debt over assets) and other balance sheet characteristics (e.g. tangible assets such as book PPE and inventory), measured at the beginning of period t. Finally, we control for size (log assets) and lagged EBITDA to focus on the impact of current EBITDA. We use firm fixed effects and year fixed effects in our baseline specifications. Internet Appendix Table IA1Debt Issuance and Investment Activities:
Industry-Year Fixed Effectstable.caption.2 shows specifications with industry-year fixed effects. Table IA2Debt Issuance and Investment Activities:
Lagged Dependent Variable Specificationtable.caption.3 shows specifications using lagged dependent variables instead of firm fixed effects. The results are similar.

As discussed at the end of Section 2.3.1, we focus on outcome variables in flows (i.e. debt issuance and investment), which lines up most closely with prior research. In particular, as we always control for lagged debt b^{old} (i.e. lagged leverage: lagged debt b^{old} normalized by lagged assets which is the common denominator in regression (2.5)), using debt issuance b on the left-hand side is equivalent to using total debt $b + b^{old}$, in terms of coefficients on the independent variables (except the coefficient on b^{old} changes by one).

Samples. We start with firms where EBCs are most relevant. We first examine large firms with earnings-based covenants, which provide a clear indication of the presence of such constraints. We use covenant information from DealScan and FISD, as described in Section 2.2.2. Table 2.2 Panel A provides summary statistics of these firms. They have high earnings, with a median EBITDA to assets ratio of 0.13, and primarily use cash flow-based lending (median is 88%). They also have a reasonable amount of debt, so the constraint becomes relevant: the median debt to EBITDA ratio is 2.2 (typical constraint is maximum debt to EBITDA around 3 or 4), and the median debt to assets ratio is 0.3.

We then examine several firm groups where EBCs are less relevant. Their summary statistics are presented in Table 2.2 Panel B. First, we analyze large firms without earnings-based covenants. These firms use cash flow-based lending (median share is 88%), but have a low level of debt and are far from the constraint. Second, we analyze a number of firm groups that rely on asset-based lending, where cash flow variables are not key determinants of borrowing constraints. As explained in 2.2.3, several distinct factors affect the prevalence of asset-based versus cash flow-based lending, including size, profitability, asset attributes, and legal environments. Correspondingly, we study small firms, low margin firms, airlines and utilities, and Japanese firms later in Section 2.3.4, where asset-based lending dominates.

The positive sensitivity of corporate borrowing and investment to EBITDA is absent in all these cases where EBCs are not prevalent. Although the comparison firms are not assigned *randomly*, EBCs are less relevant to them for distinct reasons analyzed in Section 2.2.3, which are not tied to a systematic omitted variable bias story. Table 2.2 Panel B shows these firm groups display rich heterogeneity in terms of size, profitability, leverage, asset composition, etc. As we discuss in more detail in Section 2.3.2, it appears hard to account for the different impact of EBITDA across all these comparison groups based on common alternative explanations. We also do not find significant results among these firms in the accounting natural experiment in Section 2.3.3.

Our main sample covers 1996 to 2015, since data on financial covenants were sparse prior to 1996. We can also examine comparisons of firm groups (e.g. large vs. small firms, high vs. low profitability firms, airlines and utilities) using a longer sample since 1985 (when statement of cash flow variables became systematically available in Compustat), which we show in Internet Appendix Section IA3.1Response of Debt Issuance and Investment to EBITDAsubsection.3.1.

Results

Table 2.3 reports the results of the baseline regressions for large firms with EBCs.

Debt Issuance

Table 2.3 Panel A presents results on debt issuance. Columns (1) and (2) look at our main debt issuance measure, net long-term debt issuance (from the statement of cash flows).

Column (1) follows the first line of Equation (2.5) and includes EBITDA alone. In this case, for a one dollar increase in EBITDA, net long-term debt issuance increases by 21 cents on average. As Section 2.3.1 Equation (2.4) suggests, the EBITDA coefficient here captures two components: EBITDA's impact through relaxing EBCs and EBITDA's correlation with changes in internal funds ($\frac{db^*}{d\pi} = \frac{\partial b^*}{\partial \pi} + \frac{\partial b^*}{\partial w}\frac{\partial w}{\partial \pi}$). To the extent that higher internal funds may substitute out external borrowing ($\frac{\partial b^*}{\partial w} < 0$), the coefficient in Column (1) would *understate* EBITDA's impact through relaxing EBCs. In Column (2), we control for net cash receipts OCF. In this case, for a one dollar increase in EBITDA, net long-term debt issuance increases by 27 cents on average.

The magnitude of this effect is large. As a comparison, for instance, Chaney, Sraer and Thesmar (2012) find that for a one dollar increase in firms' property value, net long-term debt issuance increases by about 4 cents. The sensitivity of 27 cents on a dollar is still lower than a typical maximum debt-to-earnings constraint of around 4, as most firms are not exactly at the constraint. As discussed in Section 2.3.1, in such cases the sensitivity of debt issuance to earnings would be less than what is specified by the constraint.

Results on the impact of EBITDA are similar using other measures of debt issuance. The response to EBITDA is 41 cents when the outcome variable is changes in book debt, holding constant OCF. Columns (5) to (8) show that secured debt and unsecured debt both respond: issuance of secured debt increases by 13 cents for a one dollar increase in EBITDA, and that of unsecured debt increases by 23 cents (the sample here is restricted to firms with data from CapitalIQ). The magnitudes of these two coefficients are roughly proportional to the share of secured to unsecured debt among this sample (40% secured and 60% unsecured for the median firm). The results suggest that EBITDA, by relaxing firm-level EBCs, expands the capacity for all types of debt.

Holding EBITDA constant, we find that firms with higher net cash receipts OCF borrow less: when OCF is higher by one dollar, net long-term debt issuance on average decreases by 11 cents. Other measures of debt issuance also show reductions in borrowing. The results suggest that holding fixed the tightness of EBCs, more internal funds do substitute out external borrowing on average.[34] The evidence is consistent with findings by Rauh (2006), who studies a shock (due to mandatory contributions to employee pension plans) that affects a firm's cash positions but does not affect its earnings. He finds that firms with higher cash positions (lower mandatory pension contributions) have lower net debt issuance.

Investment Activities

Table 2.3 Panel B turns to investment activities. In column (1), without controlling for OCF, a one dollar increase in EBITDA is on average associated with a 13 cents increase in capital expenditures. The magnitude is consistent with findings in recent studies (Baker, Stein and Wurgler, 2003; Rauh, 2006), which usually measures cash flows using earnings (most commonly net income or income before extraordinary items plus depreciation and amortization). Again, following Section 2.3.1 Equation (2.4), the EBITDA coefficient has two components: EBITDA's impact through relaxing EBCs and EBITDA's correlation with changes in internal funds ($\frac{dI^*}{d\pi} = \frac{\partial I^*}{\partial \pi} + \frac{\partial I^*}{\partial w}\frac{\partial w}{\partial \pi}$). We decompose these two pieces in column (2) by controlling for OCF. We find a coefficient on EBITDA of 10 cents on average, while the coefficient on OCF is about 5 cents on average.[35] Among firms bound by EBCs, the effect of the borrowing constraint channel appears as important as, if not economically larger, than the internal funds channel.

In addition to traditional capital expenditures, we also examine the impact on R&D spending. We find a positive correlation between EBITDA and R&D expenditures. R&D expenses, unlike CAPX, are required to be included in operating expenses, which would produce a negative link between R&D and EBITDA. Despite this negative link, in this

[34]Given accounting practices, net cash receipts from operations (OCF) are affected by inventory purchases: all else equal, a firm that buys more inventory has a lower OCF. It is possible that such a firm also needs to borrow more, which may lead to a negative relationship between OCF and debt issuance. In Internet Appendix Table IA4Debt Issuance and Investment Activities:
Controlling for Inventory Purchasetable.caption.5, we present results controlling for inventory purchase, which show similar findings.

[35]The coefficients represent the magnitude of the average response, not necessarily that of the conditional response. For example, suppose the constraints are binding 10% of the time and firms are unconstrained 90% of the time (where investment is close to first best). Then in the 10% constrained cases, the response to EBITDA and OCF would be ten times the size of the average response.

sample of firms bound by EBCs, increases in EBITDA can crowd in R&D spending (and these expenditures do not fully offset the initial increase in EBITDA). This pattern is unique to firms with EBCs.[36]

Firm Groups with Low Prevalence of EBCs

In Table 2.4, we study four groups of firms where EBCs should be less relevant, as explained in Section 2.3.2: 1) large firms w/o EBCs, which use cash flow-based lending but are far from the constraints; 2) small firms, where cash flow-based lending and EBCs are less prevalent; 3) low margin firms, where cash flow-based lending and EBCs are similarly less prevalent; 4) airlines and utilities, which utilize asset-based lending given their asset attributes and have a lower prevalence of EBCs. We also examine Japan firms in Section 2.3.4.

Across all these comparison groups, EBITDA does not have a significant impact on debt issuance. For all groups, the coefficient on EBITDA is *negative and significant* without controlling for net cash receipts OCF. This contrasts sharply with the results among firms bound by EBCs shown in Table 2.3. After controlling for OCF, the EBITDA coefficient is about zero. EBITDA also does not have an independent positive impact on capital expenditures once we control for OCF.

Among these firms, the impact of OCF is overall similar to that among firms with EBCs. OCF substitutes out borrowing in all cases. It has a positive impact on investment, which is more pronounced among capital intensive firms (e.g. airlines and utilities) and weaker among capital light firms (e.g. small firms).

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[36]We also analyze the response of cash holdings and other outcomes. Controlling for OCF, cash holdings on average increase by about 1 cent for a one dollar increase in EBITDA; they increase by 40 cents for a one dollar increase in OCF. Thus most of the association between EBITDA and cash holdings documented by Almeida, Campello and Weisbach (2004) comes from the correlation between EBITDA and net cash receipts, not from EBITDA's role in relaxing borrowing constraints. A one dollar increase in EBITDA is also on average associated with a 4 cents increase in payout and a 15 cents increase in acquisitions.

Table 2.2: *Summary Statistics of US Non-Financial Firms*

Summary statistics of non-financial firm samples. Panel A shows statistics for large firms with EBCs. Large firms are those with size (assets) above Compustat median, and EBCs are based on DealScan and FISD data. Mean, median, standard deviation, and selected percentiles are presented. Panel B shows statistics for several firm groups that are not bound by EBCs, including large firms without earnings-based covenants (primarily use cash flow-based lending but are far from constraints), as well as small firms, low margin firms, and airlines and utilities that rely more on asset-based lending. Medians are presented for each group. EBITDA is earnings before interest, taxes, and depreciation. OCF is net cash receipts from operations. MTB is market equity to book equity. Q is calculated as the sum of market value of equity and book value of debt, divided by book assets. EDF is expected default frequency. AR stands for accounts receivable, PPE is the book value of property, plant, and equipment, CAPX is capital expenditures (spending on property, plant, and equipment). As is customary, flow variables are normalized by lagged assets and stock variables are normalized by contemporaneous assets throughout the paper. CFL share is median share of cash flow-based lending in each firm group. The sample period is 1996 to 2015 because comprehensive data on financial covenants from DealScan began in 1996.

Panel A. Large Firms w/ EBCs

Variable	p25	p50	p75	mean	s.d.	N
Log assets	6.36	7.16	8.15	7.33	1.33	17,458
Log market cap	5.94	6.91	7.95	6.95	1.57	17,458
EBITDA	68.39	172.15	464.44	611.98	2110.27	17,458
EBITDA/l.assets	0.09	0.13	0.19	0.14	0.09	17,458
EBITDA/sales	0.08	0.14	0.21	0.14	0.52	17,458
Debt/EBITDA	1.03	2.18	3.80	2.70	3.49	17,458
Debt/assets	0.17	0.29	0.43	0.31	0.22	17,458
EDF	0.00	0.00	0.07	0.13	0.26	17,458
Q	0.79	1.06	1.54	1.30	0.87	17,458
MTB	1.13	1.86	3.00	2.44	2.89	17,150
OCF/l.assets	0.08	0.12	0.16	0.12	0.08	17,445
Cash/assets	0.02	0.05	0.12	0.09	0.10	17,458
PPE/assets	0.13	0.26	0.48	0.32	0.24	17,458
Inventory/assets	0.01	0.08	0.18	0.12	0.12	17,458
AR/assets	0.07	0.12	0.20	0.15	0.11	17,458
Intangible/assets	0.05	0.16	0.34	0.22	0.20	17,458
Net LT debt issuance/l.assets	-0.02	0.00	0.05	0.03	0.15	16,186
CAPX/l.assets	0.02	0.04	0.07	0.06	0.07	17,371
R&D/l.assets	0.00	0.01	0.04	0.03	0.05	8,826
CFL share	0.46	0.88	0.99	0.69	0.36	10,855

Panel B. Other Firm Groups

	Large w/o EBCs		Small		Low Margin		Air & Utilities	
Variable	p50	N	p50	N	p50	N	p50	N
Log assets	6.85	11,382	4.09	22,336	5.08	25,676	7.98	2,584
Log market cap	7.05	11,382	4.08	22,336	4.88	25,676	7.18	2,584
EBITDA	119.58	11,382	2.19	22,336	5.37	25,676	282.15	2,584
EBITDA/l.assets	0.12	11,382	0.06	22,336	0.06	25,676	0.10	2,584
EBITDA/sales	0.14	11,382	0.04	22,336	0.03	25,676	0.21	2,584
Debt/EBITDA	0.99	11,382	0.00	22,336	0.48	25,676	3.61	2,584
Debt/assets	0.18	11,382	0.07	22,336	0.18	25,676	0.36	2,584
EDF	0.00	11,382	0.01	22,336	0.02	25,676	0.00	2,584
Q	1.25	11,382	1.23	22,336	0.99	25,676	0.86	2,584
MTB	2.07	11,382	1.78	22,336	1.55	25,676	1.63	2,584
OCF/l.assets	0.11	11,377	0.05	22,289	0.06	25,631	0.10	2,580
Cash/assets	0.13	11,382	0.19	22,336	0.12	25,676	0.02	2,584
PPE/assets	0.21	11,382	0.13	22,336	0.17	25,676	0.63	2,584
Inventory/assets	0.06	11,382	0.08	22,336	0.07	25,676	0.02	2,584
AR/assets	0.11	11,382	0.15	22,336	0.13	25,676	0.06	2,584
Intangible/assets	0.08	11,382	0.04	22,336	0.07	25,676	0.02	2,584
Net LT debt issuance/l.assets	0.00	10,778	0.00	21,166	0.00	24,151	0.00	2,518
CAPX/l.assets	0.04	11,309	0.03	22,150	0.03	25,488	0.07	2,569
R&D/l.assets	0.05	7,085	0.08	15,485	0.07	16,474	0.01	89
CFL share	0.88	5,277	0.00	8,634	0.47	12,256	0.66	1,531

Table 2.3: *Debt Issuance and Investment Activities: Large Firms w/ EBCs*

Firm-level annual regressions of debt issuance and investment activities:

$$Y_{it} = \alpha_i + \eta_t + \beta \text{EBITDA}_{it} + \kappa \text{OCF}_{it} + X_{it}'\gamma + \epsilon_{it}$$

In Panel A the outcome variable Y_{it} is net debt issuance. In Columns (1) and (2) Y_{it} is our main debt issuance measure: net debt issuance in year t from the statement of cash flows, calculated as issuance minus reduction of long-term debt (Compustat item DLTIS - DLTR), normalized by assets at the end of year $t-1$. In Columns (3) to (4) Y_{it} is changes in total book debt in year t. In Columns (5) to (8), Y_{it} is changes in both secured debt and unsecured debt, using data from CapitalIQ. In Panel B, the outcome variable Y_{it} is investment activities. In Columns (1) and (2), Y_{it} is capital expenditures (Compustat variable CAPX, which covers purchases of plant, property, and equipment) in year t, normalized by assets at the end of year $t-1$. In Columns (3) and (4), Y_{it} is R&D expenditures (Compustat variable XRD, only non-missing for a subset of firms). EBITDA$_{it}$ is earnings before interest, taxes, depreciation and amortization (Compustat item EBITDA) in year t, normalized by assets at the end of year $t-1$. OCF$_{it}$ is net cash receipts from operating activities (Compustat item OANCF + XINT) in year t. Control variables X_{it} include Q (market value of equity plus book value of debt normalized by book assets) as of the beginning of year t, stock returns in year $t-1$, as well as cash holdings, book leverage (debt/assets), book PPE (plan, property, equipment), intangible assets, margin, size (log assets) at the end of $t-1$. We also control for net operating assets at the end of year $t-1$ as a proxy for accounting quality (Hirshleifer, Hou, Teoh and Zhang, 2004), and lagged EBITDA to focus on the impact of current EBITDA. Firm fixed effects and year fixed effects are included (R^2 does not include fixed effects). Sample period is 1996 to 2015. The sample is restricted to large US non-financial firms that have earnings-based covenants in year t. Standard errors are clustered by firm and time.

Panel A. Debt Issuance

	Net LT Debt Iss.		Δ Book Debt		Δ Unsec. Debt		Δ Secured Debt	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EBITDA	0.216***	0.273***	0.345***	0.412***	0.209***	0.232***	0.103***	0.125***
	(0.030)	(0.034)	(0.039)	(0.042)	(0.037)	(0.041)	(0.031)	(0.033)
OCF		-0.111***		-0.135***		-0.048		-0.045*
		(0.033)		(0.045)		(0.033)		(0.027)
Q	0.010**	0.011**	0.004	0.005	0.010**	0.011**	0.005	0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Past 12m stock ret	-0.003	-0.003	0.002	0.001	0.002	0.002	-0.008***	-0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
L.Cash holding	-0.033	-0.033	0.039	0.039	-0.117***	-0.117***	0.052	0.052
	(0.043)	(0.044)	(0.051)	(0.052)	(0.044)	(0.043)	(0.045)	(0.045)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs	15,642	15,642	15,576	15,576	11,693	11,693	11,678	11,678
R^2	0.114	0.116	0.152	0.154	0.069	0.069	0.030	0.030

Standard errors in parentheses, clustered by firm and time

Panel B. Investment Activities

	CAPX		R&D	
	(1)	(2)	(3)	(4)
EBITDA	0.129***	0.101***	0.031***	0.035***
	(0.017)	(0.019)	(0.012)	(0.013)
OCF		0.053***		-0.007
		(0.013)		(0.011)
Q	0.011***	0.011***	0.004***	0.004***
	(0.002)	(0.002)	(0.002)	(0.002)
Past 12m stock ret	0.004*	0.004*	-0.003***	-0.003***
	(0.002)	(0.002)	(0.001)	(0.001)
L.Cash holding	0.015	0.015	-0.005	-0.004
	(0.013)	(0.013)	(0.012)	(0.012)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Obs	16,907	16,907	8,588	8,586
R^2	0.156	0.160	0.108	0.108

Standard errors in parentheses, clustered by firm and time

Table 2.4: *Debt Issuance and Investment Activities: Firms w/ Low Prevalence of EBCs*

Firm-level annual panel regressions of debt issuance and investment activities on EBITDA:

$$Y_{it} = \alpha_i + \eta_t + \beta \text{EBITDA}_{it} + \kappa \text{OCF}_{it} + X'_{it}\gamma + \epsilon_{it}$$

The regressions are the same as those in Table 2.3. In Panel A, the outcome variable is net long-term debt issuance; in Panel B, the outcome variable is capital expenditures. Results are presented for several groups not bound by EBCs: large firms without earnings-based covenants, which use cash flow-based lending but have lower debt and are far from constraints; small firms, which have low prevalence of cash flow-based lending and EBCs; low margin firms, which have low prevalence of cash flow-based lending and EBCs; airlines and utilities, which have low prevalence of cash flow-based lending and EBCs. Sample period is 1996 to 2015. Standard errors are clustered by firm and time.

Panel A. Net LT Debt Issuance

	Large w/o EBCs		Small		Low Margin		Air & Utilities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EBITDA	-0.059***	0.023	-0.019***	0.001	-0.025***	-0.001	-0.093**	-0.059
	(0.021)	(0.027)	(0.007)	(0.009)	(0.008)	(0.010)	(0.045)	(0.061)
OCF		-0.127***		-0.033***		-0.039***		-0.050
		(0.027)		(0.011)		(0.010)		(0.079)
Q	0.007***	0.007***	0.004***	0.004***	0.007***	0.007***	0.042**	0.044**
	(0.003)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.018)	(0.019)
Past 12m stock ret	0.001	0.001	0.002	0.002	0.003	0.003	0.003	0.002
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.010)	(0.010)
L.Cash holding	-0.048**	-0.042*	-0.055***	-0.059***	-0.071***	-0.076***	-0.109**	-0.130**
	(0.024)	(0.024)	(0.016)	(0.017)	(0.019)	(0.020)	(0.055)	(0.063)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs	10,137	10,136	20,153	20,129	22,557	22,534	2,475	2,474
R^2	0.073	0.078	0.029	0.030	0.036	0.038	0.087	0.088

Standard errors in parentheses, clustered by firm and time

Panel B. CAPX Investment

	Large w/o EBCs		Small		Low Margin		Air & Utilities	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
EBITDA	0.053***	0.033*	0.001	-0.002	0.002	-0.004	0.079	0.025
	(0.012)	(0.019)	(0.004)	(0.004)	(0.005)	(0.004)	(0.049)	(0.046)
OCF		0.024**		0.005		0.011**		0.158***
		(0.011)		(0.004)		(0.005)		(0.038)
Q	0.004***	0.004***	0.006***	0.006***	0.006***	0.006***	0.029***	0.026***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.010)	(0.010)
Past 12m stock ret	0.006***	0.006***	0.004***	0.004***	0.004***	0.004***	0.007	0.006
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.006)
L.Cash holding	-0.019*	-0.019*	0.005	0.006	0.002	0.003	-0.018	-0.004
	(0.011)	(0.011)	(0.006)	(0.006)	(0.005)	(0.005)	(0.056)	(0.056)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs	10,683	10,681	21,249	21,222	24,045	24,020	2,535	2,534
R^2	0.107	0.108	0.043	0.043	0.046	0.047	0.122	0.144

Standard errors in parentheses, clustered by firm and time

Checks for Alternative Explanations

Results in the baseline regressions line up with predictions in Section 2.3.1. In the following, we discuss potential alternative explanations and provide empirical checks. These alternative explanations also cannot account for findings from a natural experiment we study in Section 2.3.3 due to changes in accounting rules.

Mismeasurement of Marginal Q

A central empirical issue in testing responses to cash flow variables is whether these variables are proxying for Q, due to mismeasurement of marginal Q. Specifically, firms may increase borrowing and investment because of good investment opportunities and high marginal Q. Measured Q, however, could be imprecise, and coefficients on EBITDA and other cash flow variables may be biased upward if these variables are positively correlated with marginal Q.

We do not find that mismeasurement of Q can easily account for our results. First, in Section 2.3.2, we show that the positive relationship between EBITDA and borrowing and investment does not exist among various groups of firms that are not bound by EBCs. For mismeasurement of Q to explain these findings, it needs to be that Q is less mismeasured or EBITDA is less informative across all these comparison groups, which does not appear to be the case in the data. In the Internet Appendix Section IA3.2Informativeness of EBITDA and Qsubsection.3.2, we perform detailed tests to study the informativeness of EBITDA and Q across all firm groups, including standard tests of accounting quality (e.g. net operating assets (Hirshleifer, Hou, Teoh and Zhang, 2004), accrual quality (Dechow and Dichev, 2002; Francis, LaFond, Olsson and Schipper, 2005), loss avoidance (Bhattacharya, Daouk and Welker, 2003), etc.), as well as predictive regressions of future earnings and cash receipts. As shown in Table IA8Predicting Future EBITDA and Net Cash Receiptstable.caption.9, we do not find evidence that EBITDA is less informative or Q is less mismeasured in comparison groups. If anything, in several comparison groups, we find the reverse: EBITDA appears *more informative* (e.g. more predictive of future profitability and cash receipts) and Q is *more mismeasured* (e.g. less predictive of future profitability and cash receipts). We also use the higher order cumulant estimators of Erickson, Jiang and Whited (2014). We still only find significant impact of EBITDA for firms bound by EBCs and not for the other firm groups (the magnitude of the coefficients is larger and varies with the parameters used).

Second, if EBITDA simply proxies for Q and corresponding demand for external financing, we may also expect to see impact on other types of financing activities. Thus we also study the response of net equity issuance to EBITDA. While net debt issuance increases significantly with EBITDA among firms with EBCs, we do not observe such a relationship for net equity issuance. Thus it does not appear that firms have a higher demand for external financing in general with an increase in EBITDA.

Collateral Value

We also check that the sensitivity of borrowing and investment to EBITDA is not driven by EBITDA being correlated with the value of physical collateral. In particular, we look at the issuance of unsecured debt, which is unlikely to be affected by the collateral channel. Previous research and our analysis in Appendix B.1 confirm that this type of borrowing does not respond to the value of physical assets. On the other hand, since EBCs restrict total debt of the firm, EBITDA can affect all types of debt (including unsecured debt). As we find in Table 2.3 Panel A, the issuance of unsecured debt responds significantly to EBITDA for firms bound by EBCs. We can also directly control for measures of collateral value, such as the value of real estate assets, which does not affect the coefficient on EBITDA, as shown in Internet Appendix Table IA5Debt Issuance and Investment Activities:
Controlling for Real Estate Collateral Valuetable.caption.6. We also examine the effect of property collateral value on corporate borrowing and investment in more detail in Section 2.4. In sum, the evidence suggests that EBITDA has an important impact on corporate borrowing that is separate from the collateral value channel.

Trade-Off Theory

One view of corporate financial structure is that firms choose the amount of debt by trading off the costs of having more debt against the benefits of debt. The costs of debt may include expected costs of insolvency, costs of debt overhang, etc. The benefits of debt may include tax advantage or mitigation of agency problems (e.g. debt requires firms to periodically pay out cash, which can restrict empire building).

With EBCs, violations of earnings-based covenants are an important source of the costs associated with a high level of debt. EBCs thus lead to a form of trade-off that is tied to the level of EBITDA. When a firm has higher EBITDA, it gets further away from violating earnings-based covenants, which lowers the effective costs of having more debt, as discussed in Section 2.3.1. EBITDA drives this this type of trade-off that originates from EBCs, which is part of our central mechanism.

One question is whether EBITDA may also be associated with other costs/benefits of debt, such as expected costs of insolvency/payment default, expected costs of general debt overhang problems, or benefits of committing to regularly pay out cash. First, these considerations apply to all firms. Relative to the various comparison groups, they are not uniquely relevant to firms bound by EBCs (if anything, airlines and utilities have a higher level of debt, and small firms and low margin firms have a higher likelihood of insolvency; trade-off considerations could be more significant for them). Second, we include net cash receipts, and we also examine the impact of non-operating/miscellaneous income in Internet Appendix Table IA6Debt Issuance and Investment Activities:
Impact of Non-Operating Incometable.caption.7. These other types of income can also reduce expected costs of insolvency or increase the benefits of cash payouts, although they do not relax EBCs. In the data, they do not have a significant positive impact on borrowing, but instead substitute out borrowing.

2.3.3 Exogenous Variations in Operating Earnings: An Accounting Natural Experiment

In this section, we supplement the tests above and further study the impact of EBITDA using a natural experiment due to an accounting rule change. The accounting rule modifies the calculation of earnings, and contributes to changes in EBITDA that are not related to changes in economic fundamentals or internal funds. As a result, it helps us further isolate the impact of EBITDA due to earnings-based borrowing constraints.

The accounting rule change we study is SFAS 123(r) issued by the Financial Accounting Standard Board (FASB) regarding the accounting of stock-based compensation. Before the adoption of this rule, firms' option compensation expenses do not formally count towards operating expenses, a component of operating earnings. Instead, firms make footnote disclosures at the end of their financial statements. The new rule requires firms to include option compensation expenses in operating expenses, thus they would affect operating earnings. As a result, the new rule can decrease EBITDA for firms that use option compensation, but does not have a direct impact on cash positions or company fundamentals.[37] A number of studies show that contracting frictions make it hard to neutralize changes in accounting rules, and they tend to have a significant impact on firms' financial and real decisions due to debt contracting and covenant restrictions (Brown and Lee, 2007; Frankel, Lee and McLaughlin, 2010; Moser, Newberry and Puckett, 2011; Cohen, Katz and Sadka, 2012; Shroff, 2017).[38] SFAS 123(r) is most relevant to our study, as it directly relates to the calculation of operating earnings. The rule is issued in December 2004; it becomes effective for public companies for accounting periods that began after June 15, 2005, and fiscal 2006 is the first fiscal year affected by the new rule.

We study the impact of the rule change in Table 2.5. We instrument EBITDA in 2006 (post-adoption) with the average option compensation expenses in the three years prior to

[37]SFAS 123(r) requires firms to record an expense when options are granted, based on its Black-Scholes value. It also requires firms to recognize an expense for previously granted options that vest after the adoption date of SFAS 123(r).

[38]There are two issues about EBITDA definitions in debt contracts that we need to examine. The first issue is whether covenants calculate EBITDA using fixed accounting methods ("fixed GAAP," in which case accounting changes do not affect covenant tightness), or latest accounting methods ("floating GAAP," in which case accounting changes do matter). Reviews of sample contracts show that "floating GAAP" is common (Moser, Newberry and Puckett, 2011; Shroff, 2017), given transaction costs for applying "fixed GAAP" (firms' official financial statements comply with latest accounting methods, thus to implement "fixed GAAP" the borrower needs to prepare an additional set of financial statements); thus the accounting rule change would directly affect constraint tightness. The second issue is certain debt contracts allow borrowers to exclude all expenses with no cash impact ("non-cash charges," such as depreciation, amortization, stock-based compensation, etc.) from the calculation of EBITDA, in which case SFAS 123(r) may not affect covenant tightness (since stock-based compensation is excluded). We read a set of publicly available debt contracts during this period, and do not find such exclusions to be very common.

the issuance of SFAS 123(r) in 2004, controlling for lags of EBITDA, lags of the dependent variable, as well as a set of firm characteristics (including the same controls as in Tables 2.3, book-to-market ratio, and longer lags of firm stock returns). We also control for sales and OCF given that the accounting rule change affects EBITDA through operating expenses, not sales or net cash receipts.

$$Y_i^{2006} = \alpha + \beta \widehat{\text{EBITDA}}_i^{2006} + X_i'\gamma + \epsilon_i \tag{2.6}$$

We study both net long-term debt issuance and capital expenditures as the outcome variable. We present results for large firms bound by EBCs, large firms without EBCs, and small firms.

Table 2.5 Panel A shows strong first-stage responses among all firms. Panel B shows the second stage: debt issuance and investment are significantly affected among firms with EBCs, but not among other firm groups.[39] The results are consistent with our findings above that, in the presence of EBCs, EBITDA has a key impact on firms' borrowing and investment by affecting the tightness of their borrowing constraints. In Table 2.5, the second stage coefficients on EBITDA among firms with EBCs are higher than the baseline results in Table 2.3. The estimates here are local average treatment effect (LATE), and it appears that firms which are most intensively treated (those that use a significant amount of option compensation) are more responsive. In addition, the accounting rule change induces a nearly permanent shock to earnings (the new rule permanently eliminates one way of compensating employees without booking an operating expense, while the average persistence of innovations in EBITDA in our baseline tests is about 0.3), which could make the effect size larger. In the Internet Appendix Section IA3.3Accounting Natural Experiment: Placebo Testssubsection.3.3, we perform placebo tests using other years, and verify that the

[39]The exclusion restriction here is the following: among firms bound by EBCs in particular, prior option compensation expenses do not affect subsequent borrowing and investment through channels other than EBCs. To account for our results using alternative explanations, it has to be that there are certain links between prior option compensation and subsequent changes in borrowing and investment which are *unique to firms bound by EBCs* but are not related to EBCs. We do not find a strong reason for such channels.

first-stage and reduced form results do not hold in these cases.[40]

2.3.4 Additional Discussion

Results above suggest that cash flows in the form of operating earnings have an important impact on firm borrowing constraints and outcomes when firms are bound by EBCs. We now discuss further applications of this observation.

Table 2.5: *Changes in EBITDA: Accounting Natural Experiment*

Cross-sectional instrumental variable regression

$$Y_i^{06} = \alpha + \beta \widehat{\text{EBITDA}}_i^{06} + X_i'\gamma + \epsilon_i$$

where EBITDA_i^{06} is EBITDA in fiscal year 2006 (normalized by beginning of year assets), and is instrumented with average option compensation expense (Compustat XINTOPT, normalized by assets) in fiscal years 2002 to 2004. Control variables include sales and OCF (which are not affected by the rule change), as well as three lags of the outcome variable, EBITDA, annual stock returns, and market to book ratio by 2004, as well as all the control variables in Table 2.3 as of 2004. Industry (Fama-French 12 industries) fixed effects are included; R^2 does not include fixed effects. Panel A presents the first stage. Panel B presents the IV results. In columns (1) to (3), Y is net long-term debt issuance in fiscal year 2006; in columns (4) and (6), Y is capital expenditures in fiscal year 2006. Results are presented separately for large firms with EBCs, large firms without EBCs, and small firms. Robust standard errors in parentheses.

Panel A. First Stage

	EBITDA_i^{06}		
	Large w/ EBCs	Large w/o EBCs	Small
Avg. option comp expense 02-04	-0.857***	-0.721***	-0.520**
	(0.212)	(0.134)	(0.208)
Obs	686	435	727

Standard errors in parentheses

Panel B. IV

	Net LT Debt Iss			CAPX		
	Large w/ EBCs	Large w/o EBCs	Small	Large w/ EBCs	Large w/o EBCs	Small
$\widehat{\text{EBITDA}}_i^{06}$	0.869**	-0.327	0.225	0.497**	0.014	0.002
	(0.451)	(0.344)	(0.366)	(0.225)	(0.169)	(0.136)
1st stage F	16.39	23.42	9.08	16.39	23.42	9.08
Obs	686	435	727	686	435	727

Standard errors in parentheses

[40] A special case is fiscal year 2005, which is after the rule issuance but before its implementation. In this year, we find some impact on debt issuance and a modestly significant impact on investment among firms bound by EBCs. This could result from preemptive adjustments smoothing out the impact of the new rule.

Table 2.6: *Debt Issuance and Investment Activities: Large vs. Small Firms*

Firm-level annual panel regressions of debt issuance and investment activities on EBITDA:

$$Y_{it} = \alpha_i + \eta_t + \beta \text{EBITDA}_{it} + \kappa \text{OCF}_{it} + X'_{it}\gamma + \epsilon_{it}$$

The outcome variable is net long-term debt issuance in Panel A, and capital expenditures in Panel B. Control variables are the same as those in Table 2.3. Regression results are presented separately for all large firms (assets above Compustat median) and all small firms. Firm fixed effects and year fixed effects are included (R^2 does not include fixed effects). Sample period is 1996 to 2015. Standard errors are clustered by firm and time.

Panel A. Net LT Debt Issuance

	Large Firm		Small Firm	
	(1)	(2)	(3)	(4)
EBITDA	0.092***	0.173***	-0.019***	0.001
	(0.020)	(0.023)	(0.007)	(0.009)
OCF		-0.141***		-0.033***
		(0.022)		(0.011)
Q	0.007***	0.007***	0.004***	0.004***
	(0.002)	(0.002)	(0.001)	(0.001)
Past 12m stock ret	0.001	0.000	0.002	0.002
	(0.003)	(0.003)	(0.002)	(0.002)
L.Cash holding	-0.027	-0.026	-0.055***	-0.059***
	(0.020)	(0.021)	(0.016)	(0.017)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Obs	26,165	26,164	20,153	20,129
R^2	0.076	0.080	0.029	0.030

Standard errors in parentheses, clustered by firm and time

Panel B. CAPX Investment

	Large Firm		Small Firm	
	(1)	(2)	(3)	(4)
EBITDA	0.099***	0.078***	0.001	-0.002
	(0.011)	(0.012)	(0.004)	(0.004)
OCF		0.038***		0.005
		(0.008)		(0.004)
Q	0.006***	0.006***	0.006***	0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Past 12m stock ret	0.005***	0.005***	0.004***	0.004***
	(0.002)	(0.002)	(0.001)	(0.001)
L.Cash holding	0.013*	0.014*	0.005	0.006
	(0.007)	(0.008)	(0.006)	(0.006)
Controls	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Obs	27,982	27,980	21,249	21,222
R^2	0.129	0.131	0.043	0.043

Standard errors in parentheses, clustered by firm and time

Table 2.7: *Firm Outcomes and EBITDA: US vs. Japan*

Comparison of the sensitivity to EBITDA in US and Japan. Panel A presents summary statistics of the US and Japan sample. The sample covers all large non-financial firms in US and Japan (asset above Compustat median in the respective country). Panel B presents firm-level annual regressions of debt issuance and investment activities on EBITDA:

$$Y_{it} = \alpha_i + \eta_t + \beta \text{EBITDA}_{it} + \kappa \text{OCF}_{it} + X'_{it}\gamma + \epsilon_{it}$$

The right hand side variables are the same as those in Table 2.3. The outcome variables Y_{it} include change in book debt and capital expenditures in year t, normalized by assets at the end of year $t-1$. Here we do not use net long-term debt issuance from the statement of cash flows because it is not available for Japan. Firm fixed effects and year fixed effects are included (R^2 does not include fixed effects). Sample period is 1996 to 2015. Standard errors are clustered by firm and time.

Panel A. Summary Statistics

	US					Japan				
Variables	p25	p50	p75	mean	N	p25	p50	p75	mean	N
Log assets	6.20	7.06	8.19	7.30	28,840	6.34	6.93	7.83	7.25	20,567
Log market cap	5.97	6.97	8.09	7.06	28,840	5.23	6.06	7.16	6.28	20,567
EBITDA	52.83	153.91	493.51	789.55	28,840	37.11	79.89	216.46	357.67	20,567
EBITDA/l.assets	0.08	0.13	0.19	0.13	28,840	0.05	0.08	0.11	0.08	20,567
EBITDA/sales	0.08	0.14	0.22	0.06	28,840	0.04	0.08	0.12	0.09	20,567
Debt/EBITDA	0.47	1.78	3.53	2.10	28,840	0.74	2.51	5.49	4.40	20,567
Debt/assets	0.10	0.26	0.39	0.27	28,840	0.07	0.20	0.35	0.23	20,567
Q'	0.80	1.12	1.70	1.46	28,840	0.50	0.66	0.85	0.74	20,567
MTB	1.20	1.94	3.18	2.62	28,840	0.66	0.97	1.45	1.21	20,567
OCF/l.assets	0.07	0.12	0.16	0.12	28,822	0.03	0.06	0.09	0.06	20,491
Cash/assets	0.02	0.07	0.19	0.14	28,840	0.07	0.12	0.19	0.14	20,567
PPE/assets	0.11	0.24	0.46	0.31	28,840	0.20	0.30	0.41	0.32	20,567
Inventory/assets	0.01	0.07	0.17	0.11	28,840	0.06	0.11	0.16	0.12	20,567
AR/assets	0.06	0.12	0.19	0.14	28,840	0.14	0.21	0.29	0.23	20,567
Intangible/assets	0.03	0.13	0.30	0.19	28,840	0.00	0.01	0.02	0.02	20,567
Δbook debt/l.assets	-0.02	0.00	0.05	0.03	28,783	-0.02	0.00	0.01	0.00	20,438
CAPX/l.assets	0.02	0.04	0.07	0.06	28,680	0.02	0.03	0.05	0.04	20,195

Panel B. Results

	Change in Book Debt				CAPX Investment			
	US Large NF		JPN Large NF		US Large NF		JPN Large NF	
EBITDA	0.160***	0.283***	-0.178***	-0.022	0.099***	0.078***	0.037***	0.017
	(0.028)	(0.025)	(0.021)	(0.016)	(0.011)	(0.012)	(0.012)	(0.011)
OCF		-0.194***		-0.329***		0.038***		0.020**
		(0.030)		(0.020)		(0.008)		(0.010)
Q	0.003*	0.003*	0.013***	0.011***	0.006***	0.006***	0.008***	0.008***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Past 12m stock ret	0.003	0.003	-0.004***	-0.004***	0.005***	0.005***	-0.001	-0.001
	(0.003)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
L.Cash holding	0.020	0.023	-0.072***	-0.081***	0.013*	0.014*	-0.012	-0.012
	(0.028)	(0.028)	(0.016)	(0.017)	(0.007)	(0.008)	(0.008)	(0.007)
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Obs	27,936	27,919	20,422	20,338	27,982	27,980	20,176	20,086
R^2	0.116	0.123	0.112	0.169	0.129	0.131	0.071	0.070

Standard errors in parentheses, clustered by firm and time

Are Financially More Constrained Firms More Sensitive to "Cash Flows"? A point of contention in research about investment sensitivity to cash flows is whether such sensitivity is higher among firms that are more financially constrained (Fazzari, Hubbard and Petersen, 1988, 2000; Kaplan and Zingales, 1997, 2000). In previous empirical analyses, the emphasis is cash flows increase internal funds, and the key to this debate is whether financially more constrained firms are more sensitive to *internal funds*. Nonetheless, cash flow sensitivity could arise not just because cash flows increase internal funds. As we demonstrate above, for firms bound by EBCs, cash flows in the form of operating earnings also directly affect borrowing constraints. This second channel is largely absent, for instance, among small firms (and low profitability firms), where cash flow-based lending and EBCs are much less prevalent. While consensus measures of financial constraint are also subject to debate (Farre-Mensa and Ljungqvist, 2016), small firms are plausibly more constrained than large firms (so are low profitability firms). Thus, for some of the reasonably more constrained firms, there is one less channel of cash flow sensitivity, which could contribute to empirical findings that more "financially constrained" firms may not display higher cash flow sensitivity. This observation is especially relevant when cash flows are measured based on earnings, which is common in empirical research.

Table 2.6 provides an illustration, and compares all large non-financial firms as a group with all small firms as a group. Panel A shows that among large firms, debt issuance increases significantly with EBITDA, driven by the large share of firms with EBCs. Among small firms, however, the coefficient on EBITDA is negative and significant when not controlling for net cash receipts OCF. The coefficient on EBITDA is about zero when OCF is added. Similarly, as shown in Section 2.3.3 and Table 2.5, small firms' borrowing also does not respond significantly to changes in EBITDA due to the accounting natural experiment. The results suggest that, with the absence of EBCs, small firms may have one less source of cash flow sensitivity which operates through external borrowing.

Table 2.6 Panel B presents results for capital expenditures. Columns (1) and (3) include EBITDA but not OCF, a specification similar to typical investment cash flow sensitivity regressions that measure "cash flows" using earnings. In this case, the coefficient on EBITDA is positive and significant for large firms, and insignificant for small firms. The interpretation of this result, however, is not necessarily that small firms are not sensitive to *internal funds*. Rather, it results from the absence of the EBC channel among small firms, as Panel A indicates. In Columns (2) and (4), we add OCF and its coefficient is positive in both groups, though smaller among small firms.[41]

US vs. Japan. We also contrast the US with Japan, where corporate borrowing historically relies on physical collateral, especially real estate. While cash flows in the form of operating earnings have a significant impact on debt issuance and investment among large US firms, this relationship does not hold among Japanese firms.

Table 2.7 reruns the baseline regressions among large non-financial firms (i.e. assets above median among public firms in the respective country) in the US and Japan. A majority of firms in the US large firm sample have EBCs, as shown in Section 2.2.2, while cash flow-based lending and EBCs are less common in Japan (Tan, 2004). Table 2.7 Panel A first tabulates the summary statistics for the US and Japan samples. For Japanese firms, we use data from Compustat Global, supplemented with stock price information from Datastream. Net long-term debt issuance from the statement of cash flows is not available for the Japan sample, so we measure debt issuance here using changes in total book debt. Capital expenditures and net cash receipts (OCF) are also available for a smaller set of Japan firms before 2000, and we fill in the gap using additional data from WorldScope. Firms in the US and Japan samples are similar in size as measured by assets. US firms have higher EBITDA relative to assets, as well as higher equity valuations. US firms have higher debt relative to assets, and Japanese firms have higher debt relative to EBITDA (as Japanese firms are not bound by debt to EBITDA constraints).

Table 2.7 Panel B performs the baseline regressions in the US and Japan samples. There is

[41]Capital expenditures capture spending on plant, property, and equipment, and the investment structure of large and small firms could be different. Small firms may invest more in labor and human capital or R&D, and less in traditional hard assets. Thus the empirical magnitude of the cash flow sensitivity of *capital expenditures* may also differ among these two groups for other reasons.

a strong positive relationship between debt issuance and EBITDA in the US sample (driven by firms bound by EBCs), which is absent in the Japan sample. As shown by Panel B column (3), in the Japan sample, debt issuance decreases with EBITDA in when not controlling for net cash receipts OCF. Once we control for OCF in column (4), the EBITDA coefficient becomes close to zero and OCF has a significantly negative coefficient. Similarly, EBITDA does not have an independent impact on investment in the Japan sample.

Borrowing Constraints and Cash Flow Value. Results in this section suggest that, with cash flow-based lending and EBCs, cash flows in the form of operating earnings (EBITDA) relax borrowing constraints and help firms borrow and invest more. These effects are not present, however, when asset-based lending prevails. Given contracting frictions discussed in Section 2.2.2, current EBITDA is central to commonly used, legally binding borrowing constraints (EBCs), and exhibits a disproportionate impact. While current EBITDA is an important factor and an anchor of EBCs, other factors such as expected present value of future cash flows may also play a role. For instance, a firm with high future cash flow prospects could be able to get a larger loan relative to its current EBITDA, and a higher debt to EBITDA multiple for its covenant constraints. We focus on the effect of current EBITDA as an illustration of the central role of cash flow value in corporate borrowing in the US, both because it has a disproportionate impact due to contracting frictions, and because it is directly observable in the data (the present value of future cash flows, on the other hand, is hard to empirically measure; it is also empirically hardly separable from investment opportunities).

After investigating how corporate borrowing practices shape the role of cash flows, in the next section we examine how they affect the role of physical assets to provide a fuller picture and lay out additional implications.

2.4 Property Prices, Firm Outcomes, and Financial Acceleration

In this section, we study how corporate borrowing practices also help understand firms' sensitivity to collateral value, specifically property prices, and illuminate the transmission of shocks during the Great Recession.

We first examine the general sensitivity of US firms' borrowing to property collateral value. We find that borrowing increases by about three cents for a one dollar increase in the value of real estate assets, consistent with prior research (Chaney, Sraer and Thesmar, 2012; Cvijanović, 2014). Moreover, this positive sensitivity is concentrated in asset-based debt; it is absent (if not negative) among cash flow-based debt. Thus the overall sensitivity to real estate value appears modest. The magnitude is smaller than the average sensitivity of debt issuance to operating earnings among US large non-financial firms (about 20 cents). The magnitude also suggests that a 20% property price drop would have a limited impact on the median firm with real estate holdings.

We then use this observation to shed further light on the transmission of property price declines during the Great Recession. Since the Great Recession, a vibrant literature studies the transmission of the property price collapse through household balance sheets and household demand. Much less attention is paid to firms, who in principle are also owners of real estate capital and may suffer similar collateral damage. Indeed, collateral damage to firms plays a critical role both in theories of financial acceleration (Kiyotaki and Moore, 1997; Bernanke, Gertler and Gilchrist, 1999)[42] and in some international experiences such as Japan in the early 1990s (Peek and Rosengren, 2000; Gan, 2007). Figure 2.5 shows that Japanese corporate debt experienced a sizable boom-bust cycle together with real estate value (Panel A). In sharp contrast, during the US property price cycle in the 2000s, corporate debt only budged relative to property prices and household debt (Panel B).

We tie these threads together by examining how collateral damage due to property

[42]In these models, firms' debt capacity is driven by the liquidation value of physical capital, and financial acceleration operates through fire-sale amplifications: a drop in the liquidation value of physical assets tightens borrowing constraints, squeezes firms' ability to hold capital, further compresses the price of assets, and triggers an asset price feedback loop.

price declines affected major US non-financial firms during the Great Recessions. We use firm property holdings data to further unpack the transmission of property price shocks. Consistent with our initial observation, we do not find that property price drops led to significant declines in borrowing and investment due to collateral damage. At the end, we also examine financial acceleration dynamics under different forms of borrowing constraints in a simple general equilibrium framework, following Kiyotaki and Moore (1997). Under cash flow-based lending and EBCs, financial acceleration among firms could be dampened as asset-price feedback dissipates. At the end, we compare results in the US with prior findings in Japan. The contrast suggests the transmission of property price shocks may differ depending on the predominant form of corporate borrowing.

2.4.1 Property Value and Corporate Borrowing

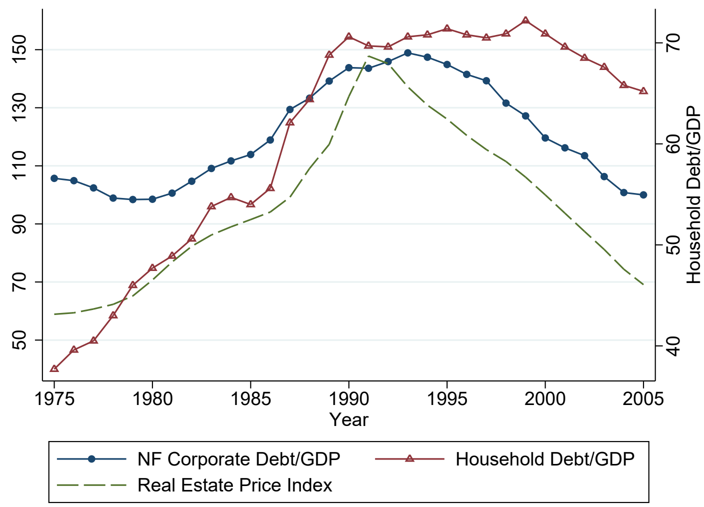
We first investigate the general sensitivity of corporate borrowing to real estate value, and the role of asset-based lending versus cash flow-based lending.

We follow the empirical specifications in prior research (Chaney, Sraer and Thesmar, 2012; Cvijanović, 2014):

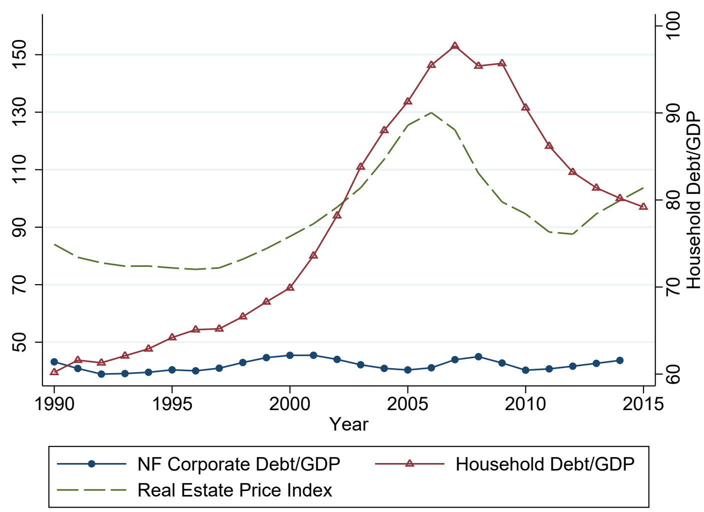
$$Y_{it} = \alpha_i + \eta_t + \beta \mathrm{RE}_{it} + X'_{it}\gamma + \epsilon_{it} \tag{2.7}$$

For the outcome variable, we study both net debt issuance as in previous work, and the issuance of cash flow-based versus asset-based debt. Since we only have detailed firm-level categorization of cash flow-based and asset-based debt starting in 2002, we focus on the sample period of 2002 to 2015; the results for overall net debt issuance are similar in a longer sample. The main independent variable RE_{it} is the market value of real estate assets, measured at the beginning of year t using two procedures described in detail below. We control for firms' operating earnings (EBITDA), net cash receipts (OCF), cash holdings, Q, and additional balance sheet characteristics such as book leverage, size (log assets), other tangible assets (measured at the beginning of year t).

Panel A. Japan



Panel B. US



Note: This plot shows the dynamics of non-financial corporate debt and household debt over the property price cycle in Japan (1975 to 2005) and the US (1990 to 2015). In each plot, the green dashed line is the real estate price index in each country. The blue line with circles is non-financial corporate debt scaled by GDP. The red ling is household debt scaled by GDP. The real estate price index in Japan uses urban land price index from the Statistic Bureau in the Ministry of Internal Affairs and Communications. The real estate price index in the US uses the Case-Shiller price index. The debt data are from the BIS database on credit to the non-financial sector.

Figure 2.5: *Property Price Cycle and Corporate Debt Cycle: Japan vs. US*

A standard empirical concern in this setting is property prices might be correlated with local demand in firms' locations. To address this problem, a commonly used approach is to instrument property prices with land supply elasticity. However, as Mian and Sufi (2014) demonstrate, land supply elasticity is a strong instrument for household housing net worth and household demand, thus correlated with local demand. Therefore, we instead draw on Mian and Sufi (2014)'s observation that tradable firms' demand is national (or global), and not systematically exposed to conditions in their locations. We present additional results for tradable firms only to further tease out potential impact of local demand.

Measuring Firms' Real Estate Value

Firms' financial statements report the book value of property (based on historical cost) rather than the market value. We estimate the market value in two ways.

Method 1: Traditional Estimates. Chaney, Sraer and Thesmar (2012) provide a standard procedure to estimate the market value of real estate using accounting data. The estimate is calculated based on the book value of real estate, accumulated depreciation, and historical property value in the firm's headquarters location. Because accumulated depreciation on real estate assets is no longer reported after 1993, this procedure requires firms to be public since 1993, which restricts the sample size. The key assumption in this estimate is that most of the real estate firms own are located near their headquarters, which is plausible as we discuss in more detail below (most firms' owned properties, such as offices and main production facilities, tend to concentrate in the headquarters region). Appendix B.5 explains the construction of our estimates by step.

Table 2.8 presents the characteristics of this sample. Given the data requirement of this method, the sample tilts towards large firms (70%). 56% of the sample have earnings-based covenants. Median market value of real estate normalized by book assets is 0.20; median market value of real estate relative to the market value of equity 0.20, very similar to Chaney, Sraer and Thesmar (2012). Table 2.8 also shows the characteristics of all public firms that own real estate (around 66% of Compustat own some real estate), measured during the same period. In comparison, firms in the Method 1 sample are slightly larger in size, but generally similar in terms of the amount of book PPE, profitability and book leverage.

Method 2: Property Ownership Information from Annual Reports. US non-financial firms are required to discuss their physical properties in annual reports. About one third of firms with real estate provide a detailed list of their owned properties, including location, property type, and square footage. We hand collect these data from 2006 filings to get more refined information about firms' property holdings. For the panel analysis in this section, we assume firms own a fixed set of properties as shown by 2006 filings, estimate the market value of each property in each year, and sum up to the firm level. Our baseline results use property locations in 2006 filings to align with the cross-sectional analysis in Section 2.4.2 (we also read filings in 2002, which produce similar results; estimates using locations in 2002 and 2006 filings are about 0.85 correlated). For the cross-sectional analysis in Section 2.4.2 focusing on the crisis period, we directly take the properties owned by the end of 2006 reported in the 2006 filings, and calculate their values through the crisis. We restrict to owned real estate located in the US, and keep firms that have information for substantially all owned properties in the US. Appendix B.5 provides examples of property holding information from 10-K filings, and detailed explanations of variable construction.

The market value of real estate measured using Method 1 and Method 2 is consistent. For firms in both samples, the estimates are 0.7 correlated. The levels also match up. The similarity is high because most firms' owned properties are limited and are concentrated in the headquarters location, so the assumption used in traditional estimates largely holds (e.g. as of 2006 Starbucks only owns some headquarters office space and four roasting facilities).

Table 2.8 also reports the characteristics of firms in the Method 2 sample. These firms are slightly smaller than those in the Method 1 sample (60% of the sample are large firms). They utilize more asset-based lending compared to the Method 1 sample, although cash flow-based lending still accounts for the majority of their debt (median share is 65%); 47% have earnings-based covenants. They are similar to other firms with real estate in terms of book PPE and profitability, and have slightly lower book leverage.

Results

Table 2.9 presents the results, for all firms where real estate value measures are available as well as the subsample consisting of tradable firms only. We get similar results across different samples. A one dollar increase in real estate value is on average associated with an increase in net long-term debt issuance of about three cents. The positive response is concentrated in asset-based debt. It is absent among cash flow-based debt. We can further break down cash flow-based debt into cash flow-based loans and bonds, and the positive sensitivity is absent in both categories. These patterns hold not just for debt issuance, but also for the level of debt, as shown in Appendix B.1 Table B.3.

Results in Table 2.9 are similar whether we restrict to tradable firms or not. Public non-financial firms in our samples are generally sufficiently large that their product demand may not be concentrated in areas where they own properties, even for some of the non-tradable firms (e.g. Starbucks is categorized as a non-tradable firm, but it owns primarily roasting facilities that are far from its product markets; however, caveats may apply to services firms that are real estate heavy and have few locations, like casinos and amusement parks, where property location and product market overlap). For most firms, property price shocks at firms' real estate locations seem sufficiently exogenous to their product demand.

In Table 2.9 the coefficients on EBITDA are significant, and the magnitudes are comparable with our findings in Section 2.3 (the EBITDA coefficients in Table 2.9 are about 0.15 to 0.2, driven by the roughly 60% of firms in these samples with EBCs). In our samples which primarily consist of large firms that borrow through cash flow-based lending, EBITDA appears to have a bigger average impact on borrowing than property collateral value (0.03).

Taken together, the results suggest that a substantial portion of large non-financial firms' debt does not rely significantly on real estate value. With these alternative venues for borrowing, the overall sensitivity to property prices appears limited. For instance, for a firm with a median level of real estate holdings (real estate value is 0.2 times book asset value), a 20% decline in property price would decrease its real estate value by about 0.04 of book asset value, and reduce its borrowing by about 0.001 of assets (0.04×0.03). This effect is small relative to a median investment rate (CAPX normalized by assets) of 0.05 and a median EBITDA to assets ratio of 0.13 among large firms. In the following, we use this observation to shed light on features of the Great Recession, and further unpack the transmission of property price declines.

Table 2.8: *Summary Statistics: Firm Property Value*

Summary statistics of firms in the samples with market value of real estate measures. The column labeled "Method 1" refers to the sample where market value of real estate estimates are available using Method 1 described in Section 2.4.1 and Appendix B.5, which follows the traditional procedure (Chaney et al., 2012). The column labeled "Method 2" refers to the sample where market value of real estate estimates are available using Method 2 described in Section 2.4.1 and Appendix B.5, which uses hand collected information from 10-K filings. The column labeled "All w/ RE" includes all non-financial firms with non-zero real estate holdings. Panel A displays statistics for the period 2002 to 2015 (sample period in Table 2.9), for which we have firm-level measures of asset-based and cash flow-based lending. Panel B displays additional statistics for the period 2007 to 2019 (sample period in Table 2.10). $\Delta \text{RE}_{06}^{07-09}/\text{sssets}_{06}$ is the gain/loss on 2006 real estate holdings during the crisis, normalized by assets in 2006. $\Delta P^{07-09}(\text{HQ})$ is the percentage change in property price index in headquarters CBSA from 2007 to 2009. The remaining statistics are changes in EBITDA, net long-term debt issuance, and capital expenditures between 2007 and 2009, normalized by assets in 2006.

	Sample		
	Method 1	Method 2	All w/ RE
	Panel A. 2002—2015		
Market Value RE/assets	0.21	0.13	-
Market Value RE/market cap	0.21	0.12	-
Book PPE/assets	0.25	0.21	0.25
EBITDA/l.assets	0.14	0.13	0.12
Q	1.15	1.14	1.10
Debt/assets	0.22	0.19	0.24
Log assets	7.08	6.30	6.84
Asset-based lending/debt	0.12	0.25	0.22
Cash flow-based lending/debt	0.85	0.66	0.74
Asset-based lending/assets	0.02	0.02	0.03
Cash flow-based lending/assets	0.16	0.09	0.14
Net LT Debt issuance/assets	0.00	0.00	0.00
CAPX/l.assets	0.04	0.04	0.04
Fraction of large firms	0.76	0.63	0.71
Fraction w/ EBCs	0.60	0.55	0.56
	Panel B. 2007—2009		
$\Delta \text{RE}_{06}^{07-09}/\text{assets}_{06}$	-0.01	-0.01	-
$\Delta P^{07-09}(\text{HQ})$	-0.07	-0.08	-0.07
$\Delta \text{EBITDA}_{06}^{07-09}/\text{assets}_{06}$	-0.02	-0.01	-0.01
$\Delta \text{Net LT Debt Iss}_{06}^{07-09}/\text{assets}_{06}$	0.00	0.00	0.00
$\Delta \text{CAPX}_{06}^{07-09}/\text{assets}_{06}$	-0.01	-0.01	-0.01

Table 2.9: *Corporate Borrowing and Property Collateral Value*

Firm-level panel regressions of debt issuance on real estate value:

$$Y_{it} = \alpha_i + \eta_t + \beta \text{RE}_{it} + X'_{it}\gamma + \epsilon_{it}$$

The outcome variable Y_{it} is net long-term debt issuance in columns (1) and (2), change in asset-based lending in columns (3) and (4), change in cash flow-based lending in columns (5) and (6), all normalized by beginning-of-year assets. The main independent variable is RE_{it}, which is beginning-of-year market value of real estate calculated using two methods described in Section 2.4.1 and Appendix B.5. Other independent variables include EBITDA and net cash receipts OCF in year t, Q, cash holdings, book leverage, inventory and receivables, and size (log assets) at the beginning of year t. Firm fixed effects and year fixed effects are included (R^2 does not include fixed effects). Panel A presents results for all firms where market value of real estate estimates are available. Panel B restricts to the subsample with firms in tradable industries only. Sample period is 2002 to 2015. Standard errors are clustered by firm and time.

Panel A. All Sample Firms

	Net LT Debt Iss		Δ Asset-Based		Δ CF-Based	
	(1)	(2)	(3)	(4)	(5)	(6)
RE (Method 1)	0.030**		0.042**		-0.007	
	(0.014)		(0.021)		(0.022)	
RE (Method 2)		0.029**		0.030**		-0.002
		(0.014)		(0.016)		(0.026)
EBITDA	0.216***	0.173***	0.151***	0.105***	0.130*	0.093***
	(0.053)	(0.029)	(0.040)	(0.031)	(0.069)	(0.035)
OCF	-0.157***	-0.194***	-0.120***	-0.152***	-0.088**	-0.072
	(0.035)	(0.043)	(0.025)	(0.030)	(0.038)	(0.047)
Q	0.011**	0.014***	-0.004	0.000	0.006	0.015***
	(0.005)	(0.005)	(0.002)	(0.004)	(0.006)	(0.005)
L.Cash holding	-0.095***	-0.073***	-0.075***	-0.044**	0.012	-0.019
	(0.027)	(0.021)	(0.027)	(0.022)	(0.032)	(0.035)
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Obs	4,999	4,551	4,999	4,551	4,999	4,551
R^2	0.116	0.120	0.196	0.217	0.193	0.244

Standard errors in parentheses, clustered by firm and time

Panel B. Tradable Firms Only

	Net LT Debt Iss		Δ Asset-Based		Δ CF-Based	
	(1)	(2)	(3)	(4)	(5)	(6)
RE (Method 1)	0.024		0.060**		-0.090***	
	(0.031)		(0.030)		(0.027)	
RE (Method 2)		0.063**		0.075*		-0.003
		(0.031)		(0.040)		(0.022)
EBITDA	0.182***	0.136***	0.119***	0.065**	0.121*	0.109**
	(0.055)	(0.043)	(0.046)	(0.033)	(0.071)	(0.050)
OCF	-0.155***	-0.170***	-0.109***	-0.141***	-0.097**	-0.089*
	(0.035)	(0.045)	(0.039)	(0.035)	(0.047)	(0.048)
Q	0.006	0.016**	-0.005*	0.003	0.002	0.013
	(0.005)	(0.007)	(0.003)	(0.003)	(0.008)	(0.008)
L.Cash holding	-0.047	-0.074***	-0.081***	-0.063**	0.040	-0.020
	(0.038)	(0.027)	(0.030)	(0.029)	(0.040)	(0.036)
Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Obs	3,174	2,820	3,174	2,820	3,174	2,820
R^2	0.111	0.122	0.212	0.234	0.211	0.195

Standard errors in parentheses, clustered by firm and time

Table 2.10: *The Great Recession: Unpacking the Property Price Effect*

Cross-sectional regression of firm outcomes in the Great Recession and value of firm real estate:

$$\Delta Y_i^{07-09} = \alpha + \lambda \Delta \text{RE}_{i,06}^{07-09} + \eta \text{RE}_i^{06} + \phi \Delta P_i^{07-09} + X_i' \gamma + u_i$$

Y_i^{07-09} is firm-level outcome from 2007 to 2009: in Panel A ΔY_i^{07-09} is the change in net long-term debt issuance between 2007 and 2009, in Panel B Y_i^{07-09} is the change in CAPX between 2007 and 2009, normalized by assets by the end of 2006. The main independent variable $\Delta \text{RE}_i^{07-09}$ is the estimated gain/loss on firm i's 2006 real estate holdings during the Great Recession, normalized by assets at the end of 2006. RE_i^{06} is the estimated market value of firm i's real estate at the end of 2006, normalized by assets at the end of 2006. ΔP_i^{07-09} is the percentage change in property value in firm i's location. The market value of firms' real estate is estimated using two different methods (labeled in the columns), as described in Section 2.4.1 and Appendix B.5. Controls include changes in EBITDA and OCF from 2007 to 2009 (normalized by assets by the end of 2006), pre-crisis Q and change in Q from 2007 to 2009, cash holdings, book leverage (debt/assets), inventory, receivables, and size by the end of 2006. Industry (Fama-French 12 industries) fixed effects are included; R^2 does not include fixed effects. Estimates using both OLS and LAD are presented. Robust standard errors in parentheses.

Panel A. Net LT Debt Issuance

	Method 1		Method 2	
ΔLT Debt Iss$^{07-09}$	OLS	LAD	OLS	LAD
$\Delta \text{RE}_{06}^{07-09}$	-0.121	-0.086	-0.135	-0.028
	(0.362)	(0.239)	(0.241)	(0.079)
RE_{06}	-0.042	-0.004	-0.009	-0.007
	(0.030)	(0.024)	(0.032)	(0.013)
ΔP^{07-09}	0.076	0.024	-0.020	0.003
	(0.082)	(0.045)	(0.059)	(0.023)
ΔEBITDA$^{07-09}$	0.189**	0.160**	0.109*	0.044
	(0.085)	(0.066)	(0.065)	(0.028)
ΔOCF$^{07-09}$	-0.189***	-0.168***	-0.218***	-0.070**
	(0.073)	(0.047)	(0.055)	(0.033)
ΔQ^{07-09}	0.019**	0.005	0.013**	0.004
	(0.007)	(0.007)	(0.006)	(0.004)
Q_{06}	-0.001	-0.005	0.006	0.002
	(0.008)	(0.005)	(0.004)	(0.006)
Cash$_{06}$	-0.018	0.006	0.041	0.012
	(0.053)	(0.043)	(0.037)	(0.022)
Obs	384	384	466	466
R^2	0.108	-	0.161	-

Standard errors in parentheses

Panel B. Capital Expenditures

	Method 1		Method 2	
ΔCAPX$^{07-09}$	OLS	LAD	OLS	LAD
$\Delta \text{RE}_{06}^{07-09}$	0.086	-0.008	0.078	0.030
	(0.120)	(0.104)	(0.075)	(0.062)
RE_{06}	0.005	-0.003	0.012	0.013
	(0.012)	(0.012)	(0.012)	(0.010)
ΔP^{07-09}	0.037	0.018	0.001	0.009
	(0.025)	(0.020)	(0.017)	(0.009)
ΔEBITDA$^{07-09}$	0.101***	0.098***	0.064**	0.061***
	(0.024)	(0.018)	(0.025)	(0.015)
ΔOCF$^{07-09}$	-0.032	-0.028*	-0.041**	-0.027**
	(0.021)	(0.015)	(0.019)	(0.013)
ΔQ^{07-09}	0.014***	0.008***	0.010***	0.007***
	(0.003)	(0.002)	(0.002)	(0.002)
Q_{06}	0.003	0.002	0.002	0.002
	(0.002)	(0.002)	(0.001)	(0.002)
Cash$_{06}$	-0.021	-0.016	0.002	0.013*
	(0.016)	(0.014)	(0.013)	(0.008)
Obs	380	380	464	464
R^2	0.262	-	0.218	-

Standard errors in parentheses

2.4.2 The Great Recession: Unpacking the Property Price Effect

Since the Great Recession, a vibrant strand of research investigates the impact of the property value collapse. The key insight is that property price declines damaged household balance sheets, dried up aggregate demand, and led to drops in investment and employment (Mian and Sufi, 2014; Giroud and Mueller, 2017). Property price declines, however, may also transmit through collateral damage to firms. Less is known about the role of this second channel in the Great Recession. Such a mechanism could be powerful if firms' debt capacity relies heavily on property collateral value; it could be attenuated if firms primarily utilize cash flow-based lending.

In the following, we examine the impact of corporate property value in the Great Recession. We proceed in two steps. We first note that the limited impact due to declines in firms' property value could be inferred from insights in the household demand channel. Specifically, Mian and Sufi (2014) study the impact of property prices on local employment growth during the Great Recession, and propose a comparison of tradable versus non-tradable industries. The key idea is that property prices affect local household demand: firms in non-tradable industries are exposed to local demand, so they should be more sensitive to local property price changes. Firms in tradable industries, on the other hand, face demand from a larger market, so they should be less sensitive. Consistent with the hypothesis, Mian and Sufi (2014) find strong responses of local employment to local house prices among non-tradable firms. They do not find any relationship among tradable firms. Giroud and Mueller (2017) find similar strong relationships among non-tradable firms, and no relationship among tradable firms.

Nonetheless, property price declines at a firm's location affect not only local demand, but also the value of the firm's real estate assets. This channel through property collateral value is relevant for *both* tradable and non-tradable firms. If this channel is strong, we would expect that *tradable firms* also display some sensitivity to local property price changes. The null result from prior work thus hints at the muted impact of property collateral damage among US non-financial firms in the Great Recession.

We then further unpack the transmission of property price declines in the Great Recession in Table 2.10. We disentangle the firm-side property collateral value channel using firm property holdings data. We exploit firms' differential exposures to property value shocks through the following cross-sectional specification:

$$\Delta Y_i^{07-09} = \alpha + \lambda \Delta \mathrm{RE}_i^{07-09} + \eta \mathrm{RE}_i^{06} + \phi \Delta P_i^{07-09} + \beta \Delta \mathrm{EBITDA}_i^{07-09} + X_i' \gamma + u_i \tag{2.8}$$

The left hand side variable Y_i^{07-09} is outcomes of firm i from 2007 to 2009. In Panel A, ΔY_i^{07-09} is the change in net long-term debt issuance from 2007 to 2009. In Panel B, ΔY_i^{07-09} is the change in capital expenditures. On the right hand side, the key variable of interest is $\Delta \mathrm{RE}_{i,06}^{07-09}$, which captures changes in firm i's real estate value from 2007 to 2009. It is measured as the market value gain/loss of firm i's pre-crisis (end of 2006) real estate holdings during the Great Recession, normalized by assets in 2006. This variable is the main focus for analyzing the property collateral channel. We also include RE_i^{06}, which controls for firm i's pre-crisis real estate holdings (normalized by assets in 2006). In addition, we control for ΔP_i^{07-09}, the percentage change in property prices in firm i's locations, which captures the impact of property prices that may work through local household demand. We also control for changes in EBITDA, net cash receipts, and Q from 2007 to 2009, as well as Q, leverage, cash holdings, size (log assets) by the end of 2006, among others.

We measure firms' real estate value using both of the methods described in the previous section. For Method 1, we calculate firm-level RE_i^{06}, $\Delta \mathrm{RE}_{i,06}^{07-09}$, and ΔP_i^{07-09} all using headquarters information. Specifically, RE_i^{06} is constructed based on the regular headquarters-based procedure, ΔP_i^{07-09} is the percent change in property prices in the headquarters location from 2007 to 2009, and $\Delta \mathrm{RE}_{i,06}^{07-09} = \mathrm{RE}_i^{06} \times \Delta P_i^{07-09}$. For Method 2, we calculate firm-level RE_i^{06}, $\Delta \mathrm{RE}_{i,06}^{07-09}$, and ΔP_i^{07-09} by aggregating information from each owned property j of firm i. Specifically, we then sum across these properties to obtain $\mathrm{RE}_i^{06} = \sum_j \mathrm{RE}_{i,j}^{06}$ and $\Delta \mathrm{RE}_{i,06}^{07-09} = \sum_j \mathrm{RE}_{i,j}^{06} \times \Delta P_{i,j}^{07-09}$, where $\Delta P_{i,j}^{07-09}$ is the percentage change in property prices in the location of owned property j of firm i. In this case, we calculate ΔP_i^{07-09} as the average of $\Delta P_{i,j}^{07-09}$; we can alternatively calculate firm-level ΔP_i^{07-09} using property price changes in firm i's headquarters or average across all locations (owned and leased), and the results are similar. The bottom of Table 2.8 shows additional summary statistics during the crisis. For firms in our sample, the median property price decline from 2007 to 2009, ΔP_i^{07-09}, is about 8%. The median decline in the market value of real estate assets from 2007 to 2009 (normalized by 2006 assets), $\Delta \mathrm{RE}_{i,06}^{07-09}$, is about 0.01.

In this setting, there could still be concerns about property prices being correlated with local demand. In our current cross-sectional set-up, this issue can drive down λ if firms that own more real estate are systematically *less* sensitive to local demand. As discussed in Section 2.4.1, the local demand issue does not appear severe for large public firms whose demand is generally not local. Nonetheless, we also perform additional checks in Internet Appendix Table IA10The Great Recession: Unpacking the Property Price Effects (Tradables Only)table.caption.11 using tradable firms only.

Table 2.10 presents results using different estimates. We tease out the outliers and make sure they do not drive our results. We also report both OLS estimates and least absolute deviation (LAD) estimates (following Gan (2007)) to further alleviate the influence of outliers and skewness in the cross-sectional data. Across different estimates, we do not find evidence that declines in firms' real estate value drove down debt issuance or capital expenditures during the Great Recession. The lack of significant results could be in part because the sensitivity is very small (as discussed in Section 2.4.1), which makes it hard to detect in a regular cross section. It could also be related to the structure of loans backed by real estate, where loan-to-value constraints affect issuance but do not always affect maintenance of existing loans.[43] Finally, in Table 2.10 the coefficients on EBITDA and OCF have the same signs and comparable magnitudes as results in Section 2.3.

In summary, our analysis suggests that property price declines during the Great Recession did not have a significant impact on firms' outcomes due to collateral damage. In the

[43]Accordingly, when property value increases, a firm can take out a larger loan based on a given loan to property value ratio that is evaluated at issuance. When the property value declines, however, the firm would not be forced to shrink the size of existing loans. The option to take out larger loans when property prices increase, coupled with the lack of forced debt reduction when property prices drop, could contribute to less sensitivity to property value in recessions than in normal times.

following, we compare and contrast results from the US housing collapse with previous research on Japan's housing collapse. We highlight substantial differences in the transmission of property price shocks under different regimes of corporate lending.

2.4.3 Property Price Declines and the Firm Collateral Channel: US and Japan

In the late 1980s and early 1990s, Japan experienced a major boom-bust cycle in property prices. The collapse of property prices had a far-reaching impact on Japan's economy. As discussed earlier, corporate borrowing in Japan traditionally relies on real estate collateral, especially before the bankruptcy reforms in the early 2000s. Thus Japan's real estate collapse took place in an environment where property value is central for corporate credit.

With the collapse of property prices, Japanese firms' debt capacity and investment activities suffered significantly, as documented by Gan (2007). Gan (2007) studies public manufacturing firms in Japan, and uses the value of firms' real estate prior to the collapse as the main measure of exposures to property price shocks (she estimates the market value of real estate from accounting data through a procedure similar to method 1 above). She finds that Japanese firms that owned more property pre-collapse suffered particularly severely during the bust: for a one dollar increase in a firm's pre-collapse land holdings in 1989, average CAPX investment is lower by 13 to 16 cents from 1994 to 1998. The impact is substantial, especially that property prices peaked around 1990, and the outcome is measured as the average over five years after 1994.

In Table 2.11, we present results in the US sample using the same regression specifications as Table 2 column (2) of Gan (2007):

$$\text{CAPX}_i^{post} = \alpha + \beta \text{RE}_i^{pre} + X_i' \gamma + v_i \tag{2.9}$$

where CAPX_i^{post} is firm i's average annual investment rate over a period of time during the property price collapse; RE_i^{pre} is the value of firm i's real estate holdings prior to the collapse, which captures firms' exposures to real estate; X_i includes firm level controls (cash flows during the post period, Q, cash holdings, a dummy indicating firms with above median real estate holdings, and interactions of cash flows and cash holdings with this dummy). This specification is different from our tests in Equation (2.8) above and provides an alternative test. As Table 2.11 shows, in the US Great Recession, we do not find results similar to what Gan (2007) found in Japan. There is no significant correlation between a firms' pre-crisis real estate holdings and its subsequent outcome. The sharp contrast suggests that the transmission mechanisms of a property price collapse could be different in different settings, depending on the lending regime and the central determinants of firms' debt capacity.

Table 2.11: *Property Price Collapse and Firm Investment: US vs. Japan*

This table compares results in Gan (2007)'s analysis of Japanese firms during Japan's property price collapse and similar specifications using US firms during the Great Recession. The specification follows Table 2 column (2) of Gan (2007):

$$\text{CAPX}_i^{post} = \alpha + \beta \text{RE}_i^{pre} + X_i'\gamma + v_i$$

CAPX_i^{post} is firm i's average annual investment rate (CAPX normalized by assets) over a period of time during the property price collapse, and the period is labeled in row "Outcome Period." RE_i^{pre} is firm i's real estate holdings prior to the collapse (normalized by pre-collapse assets). Gan (2007) uses the estimated market value of land holdings in 1989. In the US sample, we use the market value of real estate in 2006 measured using methods described in Section 2.4.1 and Appendix B.5. Controls X_i include cash flows (contemporaneous with investment), as well as Q, cash holdings and book leverage (measured prior to the outcome variable). The regression also follows Gan (2007) to include a dummy variable that is equal to one if the firm's pre-collapse real estate holdings fall into the top industry quartile, and interactions of this dummy with cash flows and cash holdings. Gan (2007) uses least absolute deviation (LAD) estimate, and we report both OLS and LAD estimates.

	CAPX Investment						
	Japan (Gan 07)	US					
Outcome Period	1994—1998	2007-2009		2007-2011		2009-2013	
Specification	LAD	OLS	LAD	OLS	LAD	OLS	LAD
RE 1989	-0.165***						
	(0.016)						
RE 2006	-	0.007	0.014	-0.001	0.007	-0.01	0.004
Method 1	-	(0.009)	(0.008)	(0.008)	(0.005)	(0.009)	(0.004)
RE 2006	-	0.007	0.002	0.008	0.005	-0.005	-0.004
Method 2	-	(0.007)	(0.004)	(0.007)	(0.005)	(0.005)	(0.005)

Standard errors in parentheses

2.4.4 Earnings Drop and Firm Outcomes in the Great Recession

Below we perform a basic assessment of the impact of earnings-based borrowing constraints during the Great Recession.

In our data, total earnings of large public firms with EBCs fell by \$123 billion from 2007 to 2009. Based on baseline results in Table 2.3, this is associated with a $33.5 billion decline in long-term net debt issuance due to EBCs, which accounts for 10.6% of the issuance decline among all public firms. It is associated with a $14 billion reduction in CAPX due to EBCs, which accounts for 8.7% of CAPX declines among public firms. If we augment the baseline regression with two dummy variables indicating covenant violation and within 0.5 standard deviations of violation to allow for discontinuity in outcome variables due to violations, the total impact increases slightly to 14.4% of declines in net long-term debt issuance and 9.5% of declines in CAPX. Finally, if we instead estimate a cross-sectional regression for firms with EBCs focusing on the Great Recession period, results are similar (EBCs account for 10.7% of declines in net long-term debt issuance and 9% of declines in CAPX).[44] Overall, the estimated impact due to EBCs is meaningful but not catastrophic.

2.4.5 Financial Acceleration in General Equilibrium: A Simple Comparison

Finally, we perform a simple analysis of financial acceleration dynamics under different forms of borrowing constraints, based on a standard general equilibrium framework following Kiyotaki and Moore (1997). We examine both collateral-based constraints (borrowing limit depends on the liquidation value of physical assets) as in the original work, and earnings-based constraints (borrowing limit depends on a multiple of cash flows/earnings). We compare the equilibrium impact of a shock to productive firms' net worth in these two scenarios (the same shock as considered by Kiyotaki and Moore (1997)), starting from the same steady state in both cases.

The results show that, after the shock hits, the impact on productive firms' capital

[44]For Estimate 1, we use the regression in Table 2.3, and calculate the change in the outcome variable predicted by the change in EBITDA. We renormalize the outcome to dollar amounts and sum across all large firms with EBCs. For Estimate 2, the procedure is the same, except we add two dummies to capture potential non-linear impact when firms violate earnings-based covenants or are very close to violation. For Estimate 3, we instead use cross-sectional regressions restricted to the Great Recession period. We run a cross-sectional regression among large non-financial firms with EBCs: $\Delta Y_i^{07-09} = \alpha + \beta \Delta \text{EBITDA}_i^{07-09} + \kappa \Delta \text{OCF}_i^{07-09} + X_i' \gamma + u_i$, where ΔY_i^{07-09} is firm i's change in net debt issuance (or CAPX) from 2007 to 2009, $\Delta \text{EBITDA}_i^{07-09}$ is its change in EBITDA; controls include changes in Q and pre-crisis Q, as well as cash holdings, book leverage, book PPE, size, among other firm characteristics measured at the end of 2006. We then calculate changes in the outcome variable predicted by changes in EBITDA. Finally, we sum up the firm level impact across all large non-financial firms with EBCs.

holding and aggregate output are much stronger with collateral-based constraints, due to the well-known asset-price feedback. This mechanism is muted with EBCs: when the market/liquidation value falls, a firm's borrowing constraint is not automatically tightened, and fire sale amplifications are not present. Using the parameterization in Kiyotaki and Moore (1997), we find the impact on productive firms' capital holding and aggregate output under collateral-based constraint is about ten times as large as that under earnings-based constraint. Dampening the asset-price feedback could be quantitatively very important. We present the details of the set-up, equilibrium dynamics, and quantitative analysis in Appendix B.6.

This analysis is admittedly stylized. It highlights that with non-financial firms and EBCs alone, financial acceleration and amplification may be dampened. The balance sheets of firms alone may not be the key financial accelerator. Nonetheless, asset-price feedback can be very important among financial institutions and households. In a fully fledged model, it could also be interesting to explore the interactions among different sectors (households, financial institutions, non-financial firms) that face different types of borrowing constraints.

Taken together, results in this section show that major US non-financial firms did not appear to suffer from significant collateral damage due to property price declines in the Great Recession. In the US setting, the impairment of banks' balance sheets (Chodorow-Reich, 2014; Becker and Ivashina, 2014; Acharya, Almeida, Ippolito and Perez-Orive, 2014; Chodorow-Reich and Falato, 2017) and household demand (Mian and Sufi, 2014) can be the primary sources of vulnerability, and non-financial firms were not the epicenter of the crisis (Gertler and Gilchrist, 2017). Our analysis of corporate borrowing helps to put this into perspective: the experiences in the US are not taken for granted; firms could have suffered more significantly from collateral damage and possibly fire sale amplifications if asset-based lending against real estate were central, like in the case of Japan.

2.5 Conclusion

In this paper, we study borrowing constraints of non-financial firms. We show that cash flow-based lending accounts for the vast majority of US large non-financial firms' debt. With cash flow-based lending, a standard borrowing constraint restraint restricts a firm's total debt based on a particular measure of cash flows, namely operating earnings. We lay out determinants of these borrowing practices, and delineate differences in the predominant form of corporate borrowing across firm groups.

These features of corporate borrowing help tie together several issues. The prevalence of cash flow-based lending and EBCs shapes the way cash flows affect corporate borrowing. In particular, cash flows in the form of operating earnings directly relax EBCs and can facilitate borrowing. This mechanism further suggests a new channel for the sensitivity of firms' investment to cash flows which operates through external borrowing. Among firms where asset-based lending prevails for a variety of reasons, these effects are absent, which helps account for variations in firm behavior. The prevalence of cash flow-based lending also alleviates firms' dependence on the value of physical assets. Correspondingly, large US firms' borrowing and investment were not particularly vulnerable to property price declines in the Great Recession through collateral damage. The results suggest that corporate balance sheets may not be the central amplifier of financial shocks in the US setting, and shed light on why the Great Recession is a crisis centered around households and banks rather than major non-financial firms.

Taken together, major US non-financial firms do face borrowing constraints, but the primary constraint appears different from the commonly studied collateral constraint; instead, cash flow-based lending and earnings-based borrowing constraints play an important role. The form of borrowing constraints can shape the impact of different financial variables and the applicability of macro-finance mechanisms.

Our study analyzes non-financial firms. A question for future work is to investigate the form of borrowing constraints among various types of financial institutions, how they differ, why, and the corresponding implications.

Chapter 3

New Experimental Evidence on Expectations Formation [1]

3.1 Introduction

The way agents update their expectations about future outcomes is at the very core of most economic models. When updating their beliefs, rational agents are supposed to combine new information with their priors using Bayes' rule. By contrast, non-rational agents might either over-react or under-react to new information, leading to predictable forecast errors.

The finance literature is somewhat divided over which effect dominates. A first branch emphasizes *over-reaction*. Shiller (1981) observes that stock prices are more volatile than dividends, and explains it via extrapolative expectations: Agents tend to assume that recent trends will continue so that prices move too much in response to recent shifts in fundamental. As a result, good news lead to over-optimistic expectations and forecast lower realized returns. This effect has been invoked to explain fluctuations in stock and bond returns, as well as phenomena such as the value premium and even overinvestment.[2] A

[1]Joint with Augustin Landier and David Thesmar

[2]For instance, Lakonishok et al. (1994) and Laporta (1996) argue that the value premium is related to extrapolative bias. De Bondt (1993) and Greenwood and Shleifer (2014b) also find evidence of extrapolation in stock-prices forecasts. Using a household survey on forecasted earnings, (Dominitz, 1998) find that revisions of

second branch of the empirical literature emphasizes the role *under-reaction* in expectation formation. In these papers, good news about fundamental are only slowly incorporated into expectations, so that good news predict positive future returns. Such under-reaction can explain momentum within and across stocks, as well as other anomalies such as the post-announcement drift, the repurchase or profitability anomalies, or even the forward premium puzzle.[3]

The goal of this paper is to directly measure belief formation in an experimental setting where agents are incentivized to provide accurate forecasts of a random variable, drawn from a stable and simple statistical process (an AR1 process). There is a large literature analyzing expectation formation from field data, with a recently renewed interest in the topic (see literature review below). Existing studies find evidence of both under-reaction and over-reaction depending on the economic variable. Our aim here is to complement this literature with evidence from the lab. While we are aware of potential external validity concerns, relying on an experiment has three main advantages over field data. First, we are able to define the process to be forecasted, so that we can overcome the problem that, in non-experimental data, the underlying data generating process is unknown to both the econometrician and the forecaster. This problem makes it difficult to precisely pin down rational vs. irrational updating, as rational agents might for instance assign a probability that the data generating process can change, leading to complex and hard-to-test

expectations are positively related to changes in realized individual earnings. More recently, Gennaioli et al. (2015) find that errors in CFO expectations of earnings growth are not rational and result from extrapolative expectations. Bordalo et al. (2017a) show that during booming bond markets (low credit spreads), agents make over-optimistic forecasts (they expect the spreads to remain low). Bordalo et al. (2017c) finds that high expected long-term growth forecasts negative stock returns.

[3]Abarbanell and Bernard (1992) show that analysts under-react to past earnings in their forecasts, which can explain the profitability anomaly (Bouchaud et al. (2018)). Ball and Brown (1968) show that firms experiencing high earnings surprises experience positive abnormal returns going forward: This post-earnings announcement drift suggests that investors under-react to the information content of earnings. Hong et al. (2000); Hou (2007), among others, explain momentum by the excessively slow diffusion of public information into prices. The market tends to under-react to public announcements such as share repurchases announcements (Ikenberry et al. (1995)) or insiders' trades (Lakonishok and Lee (2001)). Cohen and Lou (2012) find that returns of firms that operate in several industries are predictable as the market under-reacts to industry-news regarding these complicated firms. Frankel and Froot (1985) find evidence in under-reaction in expert forecasts of exchange rates. Gourinchas and Tornell (2004) calibrate a model where the foreign exchange forward-premium puzzle can arise from investors under-reaction to interest rate shocks.

bayesian updating. In the context of our empirical framework, we inform agents that the data generating process is stable and endow them with enough observations to estimate this process. In short, there is no ambiguity about what is the "rational expectation" in our experiment. The second advantage of our setting is that it is a pure exercise in time series forecasting, where agents' incentives are clearly defined: they just need to make accurate forecasts of a simple process. Also, the process is not polluted by other economic considerations such as strategic considerations or career concerns. The third advantage of running an experiment is more classical: it allows us to control the environment in a fully random way. For instance, we can change the parameters of the stochastic process. We can also modify at will the framing of the experiment. This allows us to fully control the determinants of the expectation formation process, and how robust our findings are to the environment.

By running our experiment, we generate a large panel of participant expectations and realizations of random processes, under different conditions. We use this panel to estimate an expectation formation model that includes both under-reaction and extrapolation, but nests rational expectations as a particular case. Under-reaction and extrapolation can be separately identified in the data via the term structure of expectations. Our findings are the following. First, the rational expectation hypothesis is strongly rejected in our setting (this is consistent with earlier experimental studies). This is true both for a majority of participants taken individually, but also for the average individual. On average, the score is approximately 30% below the score expected for a rational forecaster. In addition, we find little evidence that subjective forecasts converge to rational ones after 40 rounds of testing. Second, patterns of extrapolation largely dominate in explaining expectation dynamics. This is in spite of the fact that the forecasting problem is made as simple as possible. Both extrapolation and underreaction patterns are statistically discernible in the data, but extrapolation quantitatively dominates. Our model explains average expectations very well (with an R^2 of 50-60% depending on specifications). Interestingly, both biases to not decline over time, so that learning does not seem to affect expectation biases. Third, our model coefficients are surprisingly robust to experimental setting. They do not depend on the parameters of the model (our conditions span persistence parameters from 0 to 0.8 and various levels of volatility). They do not depend on the way we label the process (GDP, inflation etc.). The extent of under-reaction is a bit affected by the way we ask participant to report the term structure of their expectation, but in all cases, the amplitude of over-reaction is surprisingly stable.

The next Section (Section 3.2) is devoted to a detailed review of the experimental literature. Section 3.3 describes the econometric framework that we use. This framework contains a model of belief formation that nests rational, extrapolative and sticky expectations. Section 3.4 describes the experimental design. Section 3.5 describes the results. Section 3.6 concludes.

3.2 Related literature

In analyzing belief dynamics in the lab, we contribute to the empirical literature on expectation formation in experiments (see for instance Assenza et al. (2014), for a survey of this literature). Kahneman and Tversky (1973) offer one of the first experimental studies studying biases in forecasts. They show that subjects confuse the likelihood of a certain assertion being true with representativeness of the situation being described.

This experimental literature has taken different routes: Some papers attempt to categorize people into various types of forecasters. Only some of them can be considered rational, while others are for instance adaptive or extrapolative. Using surveys on future stock returns expectations Dominitz and Manski (2011) find that individuals form beliefs according to processes that are heterogeneous across individuals but stable at the individual level. They attempt to classify people into three types of expectation formation families: random-walk, persistence, and mean-reversion. However, they show that this representation of heterogeneity matches the data relatively poorly. Other papers embrace the view that beliefs dynamics can be explained by regime-switches, where subjects think that very different data generating processes are plausible and constantly update their beliefs on which process is more likely. Bloomfield and Hales (2002) run a trading experiment on MBA students and document that participants under-react more to changes when they follow many reversals. They interpret the result as evidence for regime-switching in beliefs dynamics, a la Barberis et al. (1998). Schmalensee (1976) finds evidence that the speed of adjustment of forecasts falls during turning point periods where the data generating process seems to be changing. Last, some of the literature focuses on equilibrium effects in set-ups where the realized variable depends on forecasts (see Hommes (2011)).

Broadly speaking the literature tends to reject simple forms of the rational expectation hypothesis (there are exceptions: In an experience run on 40 subjects, Dwyer et al. (1993b) fails to reject the rational anticipation model) and emphasizes the importance of recent lags in beliefs formation. For instance, Hey (1994b), runs an experiment where a group of 48 undergraduate students are asked to predict future realizations of a time-series drawn from a stable auto-regressive process. The study rejects rational expectations and finds evidence that adaptive expectations and extrapolation have explanatory power on beliefs dynamics. Beshears et al. (2013) shows in a experiment that agents fail to integrate long-term mean-reversion in their forecasts, while they are sensitive to short-term momentum and short-term mean-reversion. This leads to a form of extrapolative bias whereby recent trends are assumed to last excessively longer. Such long-term extrapolative forecasting is generated theoretically in Fuster et al. (2010): In their model, agents form expectations by estimating growth regressions with a small number of lagged variables whereas the true data generating process has hump-shaped dynamics.

Our paper contributes to the literature by showing the co-existence of both under-reaction and extrapolation at the individual level: We nest both effects in a simple model and find, in our estimation, parameters that are very stable across groups and speed of mean-reversion. We find that agents exhibit extrapolative behavior, but also, at the same time, excess stickiness in their forecasts. For the parameters of the model, we find that extrapolation is the dominating force. We also find that biases do not fade away over time: in our experiment agents do not learn from their past mistakes. A second differentiating feature of our paper is the use of the term-structure of forecasts: we ask agents to make predictions at several horizons. This makes the identification of under-reaction separately from over-reaction more credible. Under-reaction is measured by the extent to which current expectations are "stick to" previous forecasts. Extrapolation is identified off of the fact that current news have too much impact (i.e. beyond what is rational) on forecasts.

3.3 Expectations: Extrapolative vs. sticky

This Section explicits our econometric model, which nests rational, extrapolating and sticky expectations. Consider a random variable x_t that an agent is trying to forecast. We note $F_{t-k}x_{t+1}$ the subjective forecast of x_{t+1}, k periods ahead of date t. It may differ from $E_{t-k}x_{t+1}$, the full information rational expectation (we run robustness checks using least square learning as we discuss in Section 3.5.1).

We will write the subjective forecast $F_{t-k}x_{t+1}$ as the sum of an extrapolative (for overreaction) and a sticky (for underreaction) term. Let us first describe how the two parts are defined. Then, we will combine them in a single specification.

We model extrapolative expectations F^e as:

$$F^e_{t-k}x_{t+1} = E_{t-k}x_{t+1} + \gamma(x_{t-k} - E_{t-k-1}x_{t-k}) \tag{3.1}$$

where γ captures the strength of overreaction. This specification is similar to Bordalo et al. (2017a) and Bordalo et al. (2017c). Extrapolative individuals react too much to unexpected innovation ($\gamma > 0$). If, however, x_t has a deterministic trend and does not deviate from it, subjective expectations will be rational. Hence, only unexpected positive deviation from the trend will generate overoptimistic expectations. Another nice property of this specification is that it nests rational expectations as a special case ($\gamma = 0$).

We model sticky expectations F^s using the recursive formulation:

$$F^s_{t-k}x_{t+1} = (1-\lambda)E_{t-k}x_{t+1} + \lambda F^s_{t--k1}x_{t+1} \tag{3.2}$$

where $\lambda \in [0;1]$ measures the degree of stickiness. $\lambda = 0$ corresponds to fully rational expectations. In this specification (which for $\lambda = 0$ yields rational expectations), the agent is simply lagging in her updates. Sticky expectations can thus be seen as a form of underreaction as the agent only partially takes into account new informations and remains stuck with forecasts that were rational in the past. This modeling of sticky expectations appears in Coibion and Gorodnichenko (2015) ; It is used by them in a somewhat different context, as they try to model rational stickiness due to limited information, whereas we study irrational stickiness in a world where all agents have the same information. Our specification of sticky expectations is in line with the limited attention literature, where agents do not update their beliefs and consumption plans in continuous time. For instance, in **?**, firms update their pricing plans with Poisson probability λ and Gabaix and Laibson (2001) have a model where agents update their consumption plans periodically instead of continuously. Our modeling of sticky expectations gives a central role to the term-structure of forecasts, which is well suited for our experimental design where agents provide forecasts at various horizons.

The empirical specification that we use in this paper combines the two formulations in the following manner:

$$F_{t-k}x_{t+1} - E_{t-k}x_{t+1} = \underbrace{\lambda \left(F_{t-k-1}x_{t+1} - E_{t-k}x_{t+1}\right)}_{\text{underreaction}} + \underbrace{\gamma(x_{t-k} - E_{t-k-1}x_{t-k})}_{\text{extrapolation}} \tag{3.3}$$

In this specification, the individual forecaster can be both extrapolative $\gamma > 0$ and sticky $\lambda > 0$. These two effects can be estimated by regressing the expectation error $F_t x_{t+1} - x_{t+1}$ on past period innovation $x_t - E_{t-1}x_t$, which captures extrapolation, and past period expectation mistake $F_{t-1}x_{t+1} - E_t x_{t+1}$, which captures underreaction. Intuitively, if expectation errors can be forecasted using previous period errors, this is a sign of underreaction, and $\lambda > 0$. If expectation errors can be forecasted using past innovation, this is a sign of extrapolation, and $\gamma > 0$. Hence, individuals can be both under- and over-reacting to news, and the two effects are separately identified from the term structure of subjective forecasts $F_{t-1}x_{t+1}, F_t x_{t+1}$, and rational expectations $E_{t-1}x_{t+1}, E_t x_{t+1}$.

3.4 Experiment Design

We recruit participants using standard MTurk HITs titled "Making Statistical Forecasts." Participants are adults from across the US. They complete the experiment using their own electronic devices (e.g. computers and tablets). The MTurk platform is commonly used in experimental studies (Kuziemko et al., 2015; D'Acunto, 2015b; Cavallo et al., 2017; Dellavigna and Pope, 2017c). It offers a large subject pool and a more diverse sample compared to lab experiments. Prior research also finds the response quality on MTurk to be similar to other samples and to lab experiments (Lian et al., 2017; Casler et al., 2013).

3.4.1 Experimental conditions

Participants first read a consent form (shown in the Survey Appendix), with a brief description of the experiment, the payments, and the duration (described in detail below). Once participants agree to the consent form, they read instructions and start the experiment. In all conditions, they are first presented with 40 historical realizations a statistical process, and are asked to predict future realizations for 40 rounds. After the prediction task, participants answer some basic demographic questions. The specifics of the prediction task vary from condition to condition, and are described in the following paragraphs. We conducted 3 different experiments sequentially (the baseline, and then versions of it). For each experiment, we made sure the participants were different by excluding participants of previous batches.

Experiment 1. Experiment 1 was conducted in February 2017 and is our baseline test. The various conditions are summarized in Table 3.1, Panel A. In the experiment, each participant is presented with a different realization of an AR1 process:

$$x_{t+1} = \rho x_t + \epsilon_t \tag{3.4}$$

In each round, participants are asked to predict the value of the next two realizations x_{t+1} and x_{t+2}. Figure 3.1 provides a screen shot of the prediction page. Specifically, a series of green dots show past realizations of the statistical process. Participants can drag the mouse to indicate their prediction for the next realization, $F_t x_{t+1}$, in the purple bar, and indicate the following realization, $F_t x_{t+2}$, in the red bar. Participants' predictions are shown as yellow dots. We also display the prediction of x_{t+1} from the previous round $F_{t-1}x_{t+1}$ using a grey dot (participants can see it but cannot change it). After making their decisions, participants click "Make Predictions" and move on to the next round.

In this experiment, we use 6 different values of ρ: $\{0, 0.2, 0.4, 0.6, 0.8, 1\}$. The volatility of ϵ is 20. Each participants is randomly assigned to one value of ρ. Each participant is presented with a different realization of the process. There are 270 participants in total and about 30 participants per value of ρ (the randomization is not perfectly even across conditions in a finite sample).

Experiment 2. Experiment 2 was conducted in March 2017. Its goal is the study of potential heterogeneity in participants' responses to the same statistical process. Thus we perform an experiment that is similar to Experiment 1, except we use the same value of $\rho = 0.6$ for all participants, and only 10 (randomly generated) realizations of the AR1 process. Each participant is randomly assigned to one of the 10 paths. Other aspects of the experimental procedures are the same as Experiment 1. There are 330 participants in total, with about 30 participants per path (again the randomization is not perfectly even). Conditions are summarized in Table 3.1, Panel B.

Experiment 3. In Experiment 3, we modify Experiment 1 in several ways to perform various robustness checks. Table 3.1, Panel C, provides a summary of the conditions. Every participant is randomly assigned to one of these conditions. There are 875 participants in total, with roughly 35 participants per condition. Experiment 3 was conducted in June 2017.

The conditions in Experiment 3 are designed to help us implement three main tests (whose results we report in Section 3.5.7):

1. *Well-known economic variables vs abstract process*

   In Conditions 1 to 8, we test whether participants' forecasting behavior is different when we provide a "context" for the random process they forecast. Specifically, we estimate the properties of four major economic variables (assuming an AR1 process): U.S. quarterly GDP growth, monthly CPI, monthly S&P 500 stock returns, and monthly house price growth. We then use the estimated parameters to generate the random processes in the experiment. In Conditions 1 to 4, in the experimental instruction we explain that "the process you will see has the same property as [...]." In Conditions 5 to 8, we use the same random processes but do not provide the "context" in the experimental instruction. Everything else is the same as Experiment 1. Through this design, we can examine whether participants' behavior is influenced by the "context" by comparing Conditions 1 to 4 with their counterparts in Conditions 5 to 8.

2. *Varying other AR1 parameters than ρ: Long-term mean and volatility*

   In addition, we use Conditions 5 and 6, which both have $\rho = 0.4$ but different values for μ and σ, to test whether these other parameters affect our results. In particular, we compare them to Condition 9, which has $\rho = 0.4$ and $\mu = 0$, $\sigma = 20$ as in Experiment 1.

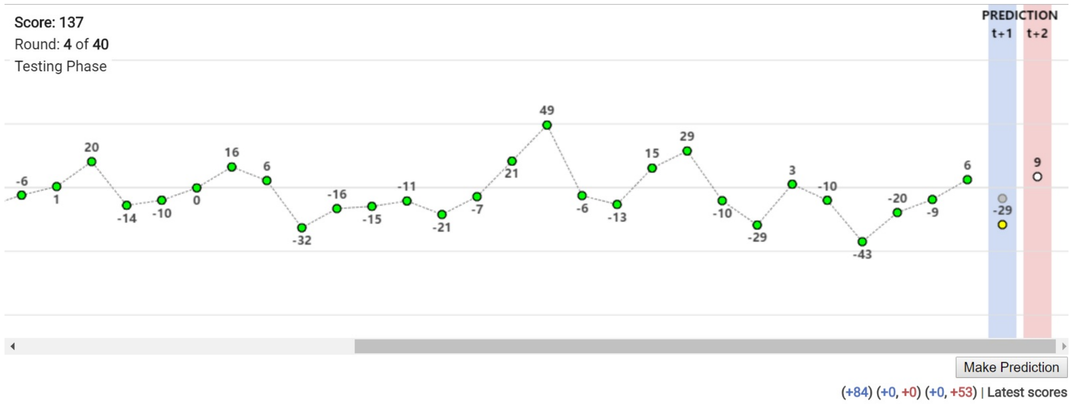
3. *The term structure of expectations*

   In the remaining conditions of Experiment 3, we test the impact of asking participants to report the term structure of expectations. In conditions 10 to 13, we ask for the $t+1$ forecast only. In conditions 14 to 17, we ask for the $t+2$ forecast only. In conditions 18 to 21, we ask for the $t+1$ and $t+5$ forecasts. Finally, in conditions 22 to 25, we ask for $t+1$ and $t+2$ forecasts, but remove the grey dot that shows the $t+2$ forecast from the previous round, i.e. $F_{t-1}x_{t+1}$.

Table 3.1: *Summary of Conditions in all Three Experiments*

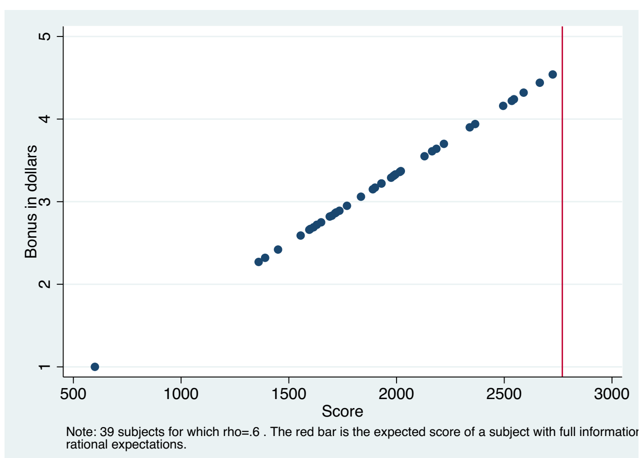
This Table provides a synthetic description of the three experiments we conducted. Each panel is devoted to one experiment, and within each panel, each line corresponds to one experimental condition The first three column (1)-(3) gives the parametrization of the AR1 process $x_{t+1} = \rho x_t + (1-\rho)\mu + \epsilon_{t+1}$ participants are asked to forecast. Column (4) shows the forecasts asked to each participants. "F1+F2" means one- and two-period ahead forecasts. Column (5) indicates if a grey dot is present on the interface to help the participant memorize the long-term forecast of the previous period. Column (6) reports the number of participants. Typically, each participant is presented with a different draw, except in experiment B, where all participants within a given condition are presented with the same draw. Participants were not allowed to participate to several experiments.

#	Short description	(1) persistence ρ	(2) AR1 process Lt mean μ	(3) Volatility σ_ϵ	(4) Forecasts asked	(5) Grey dot	(6) Number of participants
Panel A: Experiment 1 – Baseline							
A1	Baseline $\rho = 0$	0	0	20	F1+F2	Y	32
A2	Baseline $\rho = 0.2$	0.2	0	20	F1+F2	Y	32
A3	Baseline $\rho = 0.4$	0.4	0	20	F1+F2	Y	36
A4	Baseline $\rho = 0.6$	0.6	0	20	F1+F2	Y	39
A5	Baseline $\rho = 0.8$	0.8	0	20	F1+F2	Y	28
A6	Baseline $\rho = 1$	1	0	20	F1+F2	Y	40
Panel B: Experiment 2 – Common path							
B1	Path 1	0.6	0	20	F1+F2	Y	37
B2	Path 2	0.6	0	20	F1+F2	Y	32
B3	Path 3	0.6	0	20	F1+F2	Y	37
B4	Path 4	0.6	0	20	F1+F2	Y	30
B5	Path 5	0.6	0	20	F1+F2	Y	32
B6	Path 6	0.6	0	20	F1+F2	Y	33
B7	Path 7	0.6	0	20	F1+F2	Y	27
B8	Path 8	0.6	0	20	F1+F2	Y	33
B9	Path 9	0.6	0	20	F1+F2	Y	26
B10	Path 10	0.6	0	20	F1+F2	Y	43
Panel C: Experiment 3 – Robustness checks							
C1	context: quarterly GDP growth	0.4	0.40	0.55	F1+F2	Y	38
C2	context: monthly inflation	0.4	0.12	0.23	F1+F2	Y	39
C3	context: monthly stock returns	0.2	0.55	3.43	F1+F2	Y	29
C4	context: monthly house price growth	0.8	0.02	0.39	F1+F2	Y	37
C5	no context, comparison	0.4	0.40	0.55	F1+F2	Y	30
C6	no context, comparison	0.4	0.12	0.23	F1+F2	Y	34
C7	no context, comparison	0.2	0.55	3.43	F1+F2	Y	36
C8	no context, comparison	0.8	0.02	0.39	F1+F2	Y	35
C9	comparison	0.4	0	20	F1+F2	Y	30
C10	change horizon	0.2	0	20	F1	/	37
C11	change horizon	0.4	0	20	F1	/	36
C12	change horizon	0.6	0	20	F1	/	33
C13	change horizon	0.8	0	20	F1	/	38
C14	change horizon	0.2	0	20	F2	Y	38
C15	change horizon	0.4	0	20	F2	Y	51
C16	change horizon	0.6	0	20	F2	Y	32
C17	change horizon	0.8	0	20	F2	Y	42
C18	change horizon	0.2	0	20	F1+F5	Y	27
C19	change horizon	0.4	0	20	F1+F5	Y	34
C20	change horizon	0.6	0	20	F1+F5	Y	29
C21	change horizon	0.8	0	20	F1+F5	Y	41
C22	no grey dot	0.2	0	20	F1+F2	N	26
C23	no grey dot	0.4	0	20	F1+F2	N	31
C24	no grey dot	0.6	0	20	F1+F2	N	30
C25	no grey dot	0.8	0	20	F1+F2	N	42



Note: Screen shot of the prediction task. The green dots indicate past realizations of the statistical process. In each round t, participants are asked to make predictions about two future realizations $F_t x_{t+1}$ and $F_t x_{t+2}$. They can drag the mouse to indicate $F_t x_{t+1}$ in the purple bar and indicate $F_t x_{t+2}$ in the red bar. Their predictions are shown as yellow dots. The grey dot is the prediction of x_{t+1} from the previous round $F_{t-1} x_{t+1}$; participants can see it but cannot change it. After they have made their predictions, participants click "Make Predictions" and move on to the next round. The total score is displayed on the top left corner, and the score associated with each of the past prediction (if the actual is realized) is displayed at the bottom.

Figure 3.1: *Prediction Screen*



Note: Each point on this figure corresponds to one participant in one condition of the baseline experiment (Experiment 1, with $\rho = .6$). On the x-axis, we report the score obtained, and on the y-axis, the payment in $, which is equal to the score divided by 600. The vertical red line on the right represents the expected payment of a (full information) rational participant for which $F_t x_{t+1} = E_t x_{t+1} = \rho x_t$.

Figure 3.2: *Payment and scores in the Baseline Experiment*

Table 3.2: *Experimental Statistics*

Summary statistics of experiment duration and bonus payments.

	Mean	p25	p50	p75	SD	*N*
Experiment 1 (2 forecasts per round)						
Total time (min)	13.88	8.30	11.65	16.42	8.65	270
Forecast time (min)	7.10	4.49	5.77	7.85	4.39	270
per round (sec)	10.64	6.74	8.66	11.77	6.59	270
Bonus ($)	3.33	2.80	3.31	3.84	0.78	270
Experiment 2 (2 forecasts per round)						
Total time (min)	13.12	8.16	10.88	15.79	7.88	330
Forecast time (min)	6.78	4.59	5.75	7.74	4.05	330
per round (sec)	10.17	6.89	8.63	11.61	6.07	330
Bonus ($)	3.22	2.74	3.15	3.67	0.84	330
Experiment 3 (2 forecasts per round)						
Total time (min)	12.44	7.83	10.56	14.60	7.48	580
Forecast time (min)	6.69	4.42	5.73	7.67	4.17	580
per round (sec)	10.03	6.63	8.59	11.50	6.26	580
Bonus ($)	3.29	2.78	3.29	3.80	0.81	580
Experiment 3 (1 forecast per round)						
Total time (min)	11.05	6.91	9.25	13.73	6.52	295
Forecast time (min)	5.27	3.36	4.31	6.03	3.80	295
per round (sec)	7.91	5.03	6.47	9.05	5.70	295
Bonus ($)	1.62	1.31	1.62	1.92	0.48	295

Table 3.3: *Sample Demographics*

Summary statistics of participant demographics.

		N	%	*N*	%	*N*	%
Gender	Male	151	55.9	201	60.9	457	52.2
	Female	119	44.1	129	39.1	418	47.8
Age	<= 25	36	13.3	44	13.3	129	14.7
	25-45	186	68.9	224	67.9	593	67.8
	45-65	44	16.3	57	17.3	145	16.6
	65+	4	1.5	5	1.5	8	0.9
Education	Grad school	26	9.6	42	12.7	121	13.8
	College	170	63.0	200	60.6	524	59.9
	High school	74	27.4	88	26.7	224	25.6
	Below/other	0	0.0	0	0.0	6	0.7
Invest. Exper.	Extensive	7	2.6	6	1.8	23	2.6
	Some	71	26.3	74	22.4	193	22.1
	Limited	100	37.0	129	39.1	367	41.9
	None	92	34.1	121	36.7	292	33.4
Taken Stat Class	Yes	110	40.7	144	43.6	406	46.4
	No	160	59.3	186	56.4	469	53.6
Total		270	100.0	330	100.0	875	100.0

3.4.2 Payments

Each participant is offered a base payment of \$1.80. In addition to the base payment, participants also receive incentive payments that depend on their performance in the prediction task. Specifically, for each prediction, the participant receives a score that is a decreasing function of the forecasting mistake as for instance in (Dwyer et al., 1993a; Hey, 1994a):

$$S = 100 \times \max(0, 1 - |\Delta|/\sigma) \tag{3.5}$$

where Δ is the difference between the prediction and the actual realization, and σ is the volatility of the noise term ϵ. For each round, the score is between 0 and 100. We calculate the cumulative score of each participant, and convert it to dollars by dividing 600. The total score is displayed on the top left corner of the prediction screen, and the score associated with each of the past prediction (if the actual is realized) is displayed at the bottom of the screen (see Figure 3.1).

For one particular condition (Baseline, AR1 process with $\rho = .6$), we show in Figure 3.2 the joint distribution of scores and payments. Each point on this figure corresponds to the score (x-axis) and payment (y-axis) of one participant (there are 38 participants in this condition). All points are on straight line as payment is equal to score divided by 600 plus \$1.80. The expected incentive payment for a (full information) rational agent about \$5 (6.25 cents per prediction times 80 predictions). As can be seen from the figure, all agents receive payments that are below the expected rational level. Across all conditions like in the Figure, incentive payments have a mean of approximately \$3.20 (except in those conditions in Experiment 3 where participants give only one forecast per round, where the mean is roughly half as large). Table 3.2 shows the summary statistics of the incentive payments for all three experiments separately, and within experiment 3, splits between conditions with one and conditions with two forecasts. Clearly, the distribution of payments is on the left of the expected rational bonus of about \$5.

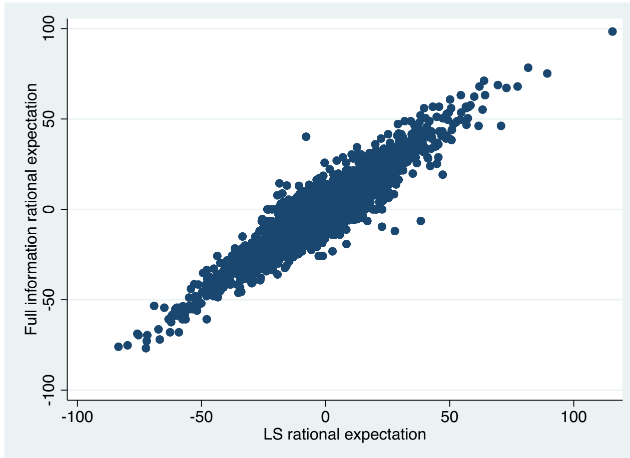
Notice that the loss function defined in equation (3.5) ensures that a rational participant will choose the rational expectation as an optimal forecast, if there is no cost to do so. This is similar to the earlier experimental literature on expectations Dwyer et al. (1993a); Hey (1994a). $E(1 - |x_{t+1} - F_t|/\sigma)$ is maximal for a forecast F_t equal to the 50^{th} percentile of the distribution of x_{t+1} conditional on x_t. Given that our process is symmetrical around the rational forecast, the median is equal to the mean, and the optimal forecast is therefore equal to the rational expectation.

Finally, the participation constraint of subjects is likely to be satisfied. The sum of the base payment and the incentive payment is about $5 (for a roughly 15 minute task), which is high compared to the average pay rate on MTurk. As far as the incentive compatibility constraint is concerned, the question is more difficult as it depends on the cost of making more rational expectations. Hozever, recent work by Dellavigna and Pope (2017c) show that participants provide high effort even when the size of the incentive payment is modest, and incentives do not appear to be a primary issue in this setting.

3.4.3 Descriptive Statistics

The distribution of duration is also presented in Table 3.2. The mean duration of participation is about 13 minutes, and we allow a maximum duration of 60 minutes. The mean duration for each round of prediction is about 10.5 seconds.

Table 3.3 shows the demographics of participants in our experiments. About 55% to 60% of the participants are male. Roughly 75% report they have college or graduate degrees, and the level of education is higher than that in the general US population (60% with college degrees or above) (Ryan and Bauman, 2015b). 40% report they have taken a statistical class. The median age is about 33, slightly lower than the general population (37) (Howden and Meyer, 2011); less than 2% of the participants are above 65.



Note: Each point on this figure corresponds to one participant in one testing round. On the x-axis, we report the LS expectations of x_t using three lags $x_{t-1}, x_{t-2}, x_{t-3}$ and coefficients estimated using OLS and all information available until date $t-1$. On the y-axis, we report the FI expectation given by ρx_{t-1}. We only focus on participants for which $\rho \geq 0$ and $\rho < 1$. Regressing y on x leads to an $R^2 = .84$ and a slope coefficient of .86.

Figure 3.3: *Full Information vs Least Square Expectations*

3.5 Empirical Results

3.5.1 Measuring rational expectations

To estimate our econometric specification, we need to compute the rational expectation of the agent, which we generically denote $E_{t-k}x_t$. We use two different measures, which we describe here. The first measure assumes that the agent knows the data-generating process. This corresponds to the full information rational expectation used in most economic models. We thus define rational expectation about x_t conditional on information available at date $t-k$ as:

$$E^{FI}_{t-k}x_t = \rho^k x_t$$

This definition of full information rational expectations will be our baseline, and for simplicity we will use it in most of our regressions.

The participant does not, however, know the data-generating process, so in practice the participant will try to infer it using the data. In robustness checks, we use a definition based on least square learning Evans and Honkapohja (2001):

$$\widehat{E}_{t-k}x_t = a_{t-k} + \sum_{i=0}^{i=n} b_{i,t-k}x_{t-k-i}$$

whereby, every period, the participant forecasts x_t using all lagged values from x_{t-k-n} until x_{t-k}. Parameters a_{t-k} and $(b_{i,t-k})_i$ are estimated using OLS and all the available past history of realizations of x_t until x_{t-k}. Because of the central limit theorem, a LS learning participant with an infinite number of data points would form full information rational expectations: $a_{t-k} = 0$, $b_{0,t-k} = \rho^k$, $b_{i,t-k} = 0$ for $i > 0$. In the paper, we set $n = 3$ but our results are insensitive to this threshold.

For the $AR1$ processes that we are using in our experiment, the difference between the two definition is not large. In Figure 3.3, we plot $E^{FI}_{t-1}x_t$ against $\widehat{E}_{t-1}x_t$ for all realizations in our data for which $0 \leq \rho < 1$. As is apparent in the picture, the correlation between the two measures is high: .84. The slope coefficient is .86, so that the two measures are highly correlated and similar in the sample we are looking at. We also show in Appendix Table A.1 that the mean squared difference between these two expectations does not decrease very fast during the time the experiment takes place. This is mostly because the experiment only starts after 40 observations, so the estimated model is already quite precise. As is well known, such similarity would not hold for a more complex data-generating process, e.g. with non-linear terms. Hence, in our experimental setting, there is little scope for learning if participants were rational. There might, however, be scope for learning if participants are not rational LS learners. We return to this issue below.

3.5.2 Main Result

We now turn to our main result. As discussed in Section 3.3, we run the following regression on the sample of all participants for which the persistence parameter $\rho \in \{0, .2, .4, .6, .8\}$. For individual i at date t:

$$F^i_t x_{it+1} - E_t x_{it+1} = \lambda \left(F^i_{t-1} x_{it+1} - E_t x_{it+1} \right) + \gamma (x_{it} - E_{t-1}x_{it}) + u_{it+1} \tag{3.6}$$

where the rational expectation $E_t x_{t+1}$ is in general measured with the full information definition $E^{FI}_{t-k} x_t$, except when noted. We use OLS and cluster the error terms u_{it+1} at the individual i level in order to account for the fact that forecast errors may be autocorrelated at the individual level.

Table 3.4: *Main Expectation Formation Model: Main results*

On the panel of participants for which $\rho \in \{0, .2, .4, .6, .8\}$, we run the following regression:

$$F^i_t x_{it+1} - E_t x_{it+1} = \lambda \left(F^i_{t-1} x_{it+1} - E_t x_{it+1} \right) + \gamma (x_{it} - E_{t-1} x_{it}) + u_{it+1}$$

In all columns but column (5), we use the FI expectation to measure rational expectations. In column (1), we set $\gamma = 0$. In column (2), we set $\lambda = 0$. Column (3) is our main specification. Column (4) allows γ to differ for both components of the trend regressor. Column (5) uses LS learning rational expectation instead of FI. Columns (6) and (7) split the sample into the first and last 20 rounds. t-stats between brackets.

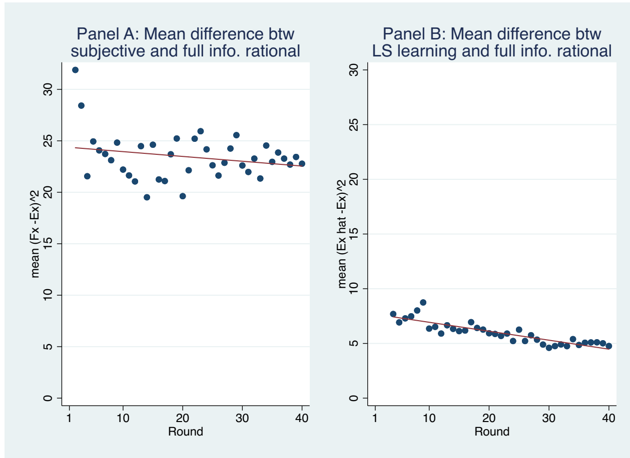
	$F_t x_{t+1} - E_t x_{t+1}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Sticky	Trend	Main		$\widehat{E}_t x_{t+1}$	$t \leq 20$	$t > 20$
$F_{t-1} x_{t+1} - E_t x_{t+1}$	.1***		.19***		.19***	.2***	.17***
	(4.9)		(8.4)		(8.9)	(6)	(5.9)
$x_t - E_{t-1} x_t$		.37***	.44***	.44***	.45***	.42***	.45***
		(15)	(19)	(16)	(20)	(13)	(14)
$F_{t-1} x_{t+1}$				.19***			
				(8.3)			
$E_t x_{t+1}$				-.21***			
				(-5.3)			
N	6346	6513	6346	6346	6012	3006	3340
r2	.018	.1	.16	.16	.18	.15	.16

Results are reported in Table 3.4. Most columns use the full information definition of expectations ($E^{FI}_{t-1} x_{it} = \rho x_{it-1}$) unless otherwise noted. Column 1 assumes no extrapolation ($\gamma = 0$). Expectation appear to be sticky with a coefficient $\lambda = .11$, strongly significant statistically (t stat of 5). An econometrician ignoring potential extrapolation would thus infer that expectations are "11%" sticky and "88%" rational. Note that this coefficient is in the ballpark of estimates of expectation stickiness in the literature (Coibion and Gorodnichenko (2015), Bouchaud et al. (2018) for instance). These estimates use field data and focus on consensus – not individual – forecasts. Column 2 makes the opposite exercise, assuming pure extrapolation, and indeed find evidence of extrapolation, with $\gamma = .36$, significant with a t-stat of 14. The two drivers are included together in column (3), which is our preferred specification. Compared to columns 1 and 2, both γ and λ increase, which is consistent with intuition. They are both very significant. Column 5 confirms our main finding by using the LS learning rational expectation instead of FI expectations. Estimates barely change. All in all, across all specification, γ hovers between .42 and .44. λ hovers between .18 and .21. We will return to magnitudes below.

We also investigate the possibility that learning takes place, reducing systematic errors over time. We do not find much evidence of learning during the 40 periods of our test. One first way of looking at this consists of splitting the sample between the first 20 and the last 20 rounds of testing. If learning takes place, we should see a reduction in the estimated γ and λ. We do this in Table 3.4, columns 6-7. Stickiness λ decreases slightly, and over-reaction γ increases a bit, but none of these changes are statistically significant. Another way to explore learning in this context consists of computing the mean squared difference between subjective forecasts and rational forecasts. We show this statistic in Figure 3.4. In panel A, we show the square root of the mean squared difference between the observed forecast $F_{t-1}x_t$ and the full information rational expectation $E_{t-1}x_t = \rho x_{t-1}$. We plot this number as a function of the round of observation in Panel A. If all participants were rational, this mean difference would be zero. Since we cannot expect participants to be FI rational (they need to learn about the model from the data), we replicate the same analysis with LS expectations, and show the reduction in the distance between LS and FI expectation in Panel B. Clearly, the distance of subjective forecasts to FI expectations is much bigger than LS learners (about 4 times bigger). Also, while this distance is reduced by about 30% after 40 rounds for LS learners, it goes down by less than 10% for the participants of our experiment. The bulk of the downward sloping learning curve is accounted for by the first couple of periods, after which essentially no learning seems to take place.

3.5.3 Robustness of the estimates to γ and λ

Table 3.5 offers further evidence that our estimates of γ and λ are very robust across subpopulations. In Panel A, we split the sample of participants by demographic category:



Note: We investigate here the speed at which participants' subjective forecasts converge to full information rational forecasts (Panel A). We compare this to what rational least-square learners would do (Panel B). We use all conditions of the experiment # 1, i.e. all participants with $\rho \in \{0, .2, .4, .6, .8\}$. For each testing round t from 1 to 40, we compute the mean square difference between the subjective forecast $F_{t-1}x_t$ and the full information rational forecast $E_{t-1}x_t = \rho x_{t-1}$. We then take the square root of this, and report it in Panel A. Hence, in Panel A, if all survey participants were full information rational, the mean difference would be equal to zero. We then repeat this procedure in Panel B, replacing the subjective forecast with the LS learning expectation $E_{t-1}^{LS}x_t$ obtained by regressing x_s on x_{s-1} for all periods between -40 and $t-1$. Hence, Panel B allows to observe the extent to which a LS learner would converge to the true rational expectation. Reading: The root mean squared difference between FIR and subjective forecasts goes down from 24 to 22 after 40 rounds. The root mean squared difference between FIR and LS learner forecasts goes down from 7 to 5 after 40 rounds.

Figure 3.4: *How Fast Do Subjective Forecasts Converge to Rational Expectations?*

Gender (columns 1-2), Age (columns 3-4) and Education (columns 5-6). In Panel B, we split the sample of participants by response to basic questions designed to test the statistical skill of participants. In columns 1-2, we focus on the "coin toss" question, designed to test if participants understand the notion of statistical independence. In columns 3-4, we look at answers to a question designed to see if participants know what a median is. In columns 5-6, we split participants into those who answered right or wrong to the "hospital" questions, which tests if people understand the law of large numbers. In all these subsamples, the stickiness estimate is strongly statistically significant and hovers between .17 and .26. The extrapolation parameter is even more significant and hovers between .41 and .47. Interestingly, our measures of statistical skill have very little effect on the estimates. Among demographics, age is the most discriminating variable, with younger participants significantly less sticky and less extrapolating.

Table 3.6 reports the estimation of equation (3.6) for each value of ρ between 0 and 1. For all stationary processes (i.e. for ρ between 0 and 0.8) the model turns out to be remarkably stable. The stickiness coefficient lies between .12 and .21, but the Fisher test cannot reject the null that all coefficients are equal (p value of .33). The same result arises for the trend parameter, which is estimated across conditions between .38 and .48, but then again, the null that all coefficients are equal across conditions is not rejected (p value of .69). The picture actually remains the same when one includes the condition where $\rho = 1$, but the estimates increase a lot: When the process is actually non stationary, participant expectations become both stickier and more extrapolative. It looks like non-stationary processes are harder to cope with. This change is apparently large, though not significant statistically.

3.5.4 Quantifying the results

In order to shed some light on the relative importance of extrapolation and stickiness in the dynamics of expectation, we start from the equivalent formulation:

$$F_t x_{t+1} = (1-\lambda) \sum_{k=0}^{\infty} \lambda^k E_{t-k} x_{t+1} + \gamma \sum_{k=0}^{\infty} \lambda^k \left(x_{t-k} - E_{t-k-1} x_{t-k} \right) \tag{3.7}$$

This formulation is equivalent to our main recursive model (3.6). We estimate it separately in Appendix C.1.1 and show the resulting coefficient to be similar to the ones we obtain in Table 3.4. As is apparent from the above equation, stickiness has itself an effect on extrapolation, through the second term. Current forecasts do not only take into account the recent surprise $x_{t-1} - E_{t-2} x_{t-1}$ but in principle all surprises before this, with exponentially decreasing weights. Hence, there is no extrapolation unless $\gamma > 0$ but large values of λ render extrapolation "sticky" and therefore more effective. Note the similarity of the second term with the expectation model in Barberis et al. (2015). We test this model in Appendix C.1.1 by regressing $F_t x_{t+1}$ on terms in $E_{t-k} x_{t+1}$ and $x_{t-k-1} - E_{t-k-2} x_{t-k-1}$, and find values consistent with exponentially decreasing parameters.

Table 3.5: *Main Expectation Formation Model: Sample Splits by Participant Groups*

Note: This Table estimates our core regression on subsamples of our experiment. On the panel of participants for which $\rho \in \{0, .2, .4, .6, .8\}$, we run the following regression:

$$F_t^i x_{it+1} - E_t x_{it+1} = \lambda \left(F_{t-1}^i x_{it+1} - E_t^i x_{it+1} \right) + \gamma (x_{it} - E_{t-1}^i x_{it}) + u_{it+1}$$

In Panel A, we focus on sociodemographic categories. In columns 1 and 2, we split the sample into male and female participants. In columns 3 and 4, we split the sample into participants above and below 35 years old. In columns 5 and 6, we split the sample into t-stats between brackets. In Panel B, we focus on groups by answers to various statistical questions. Columns 1-2 split participants into wrong and false answers to the "coin toss" question, designed to see if people understand the notion of statistical independence. Columns 3 and 4 split participants into wrong and false answers to the "median" question, designed to see if people know how to compute a median. Columns 5 and 6 split participants into wrong and false answers to the "hospital" question, designed to see if people understand the law of large number.

Dependent variable	$F_t x_{t+1} - E_t x_{t+1}$					
Panel A : Socio-demographics						
	(1)	(2)	(3)	(4)	(5)	(6)
	Male	Female	age< 35	age≥ 35	high school	college
$F_{t-1} x_{t+1} - E_t x_{t+1}$	.19***	.19***	.15***	.26***	.26***	.17***
	(5.8)	(6.7)	(5.7)	(7.7)	(5.7)	(6.8)
$x_t - E_{t-1} x_t$	.44***	.43***	.42***	.48***	.46***	.43***
	(14)	(13)	(13)	(16)	(11)	(16)
N	3458	2888	3762	2584	1710	4636
r2	.15	.16	.12	.24	.21	.14
Panel B : Answers to statistics quiz						
	(1)	(2)	(3)	(4)	(5)	(6)
	Coin toss		Median		Hospital	
	False	Right	False	Right	False	Right
$F_{t-1} x_{t+1} - E_t x_{t+1}$	.17***	.2***	.18***	.2***	.2***	.16***
	(6)	(6.2)	(5.4)	(6.4)	(9.2)	(3)
$x_t - E_{t-1} x_t$	.44***	.43***	.44***	.44***	.45***	.42***
	(10)	(16)	(13)	(13)	(17)	(9.7)
N	2356	3990	3078	3268	4294	2052
r2	.16	.15	.14	.17	.17	.13

We report the impulse response of this belief formation process in Figure 3.6. We show three lines. The first line is the impulse itself x_t: $x_0 = 1$ and $x_t = \rho x_{t-1}$ for $t \geq 1$. The second line is the rational expectation. The rational agent is first surprised by the impulse: $E_0 x_1 = 0$, then, the rational expectation is given by $E_{t-1} x_t = \rho x_{t-1}$ which is equal to the realization in our impulse response setting. The third line is the simulated forecast using formula (3.7) for $\gamma = .45$, $\lambda = .2$ and $n = 1$. From Figure 3.6, it appears quite clearly that our forecasters over-react to the impulse when compared to rational forecasters.

Table 3.6: *Main Expectation Formation Model*
Sample split by value of ρ

Note: On the panel of participants for which $\rho \in \{0, .2, .4, .6, .8, 1\}$, we run the following regression:

$$F_t^i x_{it+1} - E_t x_{it+1} = \lambda \left(F_{t-1}^i x_{it+1} - E_t^i x_{it+1} \right) + \gamma (x_{it} - E_{t-1}^i x_{it}) + u_{it+1}$$

In each column, we estimate the above equation for all participants with a given value of ρ. t-stats between brackets.

	$F_t x_{t+1} - E_t x_{t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\rho =$	0	.2	.4	.6	.8	1
$F_{t-1} x_{t+1} - E_t x_{t+1}$	.16**	.17***	.12**	.23***	.21***	.43***
	(2.2)	(4)	(2.3)	(6.5)	(6.6)	(3.7)
$x_t - E_{t-1} x_t$	.44***	.48***	.46***	.43***	.38***	.58***
	(8.2)	(7.9)	(11)	(9.3)	(8.5)	(4.8)
N	1216	1216	1368	1482	1064	1520
r2	.17	.2	.14	.15	.13	.29

In fact, overreaction clearly dominates given our estimates. Taking into account that x_t follows an AR1 process of persistence ρ, and assuming for conveinience $n = +\infty$ we can rewrite the expected error as:

$$F_t x_{t+1} - E_t x_{t+1} = \sum_{k=0}^{\infty} \underbrace{\lambda^k (\gamma - \lambda \rho^{k+1})}_{a_k} \epsilon_{t-k}$$

for which each term a_k is positive as long as $\lambda < \gamma$, which is consistently the case across our estimates. Hence, our forecasters become over-optimistic as soon as a positive shock hits the process, and remain so forever on average, even though their upward bias goes towards zero. This expression also makes clear that sequences of positive news lead to even more extrapolation, a bit like in Barberis et al. (2017). Given our parameter values. The only situation when agents are underreacting is when, say, a positive signal follows a long sequence of negative ones. In this case, the cumulative extrapolation on past negative shocks dominates the extrapolation on the more recent shock, and, overall, the agent underreact.

3.5.5 Heterogeneity

In this Section, we explore the heterogeneity that is behind our average model of belief formation. To explore this, we go back to our main model, but allow the coefficients λ and γ to vary across individuals:

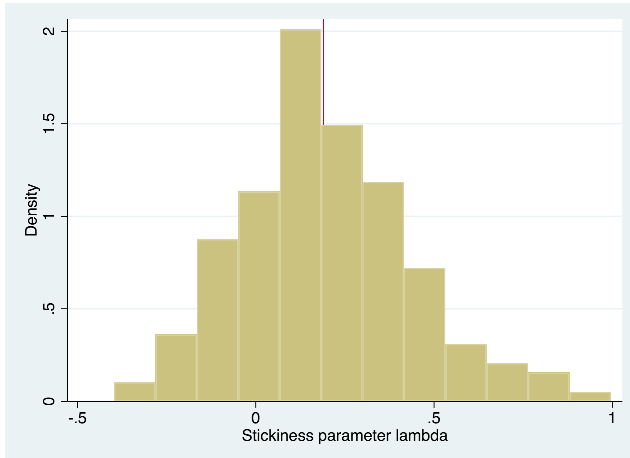
$$F_t^i x_{it+1} - E_t x_{it+1} = \lambda_i \left(F_{t-1}^i x_{it+1} - E_t x_{it+1} \right) + \gamma_i (x_{it} - E_{t-1} x_{it}) + u_{it+1} \tag{3.8}$$

i.e., we run one such regression per subject.

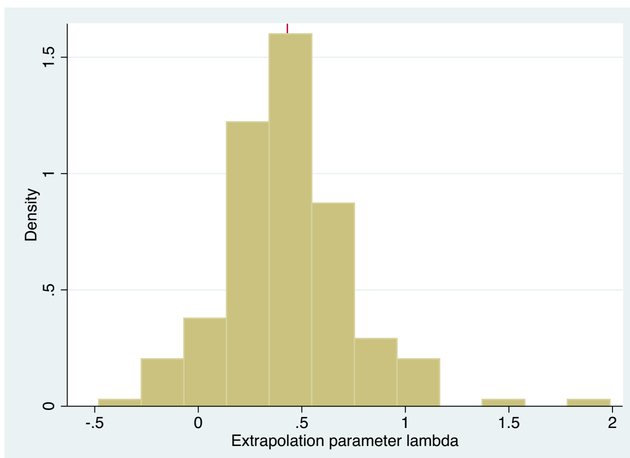
In Figure 3.5, we show the distributions of stickiness and extrapolation. Two messages emerge. First, the null hypothesis of full information rationality ($\lambda = \gamma = 0$) is rejected at 10% for 215 out of 270 subjects. Second, there is significant dispersion, but a lot of it is due to the small number of observations (39) used to estimate each parameter. To assess the heterogeneity separately from estimation noise, for each individual, we compute the p-value of a test of the null that $\lambda_i = \lambda$, taking into account the fact that both numbers are estimated (we run the two regression using the SURE approach). Individual stickiness differs from average at 5% for only 94 subjects out of 270. Individual extrapolation differs from average for 89 individuals. Overall, we cannot reject about two thirds of the individuals behave like the average model. Expectation formation is quite homogeneous.

We have nonetheless investigated the cross-sectional properties of individual parameters. To do this, we have regressed individual λ_i and γ_i on various characteristics. Consistently with our robustness checks in Tables 3.5 and 3.6, we did not find any significant and consistent relation between either of the two parameters and sociodemographics, measures of statistical literacy, or the level of ρ. λ and γ are consistent across these groups. The only cross-sectional relation that emerges if the negative correlation between λ_i and γ_i which is equal to $-.2$ and significant at 5%. Hence, sticky subjects tend to extrapolate less.

Panel A: Distribution of Stickiness λ



Panel B: Distribution of Stickiness γ



Note: On the panel of participants for which $\rho \in \{0, .2, .4, .6, .8\}$, we run the following regression:

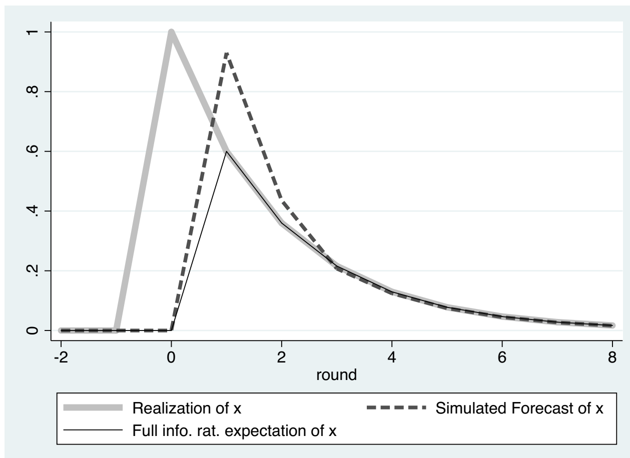
$$F_t^i x_{it+1} - E_t x_{it+1} = \lambda_i \left(F_{t-1}^i x_{it+1} - E_t x_{it+1} \right) + \gamma_i (x_{it} - E_{t-1} x_{it}) + u_{it+1}$$

where λ_i and γ_i are allowed to differ across subjects. We then report the distribution of these parameters in the two panels above. The vertical red line corresponds to the estimates of the average model in Table 3.4, column 3.

Figure 3.5: *Sample distribution in Stickiness and Extrapolation*

3.5.6 Individual-level vs Consensus Forecast

In this Section, we ask if our model of expectation formation does well to explain aggregate expectations. The model estimated in Table 3.4 has an R^2 of .15, which suggests that the error term u_{it+1} in equation (3.6) is quite volatile. This means individual expectations are hard to predict, but average expectations may be easier to predict if some of these errors are idiosyncratic. To check this, we need to make sure that several subjects in a condition are exposed to the same realization.



Note: We assume $\rho = .6$ and show the impulse response of a process x, its rational expectation and its forecast using the formulation estimated in this paper. The thick light grey line correspond to the simulation of the response of an AR1 x_t to a one time shock in ϵ equal to 1. Hence, $x_0 = 1$ and for each $t \geq 1$, $x_t = .6x_{t-1}$. The fine dark line is the full information rational expectation, equal to $E_{t-1}x_t = 0$ until $t = 0$, and equal to $E_{t-1}x_t = \rho x_{t-1}$ for $t \geq 1$. The dark dashed line corresponds to the forecasting process estimated in the paper. We use the lag formulation described in Section 3.5.4 and estimated in Appendix C.1.1:

$$\begin{aligned} F_{t-1}x_t \approx\ & .8E_{t-1}x_t + .16E_{t-2}x_t \\ & + .45\left(x_{t-1} - E_{t-2}x_{t-1}\right) + .09\left(x_{t-2} - E_{t-3}x_{t-2}\right) \end{aligned}$$

for all $t \geq 1$.

Figure 3.6: *Expectation Response to an Impulse in x*

We start with a slightly different experimental setting. We use a single process with $\rho = .6$. We then randomly sort subjects into 10 different conditions. Each condition has a different realization of the process, but within each condition, all subjects see the same realization. We then take the average expectations within each condition, and test our model within it. More specifically, we run the following regression:

$$F_t^c x_{ct+1} - E_t x_{ct+1} = \lambda\left(F_{t-1}^c x_{ct+1} - E_t x_{ct+1}\right) + \gamma(x_{ct} - E_{t-1} x_{ct}) + v_{ct+1}$$

for condition c at round t. $F_t^c x_{ct+1}$ is the *average* prediction across subjects in condition c at round t for next period realization. Hence, the panel on which we run these regressions is somewhat smaller than in Table 3.4. We only observe 40 round in 10 different conditions, hence at most 400 observations in total (vs about 6,000 in our main setting).

We report the results of this regression in Table 3.7 using the same structure as in Table 3.4: With each component of the regression separately, with LS rational expectations and full information ones, for the first and last 20 periods separately. Three salient points emerge. First, the coefficients obtained in this setting are very similar to the coefficients obtained in our main specification (.21 vs .19 for stickiness λ and .46 vs .43 for extrapolation γ). Second, the R^2 of this regression (.57) is much higher than in our main specification (.15). Thus, a big part of the error term u_{it} in the individual expectation model are idiosyncratic errors that vanish in aggregation. And overall, our model does a very good job at explaining the expectation formation process. Third, taking LS rational expectation – compared to FI rational expectations – makes a small difference at the aggregate level. The model with LS rational forecast has a higher R^2 (.66 in column 5) than the model with FI expectations. Also, the model with FI expectations works better for the last 20 rounds than in the first 20 rounds of experimentation. Both these are consistent with the idea that LS learning is more realistic.

3.5.7 Robustness to Experimental Setting

In this last Section, we investigate the robustness of our results to changes in the experimental setting.

Well-known economic variables vs abstract process

First, we check if subjects behave differently when they are forecasting the process of an "actual" economic variable. We focus on four different variables: U.S. quarterly GDP growth,

Table 3.7: *Explaining Average Expectations*

Note: This Table follows the structure of Table 3.4, except that the panel data now consists of 10 conditions followed over 40 rounds. In each condition, on average 30 participants make forecast but are exposed to the same draw of a unique AR1 process with persistence $\rho = .6$. Thus, we average forecasts and expectations across participants of each condition. We then run the following regression:

$$F_t^c x_{ct+1} - E_t x_{ct+1} = \lambda \left(F_{t-1}^c x_{ct+1} - E_t x_{ct+1} \right) + \gamma (x_{ct} - E_{t-1} x_{ct}) + u_{ct+1}$$

for condition c at round t. $F_t^c x_{ct+1}$ is the *average* prediction across subjects in condition c at round t for next period realization. The various columns are the same as in Table 3.4.

	$F_t x_{t+1} - E_t x_{t+1}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Sticky	Trend	Main		$\widehat{E}_t x_{t+1}$	$t \leq 20$	$t > 20$
$F_{t-1} x_{t+1} - E_t x_{t+1}$	-.2***		.21***		.28***	.26***	.15***
	(-7.1)		(7.1)		(12)	(6.1)	(3.9)
$x_t - E_{t-1} x_t$		.31***	.46***	.4***	.49***	.45***	.46***
		(12)	(15)	(4.2)	(23)	(9)	(16)
$F_{t-1} x_{t+1}$				.17***			
				(3)			
$E_t x_{t+1}$				-.11			
				(-.8)			
N	380	390	380	380	370	180	200
r2	.15	.48	.57	.57	.64	.48	.68

monthly CPI inflation, monthly S&P 500 returns and monthly house price growth. For each of these variables, we first estimate the process as AR1 processes, which we then simulate for each participants (each participant receives a different draw of realized innovation). We then randomly allocate subjects to two conditions: In both conditions, subjects are asked to forecast future realizations, but in one of them, they are told at the beginning of the experimental instructions that "The process you will see has the same property as quarterly US real GDP growth in the last three decades" (for the GDP growth time series). We repeat this procedure for the 4 economic variables, and run our main specification of column 3, Table 3.4, separately in each condition.

We report the results in Table 3.8. For each of the four economic variables (GDP, inflation, stock market and housing market returns), we report the estimated equation (3.6) separately for the two conditions with and without process description. We then test equality of estimated γ and λ across the two conditions, and provide p-values in the bottom two lines. For both parameters, and for all four variables, we cannot reject the null hypothesis that the two models are identical. We deduct from this that knowing subjects' priors about the nature of the variable to predict does not strongly affect their forecasting rule.

Varying other parameters than ρ

Second, we check that the estimated γ and λ do not significantly change when we vary the parameters of the process. We do this by exploiting the conditions described above. In Table 3.6, we started from our main process, for which $Ex_t = 0$ and $\sigma = 20$, and varied ρ from 0 to 1. We showed that λ and γ did not vary significantly across conditions. In this Section, we use the conditions described in the previous Section where we calibrate the process on existing economic variables (GDP growth, CPI inflation, stock market and housing returns). To make things comparable, we focus on the conditions where subjects were not told anything about these processes. In these different conditions, not only ρ, but also Ex_t and σ vary. This allows us to test if the expectation formation equation changes.

In Table 3.9, we implement these tests. Columns 2-4 report the regression results for the four economic variables (again, in the conditions where subjects are not told how the process was calibrated). Column 1 shows the baseline condition, for which $Ex_t = 0$, $\sigma = 20$ and $\rho = .4$. The numbers differ slightly from Table 3.6 because this condition was part of our third batch of experiments, along with all results discussed in Section 3.5.7. Volatility varies widely, from .23 (inflation) to 20 (baseline condition). The long-term mean goes from 0 (baseline) to .55 (stock returns). The p-value of tests of equality between each of the four conditions and the baseline are in the bottom panel of the Table. We can never reject the null hypothesis that the two models are identical. From this, we deduct that our model is robust to parameter changes.

Table 3.8: *Sensitivity to Context*

We test here whether "labelling" the process affects the forecasts. For each condition, we run the following regression:

$$F_t^i x_{it+1} - E_t x_{it+1} = \lambda \left(F_{t-1}^i x_{it+1} - E_t^i x_{it+1} \right) + \gamma (x_{it} - E_{t-1}^i x_{it}) + u_{it+1}$$

Columns 1-2 investigate the impact of labelling the process "GDP growth". We estimate delta log GDP as an AR1 on quarterly US data, which leads to $x_t = .40 + .4x_{t-1} + .55\epsilon_t$. We then simulate one path per individual. In column 1, individuals are not told how the process was estimated. This condition is essentially similar – up to a change in innovation volatility and average – to our main tests in Table 3.6. In column 2, we write at the beginning of the consent form that the process shown replicates that of US GDP growth. We then report p-values of equality tests of λ and γ across samples in the bottom panel of the Table. In columns 3-4, we simulate a process estimated on monthly US CPI inflation. In columns 5-6, we simulate a process estimated on monthly S&P 500 returns. In columns 7-8, we simulate a process estimated on monthly house price growth. Each subject has a different draw of the process, so we cluster error terms at the subject level – thus allowing for within subject correlation of errors but not across subjects. t-stats are between brackets.

	$F_t x_{t+1} - x_t$							
	"GDP growth"		"Inflation"		"Stock returns"		"House price"	
	Without	With	Without	With	Without	With	Without	With
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$F_{t-1}x_{t+1} - E_t x_{t+1}$	.21***	.26***	.3***	.31***	.34***	.19**	.39**	.27***
	(4)	(7.2)	(4.6)	(5.8)	(4.4)	(2.5)	(2.7)	(3.3)
$x_t - E_{t-1}x_t$	.38***	.44***	.37***	.38***	.51***	.45***	.51***	.42***
	(5.9)	(7.8)	(9)	(7)	(8.3)	(6.8)	(4.6)	(4.4)
N	1140	1444	1292	1482	1368	1102	1330	1406
r2	.15	.16	.16	.2	.22	.19	.22	.14
Test of equality – p value								
Stickiness	0.37		0.92		0.18		0.45	
Extrapolation	0.46		0.91		0.51		0.55	

Table 3.9: *Sensitivity to Process Parameters Beyond Changes in ρ*

We test here whether changes in σ, the volatility of innovation, and μ, the long term mean of the process, affect our estimates of λ and γ. In each of these conditions, the process for participant i is given by $x_{it+1} = \rho x_{it} + (1-\rho)\mu + \sigma\epsilon_{it}$ where ϵ_{it} is standardized normal. Each column corresponds to a condition where σ and μ are different. For each condition, we then run the regression:

$$F^i_t x_{it+1} - E_t x_{it+1} = \lambda\left(F^i_{t-1} x_{it+1} - E^i_t x_{it+1}\right) + \gamma(x_{it} - E^i_{t-1} x_{it}) + u_{it+1}$$

Columns 1 is the benchmark model (it slightly differs from Table 3.4, column 3 because the data come from a different draw of innovations). Column 2 uses the process fitted on US quarterly GDP growth. Column 2 uses parameter from US monthly CPI inflation, column 3 from stock market returns and column 4 from housing returns. These data – and therefore the coefficients – are the same as in Table 3.8, columns 1,3,5,7. We then report, in the bottom panel, p-value of tests of equality between coefficients of these processes and the benchmark setting of column 1. These tests are done by running the two regressions as SURE. Each subject has a different draw of the process, so we cluster error terms at the subject level – thus allowing for within subject correlation of errors but not across subjects. t-stats are between brackets.

Dependent variable			$F_t x_{t+1} - x_t$		
Condition	Main setting	GDP growth	CPI Inflation	S&P returns	House Inflation
Long-term mean $\mu =$	0	0.40	0.12	0.55	0.02
Persistence $\rho =$	0.4	0.4	0.4	0.2	0.8
Innovation vol. $\sigma =$	20	0.55	0.23	3.43	.39
	(1)	(2)	(3)	(4)	(5)
$F_{t-1} x_{t+1} - E_t x_{t+1}$	.24***	.21***	.3***	.34***	.39**
	(4.9)	(4)	(4.6)	(4.4)	(2.7)
$x_t - E_{t-1} x_t$	.47***	.38***	.37***	.51***	.51***
	(9.6)	(5.9)	(9)	(8.3)	(4.6)
N	1596	1140	1292	1368	1330
r2	.23	.15	.16	.22	.22
Test of equality with main setting – p value					
Stickiness	.	0.60	0.51	0.30	0.33
Extrapolation	.	0.23	0.11	0.68	0.77

Reporting the term structure of expectations

Our last robustness check is about the effect of reporting the term structure of expectation. A key dimension of our experimental setting is that we ask subjects to provide us with long-term expectations. This may cause under-reaction via anchoring: Because they are asked to report long-term expectations ($F_t x_{t+2}$), subject may have a propensity to under-react to information available at $t+1$ in order to not modify their long-term expectation too much. We investigate this in several experimental conditions, and report the results in Table 3.10. Our tests suggest that stickiness is indeed affected the reporting of long-term expectations, in the direction of expectations begin stickier. However, the extrapolation coefficient is surprisingly robust across all conditions.

First, in Table 3.10 columns 1-2, we ask if our visual presentation of past long-term expectations affects reporting and expectation formation. In our baseline experimental treatment, we assist the participant's memory by figuring, in round t, her past long-term expectation $F_{t-1}x_{t+1}$ as a grey dot on the graphical interface. Thus, when she makes forecasts $F_t x_{t+1}$ and $F_t x_{t+2}$, she sees – via the gray dot – what she had anticipated for x_{t+1} in the previous round. The gray dot helps remember past forecasts, but also may reinforce anchoring of expectations. So we sort individuals into two conditions, both asking for short- and long-term forecasts but in one condition we do not include the gray dot. We run our main specification (3.6) and report the results in column 1 (baseline condition) and column 2 (baseline condition without gray dot). Obviously, estimates in column 1 are exactly the same as in Table 3.9, column 1. We test the equality of coefficients in the bottom panel. The extrapolation coefficient γ is not statistically different across both conditions (.49 without gray dot against .47 in the baseline). The stickiness coefficient λ is however significantly higher with a p value of .03. It is equal to $.24^{***}$ in the baseline condition versus a barely significant $.10^{*}$ in the condition without gray dot. Thus, the presence of the gray dot tends to make the subjects significantly more sticky. Note however that the dominant feature of the data – extrapolation – is unchanged by the absence of the gray dot.

Second, we ask if the mere fact of reporting long-term expectations tends to make short term expectation stickier. We implement these tests in columns 3-5. In column 3, we show the baseline condition. In column 4, we report the results of a conditions where subjects are only required to provide short-term expectations, $F_t x_{t+1}$, and not long-term ones $F_t x_{t+2}$. In column 5, we on the contrary analyze a condition where subjects report short-term expectations and very long-term ones $F_t x_{t+5}$. To compare these three conditions, we cannot run our main specification (3.6) since it requires both $F_t x_{t+1}$ and lagged $F_t x_{t+2}$, which we don't have the two alternative conditions. Instead, we run the lagged equivalent of (3.6):

$$F_t^i x_{t+1} = (1-\lambda) \sum_{k=0}^{2} \lambda^k E_{t-k}^i x_{it+1} + \gamma \sum_{k=0}^{2} \lambda^k \left(x_{it-k} - E_{t-k-1}^i x_{it-k} \right) + \eta_{it} \tag{3.9}$$

which is the same equation as in (3.7) limited to three lags – coefficients are supposed to be negligible after 2 lags which is the case in the regressions. Notice that the coefficient on $E_t^i x_{it+1}$ is equal to $1-\lambda$, while the coefficient on current innovation $x_{it} - E_{t-1}^i x_{it}$ is equal to γ. This regression is run columns 3-5, and in the bottom panel we test equality on these two coefficients. The first result is that reporting $F_t x_{t+2}$ does not affect extrapolation γ at all but makes expectation formation significantly less sticky ($1-\lambda$ is .85*** instead of .55***, with a p value of .05). The second result is more intuitive: Asking for very long term expectations $F_t x_{t+5}$ makes expectations significantly stickier than asking for medium term expectations $F_t x_{t+2}$ ($1-\lambda = .55$ compared to .85 in the baseline). In both alternative conditions, however, the γ coefficient is almost unchanged to .5 (instead of .48). Overall, stickiness is affected by elicitation of long-term expectations, but the quantitatively dominant force, extrapolation, is unchanged.

Third, we also ask if eliciting short-term expectations $F_t x_{t+1}$ affects the reporting of long-term expectation $F_t x_{t+2}$. We do this in columns 6 and 7, where we compare the baseline with a condition where subjects are only asked to report $F_t x_{t+2}$. Like in the previous test, since we only have one expectation and not two, we need to use the lag formulation of our test, except that now we seek to explain $F_t x_{t+2}$ (which is present in both conditions) and not $F_t x_{t+1}$. The extension of equation (3.7) to this case yields:

$$F^i_{t-1}x_{t+1} = (1-\lambda)\sum_{k=0}^{1}\lambda^k E^i_{t-1-k}x_{it+1} + \gamma\sum_{k=0}^{1}\lambda^k\left(x_{it-k} - E^i_{t-1-k}x_{it-k}\right) + \eta_{it} \tag{3.10}$$

where the coefficient on $E^i_{t-1}x_{it+1}$ is equal to $1-\lambda$ and the coefficient on $x_{it} - E^i_{t-1}x_{it}$ is equal to γ. We run the regression separately for the two conditions in columns 6 and 7. We find that both coefficients are similar across both settings. Long-term expectations do not seem to be too affected by short-term expectation reporting. The stickiness coefficient is marginally affected, in the direction of long-term expectations being stickier when short-term ones are reported, but the p value is on the high side (p=.13).

Table 3.10: *Sensitivity to Term Structure Reporting*

We test here whether the reporting of both short-term and long-term expectations. In columns 1 and 2, we test whether the presence of a gray dot, to help subjects remember their past two-periods ahead forecast, affects expectation formation. In column 1, we report the results of our baseline setting, identical to Table 3.9, column 1. In column 2, we use exactly the same parameters and setting but remove the grey dot designed to help subject remembering $F_{t-1}x_{t+1}$ when they need to report $F_t x_{t+1}$ and $F_t x_{t+2}$. We run our main specification (3.6) on both conditions and test the equality of coefficients in the bottom panel. In columns 3-5, we test whether the reporting of long-term expectations affects the reporting of short-term ones. In these columns, we use the specification with lags (3.7), where we regress $F_t x_{t+1}$ on lagged values of rational expectations $E_{t-k}x_{t+1}$ and past innovations of $x_{t-k} - E_{t-k-1}x_{t-k}$ for $k \geq 0$. Under our recursive model (3.6), the coefficient on the first lags $E_t x_{t+1}$ and $x_t - E_{t-1}x_t$ are equal to $1-\lambda$ and γ respectively. In column 1, we report the baseline condition of column 1, but using the "lag" specification. In column 2, we report the condition where subjects are confronted with the same process, but are not required to report the "long-term" expectation $F_t x_{t+2}$. In column 3 on the contrary, subjects are required to report very long-term expectations $F_t x_{t+5}$. We test equality of these coefficients with estimates of column 3 in the bottom panel. In columns 6-7, we test the effect of reporting short-term expectations on long-term ones. The methodology is identical to columns 3-5, except that now we regress $F_{t-1}x_{t+1}$ on lagged values of rational expectations $E_{t-k}x_{t+1}$ and past innovations of $x_{t-k} - E_{t-k-1}x_{t-k}$ for $k \geq 1$. The coefficients on $E_{t-1}x_{t+1}$ and $x_{t-1} - E_{t-2}x_{t-1}$ are in theory equal to $1-\lambda$ and γ. In column 6, we report regression results for the baseline condition as in columns 1 and 3. In column 7, we report regression results for the condition where participants are only required to forecast $F_t x_{t+1}$ – thus not the short-term expectation. We test equality of coefficients on the first lags in the bottom panel. Each subject has a different draw of the process, so we cluster error terms across the two conditions at the subject level – thus allowing for within subject correlation of errors but not across subjects. t-stats are between brackets.

Table 3.10 (Continued)

Dependent variable	$F^i_t x_{it+1} - E_t x_{it+1}$		$F_t x_{t+1}$			$F_{t-1} x_{t+1}$	
	Grey dot		Effect of reporting LT expec.			Effect of reporting ST expec.	
	Main setting	Without	Main setting	$F_t x_{t+1}$ only	$F_t x_{t+1}$ & $F_t x_{t+5}$	Main setting	$F_t x_{t+2}$ only
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$F_{t-1} x_{t+1} - E_t x_{t+1}$	.24***	.096*					
	(4.9)	(1.9)					
$x_t - E_{t-1} x_t$	.47***	.49***					
	(9.6)	(7.9)					
$E_t x_{t+1}$			.85***	.51***	.55***		
			(7.5)	(4)	(3.7)		
$E_{t-1} x_{t+1}$			.21*	.36***	.24*	.97***	.63***
			(1.7)	(2.9)	(1.8)	(5.9)	(4.1)
$E_{t-2} x_{t+1}$			.047	.38**	.17**	.22	.63***
			(.56)	(2.5)	(2)	(1.3)	(4.3)
$x_t - E_{t-1} x_t$			.48***	.5***	.5***		
			(8.6)	(7.7)	(6.3)		
$x_{t-1} - E_{t-2} x_{t-1}$			.0058	.021	.05	.45***	.54***
			(.18)	(.7)	(1.6)	(10)	(9.8)
$x_{t-2} - E_{t-3} x_{t-2}$			-.027	-.058***	-.021	.033	.015
			(-1.5)	(-2.9)	(-1)	(1.3)	(.53)
N	1596	1026	4884	5032	4736	4884	5883
r2	.23	.15	.49	.45	.39	.34	.29
Test of equality with main setting – p value							
Stickiness	.	0.03	.	0.05	0.10	.	0.13
Extrapolation	.	0.83	.	0.79	0.80	.	0.18

3.6 Conclusion

In this paper, we run a large scale experiment to investigate how people form forecasts of a variable when faced with past realizations of that variable. At both the individual and the aggregate levels, find strong evidence of extrapolative bias and of forecast stickiness. We calibrate a simple model that nests rational expectations, in which both biases can coexist. Extrapolation turns out to be quantitatively the most important bias. Interestingly, we find our parameters to be relatively independent of the process statistical characteristics. Stickiness is stronger when agents are reminded in a more salient manner of their past forecasts. Apart from this, we find that context elements and framing of the experiment do not affect significantly our estimations. We also find that agents do not improve the quality of their forecasts over time.

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Appendix A

Appendix to Chapter 1

A.1 Proofs

A.1.1 Proof of Proposition 1

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

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

Therefore,

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

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

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

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

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

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

A.1.2 Proof of Proposition 2

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

We can write function u as

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

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

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

where f is the probability density function of the distribution of excess returns x, the first

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

term captures expected investment returns in excess of the reference point, and the second term captures the utility loss from loss aversion in the region below the reference point. Take derivatives with respect to ϕ, we have

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

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

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

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

When $r_d > 0$,

$$\phi^* = \min\left\{\frac{r_d}{\overline{b}}, 1\right\}. \tag{A.2}$$

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

When $r_d < 0$,

$$\phi^* = \min\left\{-\frac{r_d}{\underline{b}}, 1\right\}. \tag{A.3}$$

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

Based on Equations (A.2) and (A.3), we have that the optimal allocation to the risky asset ϕ^* is (weakly) increasing in r_d (and (weakly) decreasing in r_f) if $r_r > r_f$, and (weakly) decreasing in r_d (and (weakly) increasing in r_f) if $r_r < r_f$.

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

A.1.3 Proof of Corollary 1

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

A.1.4 Proof of Proposition 3

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

A.1.5 Influence of Gross Framing

Let ϕ_s^* denote a salient investor's optimal allocation in the risky asset with baseline framing in Experiment T3, according to Equation (1.5) in the paper. Define $\phi_{s,gross}^*$ as a salient investor's optimal allocation in the risky asset with gross framing in Experiment T3, according to:

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

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

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

Lemma 1. *For a given distribution of the excess returns x and a given risk-free rate $r_f > 0$, the optimal allocation to the risky asset with baseline framing is always (weakly) larger than that with gross framing, i.e.* $\phi^*_{s,gross} \leq \phi^*_s$.

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

A.2 Additional Discussions

A.2.1 Dynamic Portfolio Choice

In Section 1.3.1 we follow the experiment in Section 1.2 and study a static portfolio choice problem. In this section, we discuss the impact of interest rates on portfolio allocations in other environments, such as dynamic portfolio choice with life cycle motives or hedging motives. While they do not map directly into the setting of our simple experiments, we explain the forces in these environments and predictions that are different from our results.

Life Cycle Portfolio Choice

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

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

However, for this mechanism to be powerful, the change in interest rates needs to be fairly persistent. Moreover, given that older people have much less future labor income, this force would become minimal. In our data, the reaching for yield behavior we document does not diminish among the elderly. For example, as shown in Appendix A.3.2, the majority of participants in the Dutch sample are 60 years old or above. Reaching for yield is highly significant in that sample. For instance, for the baseline interest rate conditions (1% vs. 5% interest rates), the difference in mean allocations is 10.2 percentage points in the Dutch data, slightly higher than that the baseline samples in the US (7 to 9 percentage points as shown in Table 1.2, where the participants are primarily under 40).

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

Dynamic Hedging

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

A.2.2 Diminishing Sensitivity

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

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

We analyze a set-up that includes both loss aversion around the reference point as in Section 1.3.2 and diminishing sensitivity. The investor's optimization problem is the same as Equation (1.2) in the main text, except the utility function u features both loss aversion around the reference point and diminishing sensitivity, specified as follows:

Assumption 3.

$$u\left(1+r_p\right)=\begin{cases}\frac{1}{\alpha}\left[\left(\left(r_p-r_r\right)+1\right)^{\alpha}-1\right] & r_p\geq r_r\\ -\frac{\lambda}{\beta}\left[\left(-\left(r_p-r_r\right)+1\right)^{\beta}-1\right] & r_p<r_r\end{cases} \tag{A.4}$$

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

Here we specify the gain loss utility as a function of investment returns instead of the wealth level. Effectively, we analyze the case where the gain loss utility scales linearly with initial wealth, as opposed to having additional curvature driven by initial wealth.[3] The curvature of utility driven by initial wealth can be separately captured by a CRRA component, as discussed in footnote 2 of Section A.1.2. In addition, our specification avoids the property in the Tversky and Kahneman (1992) specification that marginal utility at the reference point is infinity,[4] which complicates the analysis and is also somewhat counterfactual. Instead, Equation (A.4) normalizes the curvature of the utility function just above the reference point to 1 and the curvature of the utility function just below the reference point to λ, consistent with the utility function in Assumption 1.

We now analyze how the optimal allocation to the risky asset ϕ^* moves with the risk-free rate r_f (reference point r_r) under Assumption 3. We begin with a decomposition that illustrates how different channels influence the comparative statics of the optimal allocation ϕ^* with respect to the risk-free rate r_f and the reference point r_r. As in the proof of Proposition 2, let $r_d = r_r - r_f$ denote the difference between the reference point and the risk-free rate. We can rewrite the utility function u as

$$u\left(1+r_p\right) = \begin{cases} \frac{1}{\alpha}\left[\left(\left(\phi x - r_d\right)+1\right)^{\alpha} - 1\right] & \phi x \geq r_d \\ -\frac{\lambda}{\beta}\left[\left(\left(r_d - \phi x\right)+1\right)^{\beta} - 1\right] & \phi x < r_d \end{cases}. \tag{A.5}$$

Let

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

where f is the probability density function of the distribution of the excess returns x.[5]

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

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

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

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

The first term captures the utility gain when investment returns are above the reference point, and the second term captures the utility loss when investment returns are below the reference point. By Topkin's Theorem, to study how $\arg\max_{0\leq\phi\leq 1} h(\phi, r_d)$ moves with respect to r_d, we only need to study the sign of $\frac{\partial^2}{\partial\phi\partial r_d} h(\phi, r_d)$, that is, how the marginal gain of investing in the risky asset changes with respect to r_d.

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

$$\begin{aligned}\frac{\partial^2}{\partial\phi\partial r_d} h(\phi, r_d) = &(1-\alpha) \int_{\frac{r_d}{\phi}}^{+\infty} x\left((\phi x - r_d) + 1\right)^{\alpha-2} f(x)\, dx \\ &- \lambda(1-\beta) \int_{-\infty}^{\frac{r_d}{\phi}} x\left(1 + (r_d - \phi x)\right)^{\beta-2} f(x)\, dx + (\lambda - 1) \frac{r_d}{\phi^2} f\left(\frac{r_d}{\phi}\right).\end{aligned} \tag{A.6}$$

Let us consider two cases.

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

The first term in (A.6), $(1-\alpha) \int_{\frac{r_d}{\phi}}^{+\infty} x\left((\phi x - r_d) + 1\right)^{\alpha-2} f(x)\, dx \geq 0$, since $\alpha \leq 1$. When the realized portfolio returns are above the reference point, the marginal gain of investing in the risky asset is higher as the risk-free rate decreases (the reference point increases), due to diminishing sensitivity. This force contributes to reaching for yield.

The second term in (A.6), $-\lambda(1-\beta) \int_{-\infty}^{\frac{r_d}{\phi}} x\left(1 + (r_d - \phi x)\right)^{\beta-2} f(x)\, dx$, can be further decomposed into

$$\begin{aligned}-\lambda(1-\beta) \int_{-\infty}^{\frac{r_d}{\phi}} x\left(1 + (r_d - \phi x)\right)^{\beta-2} f(x)\, dx = &-\lambda(1-\beta) \int_{0}^{\frac{r_d}{\phi}} x\left(1 + (r_d - \phi x)\right)^{\beta-2} f(x)\, dx \\ &- \lambda(1-\beta) \int_{-\infty}^{0} x\left(1 + (r_d - \phi x)\right)^{\beta-2} f(x)\, dx.\end{aligned} \tag{A.7}$$

The first term in (A.7), $-\lambda(1-\beta) \int_{0}^{\frac{r_d}{\phi}} x\left(1 + (r_d - \phi x)\right)^{\beta-2} f(x)\, dx \leq 0$, since $\beta \leq 1$. This term reflects the situation where the portfolio returns are below the reference point but the excess returns of the risky asset are positive. In this region, the marginal gain of investing in the risky asset is lower as the risk-free rate decreases (the reference point increases), due to diminishing sensitivity. This force works against reaching for yield.

The second term in (A.7), $-\lambda(1-\beta)\int_{-\infty}^{0} x\left(1+\left(r_d-\phi x\right)\right)^{\beta-2} f\left(x\right) dx \geq 0$, since $\beta \leq 1$. This reflects the situation where the portfolio returns are below the reference point and the excess returns of the risky asset are negative. In this case, the marginal loss of investing in the risky asset is lower as the risk-free rate decreases (the reference point increases), due to diminishing sensitivity. This force contributes to reaching for yield.

The third term in (A.6), $(\lambda-1)\frac{r_d}{\phi^2} f\left(\frac{r_d}{\phi}\right) \geq 0$, since $\lambda \geq 1$. This is exactly the term that reflects how loss aversion around the reference point affects reaching for yield, as in Proposition 2 in the main text. When $r_d > 0$, this force contributes to reaching for yield.

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

The first term in (A.6), $(1-\alpha)\int_{\frac{r_d}{\phi}}^{+\infty} x\left(\left(\phi x - r_d\right)+1\right)^{\alpha-2} f\left(x\right) dx$, can be further decomposed into

$$(1-\alpha)\int_{\frac{r_d}{\phi}}^{+\infty} x\left(\left(\phi x - r_d\right)+1\right)^{\alpha-2} f\left(x\right) dx = (1-\alpha)\int_{0}^{+\infty} x\left(\left(\phi x - r_d\right)+1\right)^{\alpha-2} f\left(x\right) dx$$
$$+ (1-\alpha)\int_{\frac{r_d}{\phi}}^{0} x\left(\left(\phi x - r_d\right)+1\right)^{\alpha-2} f\left(x\right) dx \quad \text{(A.8)}$$

The first term in (A.8), $(1-\alpha)\int_{0}^{+\infty} x\left(\left(\phi x - r_d\right)+1\right)^{\alpha-2} f\left(x\right) dx \geq 0$, since $\alpha \leq 1$. This reflects the situation where the portfolio returns are above the reference point, and the excess returns of the risky asset are positive. In this case, the marginal gain of investing in the risky asset is higher as the risk-free rate decreases (the reference point increases), due to diminishing sensitivity. This force contributes to reaching for yield.

The second term in (A.8), $(1-\alpha)\int_{\frac{r_d}{\phi}}^{0} x\left(\left(\phi x - r_d\right)+1\right)^{\alpha-2} f\left(x\right) dx \leq 0$ since $\alpha \leq 1$. This reflects the situation where the portfolio returns are above the reference point, but the excess returns of the risky asset are negative. In this case, the marginal loss of investing in the risky asset is higher as the risk-free rate decreases (the reference point increases), due to diminishing sensitivity. This force works against reaching for yield.

The second term in (A.6), $-\lambda(1-\beta)\int_{-\infty}^{\frac{r_d}{\phi}} x\left(1+\left(r_d-\phi x\right)\right)^{\beta-2} f\left(x\right) dx \geq 0$ since $\beta \leq 1$. When the realized portfolio returns are below the reference point, the marginal loss of investing in the risky asset is lower as the risk-free rate decreases (the reference point increases), due to diminishing sensitivity. This force contributes to reaching for yield.

The third term in (A.6), $(\lambda - 1)\frac{r_d}{\phi^2} f\left(\frac{r_d}{\phi}\right) \leq 0$ since $\lambda \geq 1$. Again, this is exactly the term that reflects how loss aversion around the reference point affects reaching for yield, as in Proposition 2 in the main text. When $r_d < 0$, this force works against reaching for yield.

The proposition below summarizes predictions in two special cases:

Proposition 5. *Under Assumption 3, for a given distribution of the excess returns x, if*

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

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

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

then we have $\phi^{*'} \geq \phi^*$.[6]

Proof. Consider the case that either

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

(otherwise we can directly apply Propostion 2 in the main text). From the decomposition in (A.6) and Topkin's Theorem, we know that either

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

which proves the Proposition, or

$$\phi^* > \phi^{*'} \quad \text{and} \quad \left\{\phi^*, \phi^{*'}\right\} \subseteq \arg\max_{0 \leq \phi \leq 1} h(\phi, r_d) \cap \arg\max_{0 \leq \phi \leq 1} h\left(\phi, r_d'\right).$$

However, if either

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

we have $\frac{\partial^2}{\partial\phi\partial r_d} h(\phi, r_d) > 0$ according to the decomposition in (A.6). As a result, it is impossible that

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

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

The proposition is thus proved. $\square$

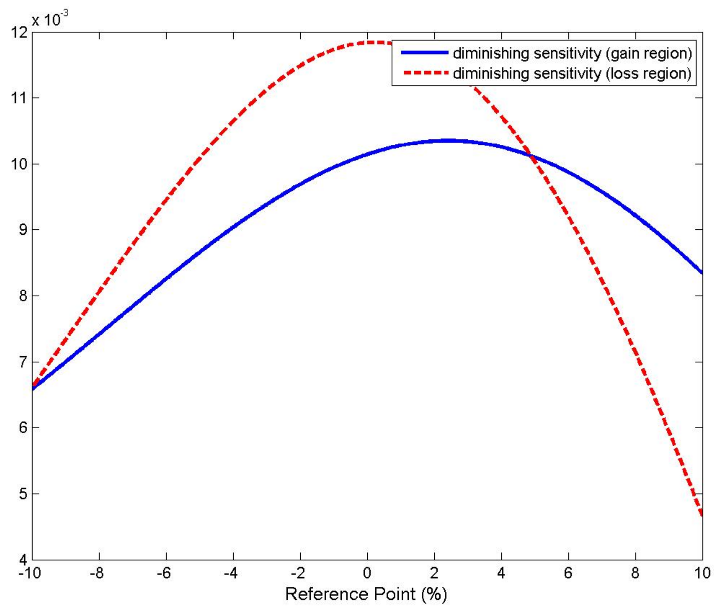
The first part of Proposition 5 shows that if the reference point is above the interest rate and we shut down diminishing sensitivity in the loss region, the framework introduced in Assumption 3 unambiguously contributes to reaching for yield. The second part of Proposition 5 shows that if the reference point is below the interest rate and we shut down diminishing sensitivity in the gain region as well as loss aversion, the framework introduced in Assumption 3 also unambiguously contributes to reaching for yield.

Unfortunately, without these further restrictions, analytically it is not clear whether diminishing sensitivity contributes to or works against the reaching for yield behavior documented in Section 1.2, as discussed above. Therefore, we perform a numerical exercise to evaluate the relative importance of the different terms in Equation (A.6) in our setting.

We use the canonical Prospect Theory parameter values (Tversky and Kahneman, 1992; Barberis et al., 2006) to specify the degree of diminishing sensitivity. Specifically, we set $\alpha = \beta = 0.88$ and $\lambda = 2.25$. We start by examining how the diminishing sensitivity component in Assumption 3 influences the response of investment decisions to a small perturbation of the risk-free rate in the low interest rate condition in the benchmark experiment in Section 1.2 of the main text. In other words, we evaluate the influence of the first two terms in Equation (A.6). We assume the mean excess returns $\mathbb{E}x = 5\%$, the volatility of the excess returns $\sqrt{Var(x)} = 18\%$, and the risk-free rate $r_f = 1\%$, as in our benchmark experiment in Section 1.2. We use $\phi = 60\%$, roughly matching the level of allocations to the risky assets in the low interest rate condition in the experiment. In Figure A.1, we plot the first two terms in Equation (A.6) as a function of the reference point r_r, ranging from -10% to 10%. We find that the terms are both positive, that is, diminishing sensitivity above and below the reference point both contribute to reaching for yield for all levels of the reference point.

We also find the loss aversion component in Assumption 3 influences the optimal allocation more than the diminishing sensitivity component. In Figure A.2, we consider the same exercise and same parameter values as those in Figure A.1. Here we plot the effect of diminishing sensitivity (the sum of the first two terms in Equation (A.6)) and the effect of loss aversion (the last term in Equation (A.6)), as a function of the reference point r_r. Figure A.2 suggests that the loss aversion component has a much larger influence than the diminishing sensitivity component. The comparative static of how allocations to the risky asset move with the risk-free rate is dominated by the loss aversion component. In addition, if we shut down the loss aversion component (i.e. setting $\lambda = 1$ in Assumption 3) and keep the other parameter values the same as in Figures A.1 and A.2, investors would invest 100% in risky assets.

Figure A.1: *Impact of Diminishing Sensitivity in Equation* (A.6), $r_f = 1\%$

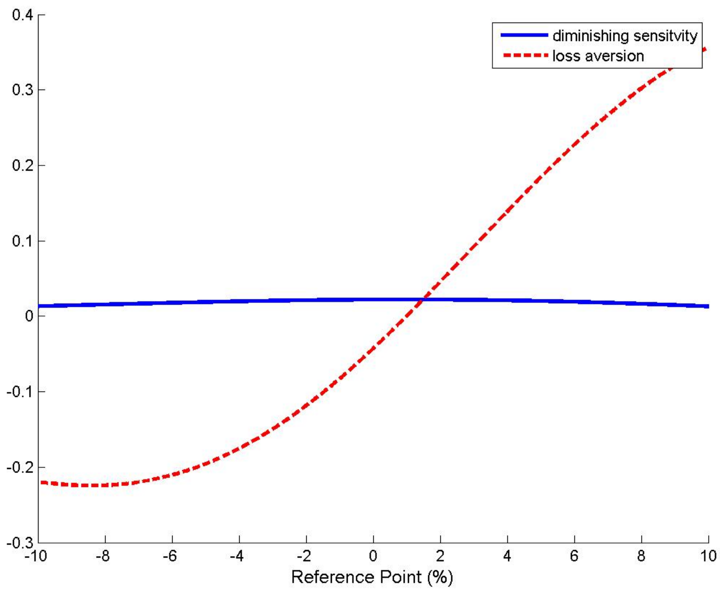


Taken together, diminishing sensitivity may contribute to reaching for yield in our setting, but diminishing sensitivity *alone* may not fully explain the reaching for yield behavior documented in Section 1.2.

A.2.3 Reference Point in Expected Returns

Here we provide an alternative formulation of reference dependence. In this formulation, investors experience discomfort when the expected returns of the portfolio are below the

Figure A.2: *Impact of Diminishing Sensitivity and Loss Aversion in Equation* (A.6), $r_f = 1\%$



reference point. In contrast, in the conventional Prospect Theory formulation discussed in Section 1.3.2, investors suffer from loss aversion in each state where the realized return is below the reference point. This alternative formulation of reference dependent loss aversion would modify Proposition 2, keeping predictions of reaching for yield, and eliminating predictions of reaching against yield when interest rates are sufficiently high.

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

$$\phi^*_{mv,r} \triangleq \arg\max_{0\leq\phi\leq 1} v\left(\mathbb{E}r_p, r_r\right) - \frac{\gamma}{2} Var\left(r_p\right), \tag{A.9}$$

where

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

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

Proposition 6. *For a given distribution of the excess returns x, the optimal allocation to the risky asset, $\phi^*_{mv,r}$ is (weakly) decreasing in r_f.*

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

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

As a result,

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

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

A.2.4 Reference Point Formation

In the following, we discuss in detail the leading theories of reference point formation. We explain why investors' past interest rate experiences appear to be the main contributor to the type of reference dependence that generates reaching for yield under the framework of Section 1.3.2 and Assumption 1.

1. The reference point is the status quo wealth level (Kahneman and Tversky, 1979), or $r_r = 0$. This captures the notion that people experience "loss" when their final wealth falls below their original wealth level. It turns out that loss aversion around zero *alone* cannot explain the reaching for yield behavior documented in Section 1.2. This is because when $r_r = 0$, the reference point is below a positive risk-free rate, which falls into the second case of Proposition 2. As a result, loss aversion around zero *alone* can only generate "reaching against yield" in the setting of the benchmark experiment, contrary to the empirical evidence. That said, we are not suggesting that loss aversion at zero does not matter. It is perhaps important for many behavior (e.g. aversion to

small risks), but it does not appear to be the key driver of reaching for yield, if not partially offsetting it.

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

   Lemma 2. *Under Assumption 1, if $r_r = r_f$, for a given distribution of the excess returns x, the optimal allocation to the risky asset ϕ^* is independent of r_f.*

   Proof. Note that

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

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

   The intuition behind Lemma 2 is that as the risk-free rate r_f changes, returns on the safe asset, returns on the risky asset, and the reference point move in parallel. Accordingly, the trade-offs in the investment decision are essentially unchanged. As a result, the optimal allocation to the risky asset ϕ^* is independent of r_f.

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

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

   Lemma 3. *Under Assumption 1, if $r_r = (1-\omega) r_f + \omega\left(r_f + \mathbb{E}x\right)$, for a given distribution* *of the excess returns x, the optimal allocation to the risky asset ϕ^* is independent of the risk-free rate r_f.*

Proof. Note that

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

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

The intuition of Lemma 3 is similar to that of Lemma 2: when the risk-free rate r_f changes, returns on the safe asset, returns on the risky asset, and the reference point move in parallel.

b). The reference point is the expected returns of the *optimal* portfolio. That is, $r_r=(1-\phi^*)r_f+\phi^*(r_f+\mathbb{E}x)$, where ϕ^* is the *endogenous* optimal allocation defined in Equation (1.2). At the same time, the investor's utility in turn depends on r_r (based on Assumption 1). This follows the concept of the personal equilibrium in Kőszegi and Rabin (2006). In other words, the investor's reference point is determined by the optimal allocation, while the optimal allocation in turn depends on the reference point.

Lemma 4. *Under Assumption 1, if $r_r=(1-\phi^*)\,r_f+\phi^*\left(r_f+\mathbb{E}x\right)$, for a given distribution of the excess returns x, the optimal allocation to the risky asset ϕ^* is independent of the risk-free rate r_f.*

Proof. Note that

$$u\left(w\left(1+r_p\right)\right)=\begin{cases} w\left(r_p-r_r\right)=w\left(\phi x-\phi^*\mathbb{E}x\right) & \phi x\geq\phi^*\mathbb{E}x \\ -\lambda w\left(r_r-r_p\right)=\lambda w\left(\phi x-\phi^*\mathbb{E}x\right) & \phi x<\phi^*\mathbb{E}x \end{cases} \tag{A.10}$$

where ϕ^* solves

$$\phi^* = \arg\max_{\phi\in[0,1]} \mathbb{E}u\left(w\left(1+r_p\right)\right). \tag{A.11}$$

Because u in Equation (A.10) is independent of r_f, the ϕ^* jointly determined by Equations (A.10) and (A.11) is independent of r_f. □

The intuition here is similar to the intuition of Lemma 2 and Lemma 3: when the risk-free rate r_f changes, returns on the safe asset, returns on the risky asset, and the reference point move in parallel. This leaves the investment decision unchanged.

4. The reference point is influenced by individuals' past experiences (Kahneman and Miller, 1986; Simonsohn and Loewenstein, 2006; Malmendier and Nagel, 2011; Bordalo et al., 2017b). In our setting, one intuition is that people adapt to or anchor on some level of investment returns based on past experiences. When the risk-free rate falls below the level they are used to, people experience discomfort and become more willing to invest in risky assets. Formally, the reference point is given by a weighted average of the risk-free rate and realized returns of risky assets in the past. That is, $r_r = (1-\omega)\, r_{f,past} + \omega\left(r_{f,past} + x_{past}\right)$, where ω can be either an exogenous weight or a weight that depends on investors' past portfolio choices.[7] Note that ω, $r_{f,past}$, and x_{past} are all predetermined. As a result, this case can be analyzed with Proposition 2. Given the economic environment in the decades prior to the Great Recession, reference points from past experiences appear in line with the popular view among investors that 1% or 0% interest rates are "too low," which predicts reaching for yield behavior.

A.2.5 Additional Experiments on History Dependence

As mentioned in Section 1.4.2 of the main text, there are alternative research designs to test the history dependence of reaching for yield. Below we present a design where all participants face the same interest rate environment in the final round, but prior to that,

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

one group starts with an environment with higher interest rates, while another group starts with an environment with lower interest rates.[8] We show results from two settings that follow this design.[9]

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

The second setting is an incentivized experiment with two rounds of investment decisions: participants in Group 1 first consider a high interest rate environment (5% safe returns and 10% average risky returns), and then consider a medium interest rate environment (2% safe returns and 7% average risky returns); participants in Group 2 first consider a low interest rate environment (1% safe returns and 6% average risky returns), and then consider a medium interest rate environment (2% safe returns and 7% average risky returns). We performed this experiment on MTurk in December 2016. There are again 200 participants in

[8]One possible concern with the design of Experiment T2 in Section 1.4.2 is that we find substantially higher risk taking in the low interest rate condition if participants first consider the high interest rate condition, but this could be driven by an order issue: for some reasons, participants take more risks in the second round of investment decision in general. We do not find evidence for this concern in the data. Results in Section 1.4.2 in the main text and in this section show that risk taking does not increase in general after the first round. It only increases if interest rates fall significantly. The alternative design also verifies that the concern does not affect our results.

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

Group 1 and 200 participants in Group 2. We do not perform a hypothetical experiment with the same investment pay-offs, since by this time our previous experiments have used more than 6,000 MTurk workers and our additional experiments are experiencing capacity constraints and lower data quality (Stewart et al., 2015).

Table A.4 presents the results. In both settings, participants in Group 1 invest more aggressively in the final round than participants in Group 2. The results are consistent with history-based reference dependence discussed in Section 1.3.2.[10]

A.2.6 Salience and Related Models

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

Salience of Attributes vs. Salience of States

First, we discuss the relationship between the salience theory applied in Section 1.3.3 (which follows Bordalo et al. (2013b, 2016) and adapts this framework to portfolio allocations), and several related ways of modeling salience. Specifically, we discuss the relationship between our formulation and Bordalo et al. (2012) and Bordalo et al. (2013a), which use a different formulation of the salience theory in the context of choice under risk.

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

It seems plausible that the first approach is a better approximation of investor behavior, as investors do not necessarily have a clear mental representation of all possible economic states when making investment decisions. In fact, the second approach generates predictions

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

of reaching against yield, which is contrary to the findings we document in Section 1.2. The intuition is that people focus on downside risks more than upside risks. As interest rates fall, holding the distribution of the excess returns fixed, there is a downward shift in the returns of all assets in all states, which makes the downside risk more salient.[11] Our findings provide some evidence for the way salience operates in the context of investment decisions and choice under risk, and may help to guide related models.

Discrete vs. Continuous Choices

Second, we note that in the models of Bordalo et al. (2013b) and Bordalo et al. (2016), the decision problem is a discrete choice problem. In the portfolio choice problem we consider in Section 1.3.3, however, the decision is continuous. Our set-up makes the following departure from Bordalo et al. (2013b) to streamline the investor's decision problem. In Bordalo et al. (2013b), the salience of an attribute is choice-specific. Accordingly, the relative salience of the return dimension will be different for different portfolios. In other words, a strict adherence to such a choice-specific salience function requires the relative salience of the return dimension in Equation (1.5), δ, to be a function of the asset allocation in the portfolio, ϕ. When the choice variable is continuous, this approach could become quite cumbersome. Instead, in our formulation (Assumption 2) δ is a function of the properties of assets in the underlying choice set, independent of portfolio allocation ϕ. We use this formulation as a parsimonious way to capture the idea that when interest rates are low and the ratio of the expected returns of the two assets is high, the expected return dimension becomes more salient. Fernandes (2016) also shows that the salience function should depend on the properties of the available assets and be independent of the portfolio allocation.

"Salience" and Proportional Thinking

Third, we discuss the subtle difference between the notion of salience defined in Bordalo et al. (2013b) and the intuition of proportional thinking in our setting. Bordalo et al. (2013b) emphasize that choices have different attributes/dimensions (return vs. risk, price vs.

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

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

In application, this distinction seems quite subtle and not very important. Because the relative importance of the return dimension according to the salience function a la Bordalo et al. (2013b) is essentially driven by the ratio of the average returns (and the ratio of the risks, which are kept fixed in our experiments), the investor's optimal portfolio choice problem is essentially the same with both interpretations. Equation (1.5) in the main text nests both interpretations. δ in Equation (1.5) can be interpreted both as the salience of the return dimension (relative to the risk dimension), and as a way to effectively link the attractiveness of the risky asset to the ratio of average returns. In the main text, we use the most straightforward explanations to explain the intuition behind investor behavior, and do not draw distinctions between the notion of salience and proportional thinking.

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

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

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

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

A.2.7 Inflation

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

First, in our randomized experiments, we study how investment allocations change with respect to interest rates, holding constant inflation.[12] Participants in all treatment conditions face the same inflation environment; different treatment conditions lead to differences in

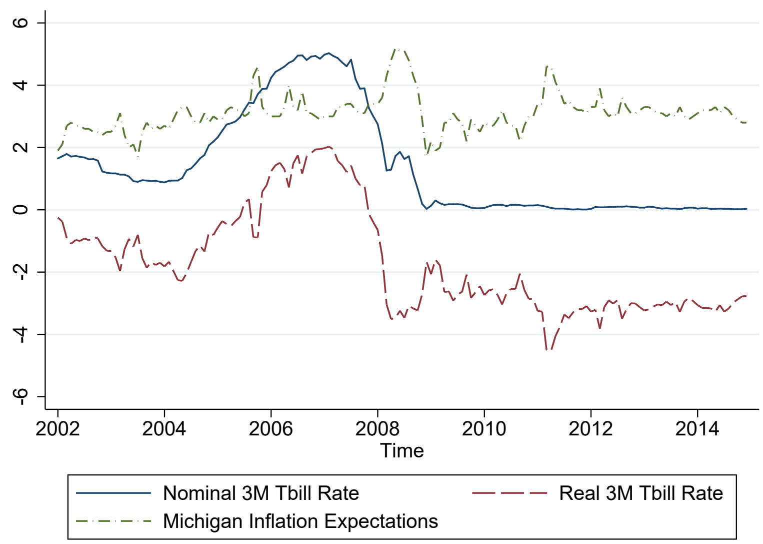
[12] In the demographics section, we also ask participants their inflation expectations, which are very similar across different treatment conditions, at about 3%.

both nominal and real returns. In this setting, the predictions for reaching for yield follow exactly from Section 1.3.

In recent years in the US, inflation and inflation expectations have stayed relatively stable, and both nominal and real interest rates declined as shown in Figure A.3 below. This maps closely into the setting above.

Figure A.3: *Nominal and Real Interest Rates in the US*

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



Then, we discuss two main questions related to inflation outside of our experiments. We explain how to understand these situations in the conventional portfolio choice framework in Section 1.3.1, the reference dependence mechanism in Section 1.3.2, and the salience/proportional thinking framework in Section 1.3.3. The results from observational data in Section 1.5 may shed some light on these questions.

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

   For example, consider 5% interest rates and 10% average returns on the risky asset. Does it matter if this is coming from, for instance, a) 5% and 10% real returns respectively and 0% expected inflation vs. b) 1% and 6% real returns respectively and 4% expected inflation?[13]

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

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

Conventional Portfolio Choice (Section 1.3.1)

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

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

Reference Dependence (Section 1.3.2)

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

For Question 1:

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

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

For Question 2:

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

Salience and Proportional Thinking (Section 1.3.3)

For Question 1:

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

For Question 2:

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

Based on the observational data in Section 1.5, we find that changes in nominal interest rates appear to have a stronger impact on investment allocations than changes in real interest rates, which suggests that reference dependence or salience/proportional thinking could be more about nominal returns in the US data.

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

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

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

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

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

A.3 Additional Tables and Figures

A.3.1 Additional Experimental Results

Table A.1: *Subsample Results in Benchmark Experiments*

This table shows the regression coefficient β in

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

for subsamples in the benchmark experiments, where Y_i is the allocation to the risky asset, and Low_i is an indicator variable that takes value one if the participant is in the low interest rate condition. The regression is estimated for each subsample; β, the associated t-statistics, and the number of participants in the subsample are reported. Controls are the same as in Table 1.2 in the paper, except that variables are dropped from the controls when they are used to split the sample. We did not include wealth in the MBA survey because it could be a sensitive question.

Panel A. Experiment B1: MTurk, Hypothetical

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

Panel B. Experiment B2: MTurk, Incentivized

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

Panel C. Experiment B3: MBA, Incentivized

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

Table A.2: *Robustness Checks of Benchmark Experiments*

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

Panel A. Mean Allocations to Risky Asset (%)

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

Panel B. Differences Controlling for Individual Characteristics

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

Table A.3: *Experimental Decisions and Household Portfolio Allocations*

Cross-sectional regression:

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

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

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

Robust t-statistics in brackets

Table A.4: *Additional Results on History Dependence*

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

Panel A. Setting 1 (Hypothetical Experiment)

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

Panel B. Setting 2 (Incentivized Experiment)

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

Table A.5: *Baseline and Net Framing*

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

Panel A. Mean Allocations to Risky Asset (%)

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

Panel B. Differences Controlling for Individual Characteristics

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

Discussion of Table A.5: In our data, the degree of reaching for yield is about the same with baseline framing and with net framing. The level of allocations to the risky asset is lower with net framing. This could be because net framing makes losing money more salient and decreases the general risk taking propensity.

Table A.6: *Demographic Information of Experiment T1 (Mapping Gradient) Sample*

This table presents the demographics of Experiment T1. The first row denotes the risk-free rate in different conditions; the mean excess returns of the risky asset is 5% in all conditions. The statistics are the same as those in Table 1.1.

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

Table A.7: *Demographic Information of Experiment T2 (History Dependence) Sample*

This table presents the demographics of Experiment T2. Participants in Group 1 first make investment decisions in the high interest rate condition (5% risk-free rate and 10% average returns on the risky asset), and then make decisions in the low interest rate condition (1% risk-free rate and 6% average returns on the risky asset). Participants in Group 2 first make investment decisions in the low rate condition, and then make decisions in the high rate condition. The statistics are the same as those in Table 1.1.

Panel A. Hypothetical

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

Panel B. Incentivized

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

Table A.8: *Demographic Information of Experiment T3 (Salience and Proportional Thinking) Sample*

This table presents the demographics of Experiment T3. In the Low condition, the risk-free rate is 1%; in the High condition, the risk-free rate is 5%. The mean excess returns of the risky asset is 5% in both conditions. The statistics are the same as those in Table 1.1.

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

A.3.2 Dutch Replication

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

The AFM conducted the experiment among 901 Dutch households, drawn from an online AFM consumer panel. Participants are randomly assigned into conditions with interest rates from -1% to 10% (holding fixed the excess returns of the risky asset and 5% risk premium as in Section 1.2 and Section 1.4). The Dutch experiments used the hypothetical version of our protocol, translated into Dutch. Respondents do not receive financial payments, but do have high response rates (>50%).

Table A.9 shows the overall demographics of the Dutch sample. The AFM consumer panel tilts toward the elderly, and 58% are 60 years old or above. Participants are predominantly male. They are well-educated and financially well-off, and most have some investment experience.

Figure A.4 and Table A.10 show the results in the Dutch sample (red diamonds). There is again significant reaching for yield and substantial non-linearity. The reaching for yield effect seems slightly higher in the Dutch sample: for example, the difference in mean allocations between the 1% interest rate condition and the 5% interest rate condition is 10.16 percentage points in the Dutch sample, compared to around 8 percentage points in the US sample shown in Table 1.2.

Table A.9: *Demographics of the Dutch Sample*

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

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

Figure A.4: *Mean Allocations Across Interest Rate Conditions: Dutch Sample*

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

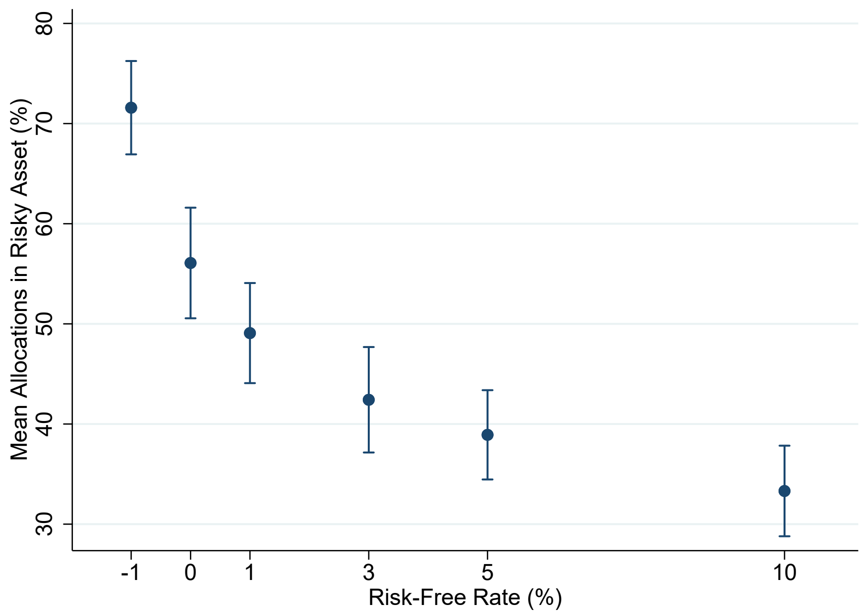


Table A.10: *Mean Allocations Across Interest Rate Conditions: Dutch Sample*

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

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

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

A.3.3 Additional Results in Observational Data

Interest Rates and Household Investment Allocations

Table A.11: *Interest Rates and AAII Portfolio Allocations: Specification in Changes*

Monthly time series regressions:

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

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

Panel A. Interest Rates and Mean Allocations to Stocks

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

Newey-West t-statistics in brackets

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

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

Newey-West t-statistics in brackets

Table A.12: *Interest Rates and Investment Allocations: Results with Monetary Policy Shocks*

Time series regressions:

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

where r_s is a measure of monetary policy shock, following Romer and Romer (2004) and Gertler and Karadi (2015) (current month Fed Funds futures). In Panels A to D, the regressions are monthly, and the outcome variables are respectively changes in mean allocations to stocks and cash from AAII, and flows into equity and high yield corporate bond mutual funds (normalized by net asset value) respectively. In Panels E and F, the regressions are quarterly, and the outcome variables are respectively household sector flows into stocks and interest-bearing safe assets (normalized by household financial assets). The outcome variables are the same as those in Table A.11 and Table 1.8, and the same controls X are used in each case. The Romer-Romer shocks end in December 2007; the Gertler-Karadi shocks end in June 2012. Standard errors are Newey-West, using the automatic bandwidth selection procedure of Newey and West (1994).

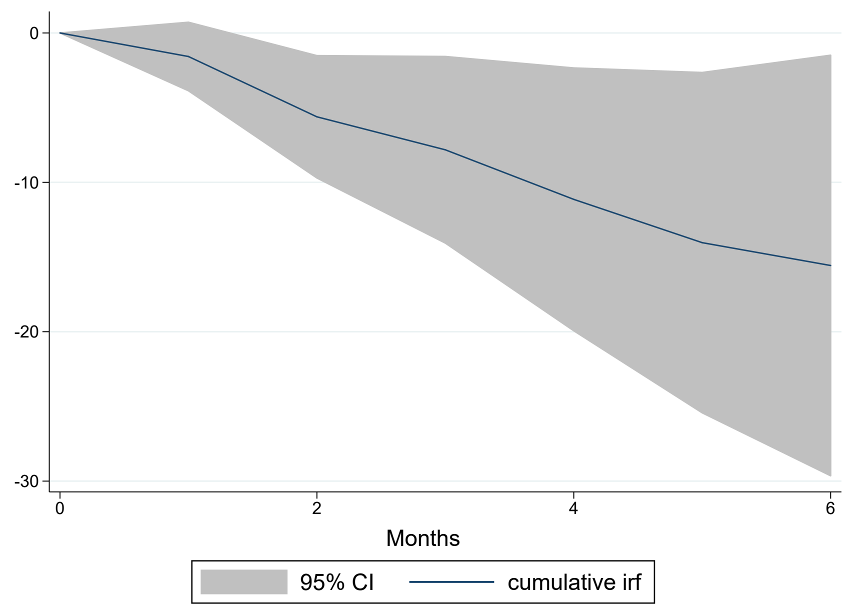
Panel A. Change in Mean Allocations to Stocks (AAII)								
Romer-Romer	-3.89	-4.48	-4.24	-5.05				
	[-2.82]	[-2.89]	[-2.77]	[-3.12]				
Gertler-Karadi					-3.52	-2.73	-2.87	-3.66
					[-1.06]	[-0.80]	[-0.83]	[-1.03]
Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Observations	235	235	235	235	284	284	284	284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

Newey-West t-statistics in brackets

Figure A.5: *Interest Rates and AAII Portfolio Allocations: sVAR Impulse Response*

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

Panel A. Mean Allocations to Stocks



Panel B. Mean Allocations to "Cash"

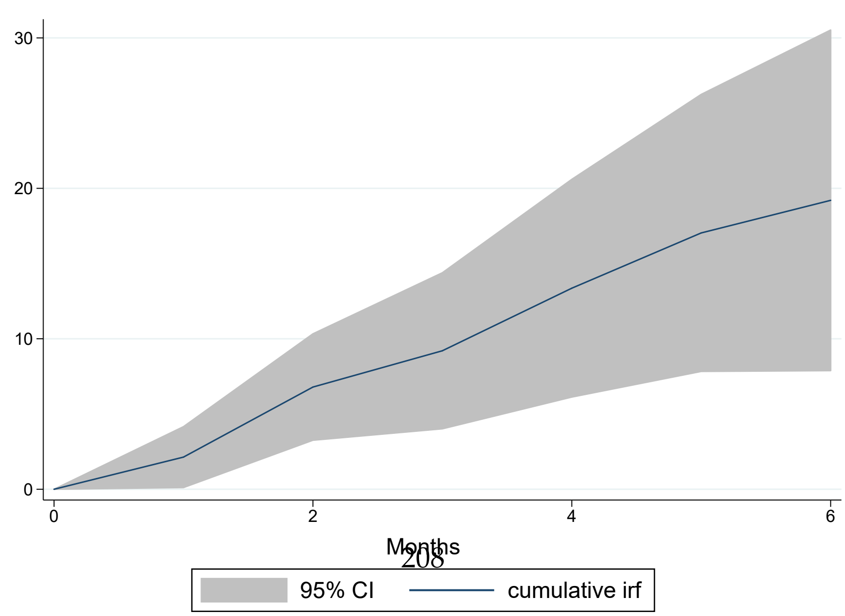
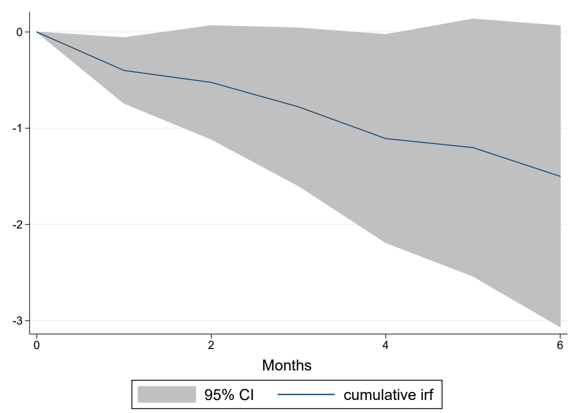
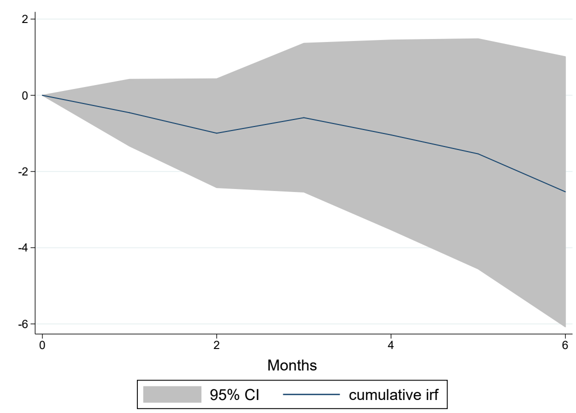


Figure A.6: *Interest Rates and Household Investment Flows: sVAR Impulse Response*

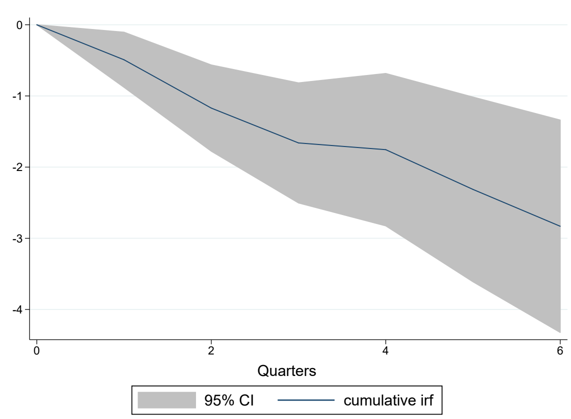
Impulse response plots of household investment flows to innovations in interest rates. Plot (a) shows monthly sVAR results of equity mutual fund flows (normalized by equity mutual fund net asset value) using data from the Investment Company Institute (ICI). Plot (b) shows monthly sVAR results of high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



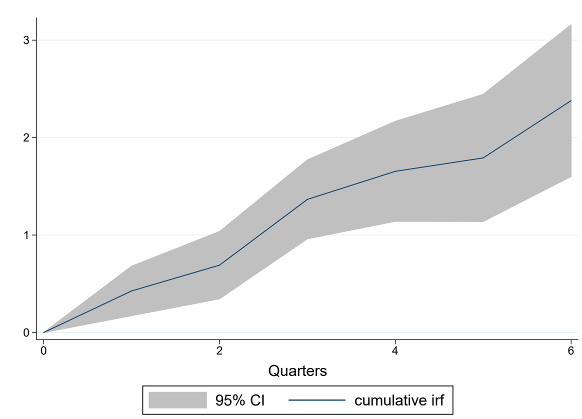
(a) *Equity Mutual Fund Flows (ICI)*



(b) *High Yield Mutual Fund Flows (ICI)*



(c) *Household Flows into Stocks (FoF)*



(d) *Household Flows into Deposits (FoF)*

Figure A.7: *Impulse Response of Excess Stock Returns to Interest Rate Innovations*

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

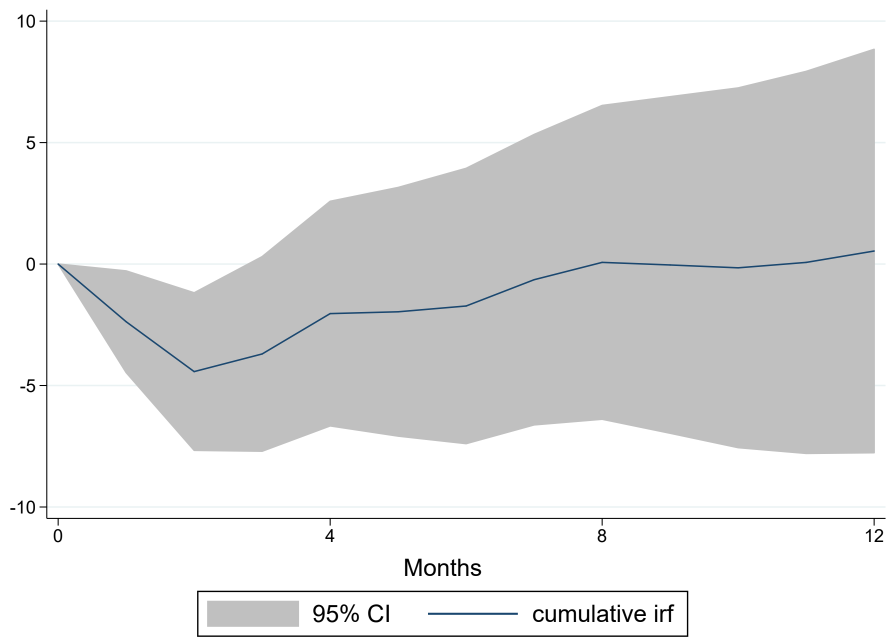


Table A.13: *Flows and Issuance by Sector*

Time series regressions:

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

where r_f is 3-month Treasury rate; F is quarterly net flows into corporate equities (normalized by US GDP) in columns (1) to (3), and quarterly net equity issuance of equities (normalized by US GDP) in columns (5) to (7); X includes controls in Table 1.7: Spec 1 has the same controls as Table 1.7 column (2), Spec 2 has the same controls as Table 1.7 column (3), and Spec 3 has the same controls as Table 1.7 column (4). All regressions include four lags of F. Outcome variables are from the beginning of 1985 to the end of 2014, but AAII sentiment is only available starting August 1987. Standard errors are Newey-West, using the automatic bandwidth selection procedure of Newey and West (1994). Regression coefficient β and the associated t-statistics are reported. Data on flows and issuance are from Flow of Funds, and they are in net terms. Flows from all sectors sum up to issuance by all sectors. On the flow side, all sectors include households, domestic financial sector, rest of the world, as well as a few other components such as government and non-financial corporations' holdings of mutual fund shares.

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

History-Dependent Reference Points: Results from the SCF

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

Figure A.8 follows Figure 1 in Malmendier and Nagel (2011), and plots the differences in mean allocations to stocks (as well as deposits) between old and young against the differences in experienced past interest rates. It shows that in periods where old individuals' experienced interest rates are significantly higher than young individuals, old individuals' propensity to invest in stocks is also much higher.

Table A.14 presents regressions following Malmendier and Nagel (2011):

$$Y_{it} = \alpha + \eta_t + \beta \bar{r}_{f,it} + \gamma \bar{r}_{x,it} + \xi' X_{it} + \epsilon_{it} \tag{A.12}$$

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

Table A.14 shows that, at a given point in time, individuals that experienced high interest rates in the past invest less in deposits and have a higher propensity of risk taking. For a one percentage point increase in average experienced past interest rates, portfolio shares in stocks (deposits) on average increase (decrease) by about 1.5 percentage points. The changes in portfolio shares are more pronounced among stock market participants. This pattern is consistent with the idea that these individuals are accustomed to higher levels of interest rates and are less satisfied with the current interest rates. Thus they invest less in deposits and are more likely to invest in risky assets.

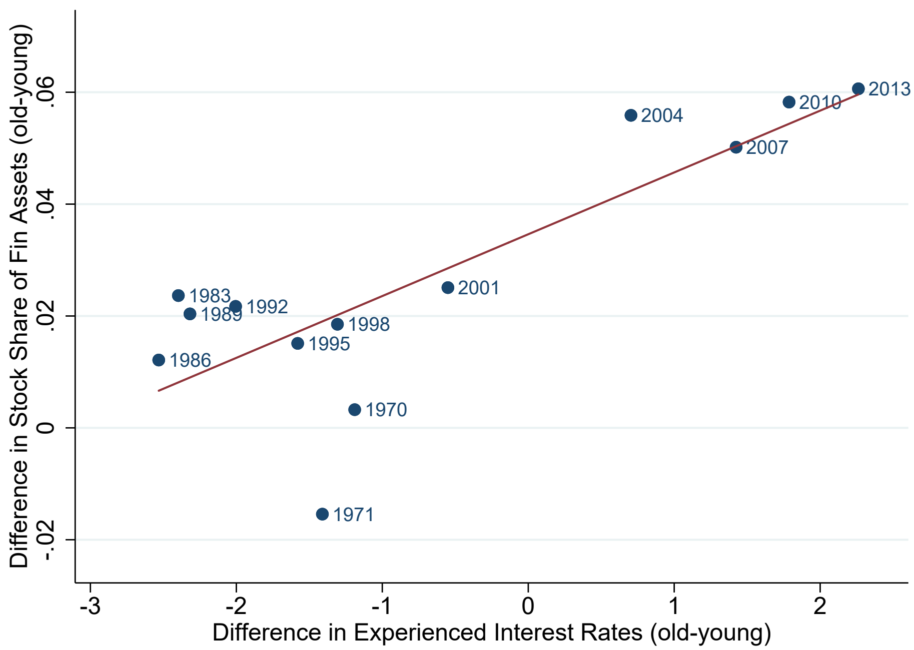
There are, however, several caveats in this analysis using observational data. First, the SCF does not have data on beliefs about the risky asset's returns and risks. Thus it is challenging to adequately control for potential heterogeneity in beliefs. For instance, to the extent that interest rates tend to be higher in booms and lower in recessions, individuals who experienced higher past interest rates may have more experiences of booms and are thus more optimistic. Second, in the past half a century, interest rates experienced a secular decline, so the gap in interest rate experiences is correlated with the age gap: as can be seen in Figure A.8, both differences in old and young individuals' experienced interest rates and differences their investment shares in stocks secularly increase. Thus it may be hard to rule out influences from systematic demographic shifts. Finally, the reference points in the reference dependence model of Section 1.3.2 could be influenced by experiences of both past interest rates and past stock returns. Accordingly, in the SCF data it could be hard to tease apart experience effects that work through history-dependent reference points from experience effects that work through beliefs and other channels.

In sum, there are multiple challenges in observational data that can make it harder to cleanly isolate the underlying mechanisms. Nonetheless, the patterns in the observational data appear in line with our findings in the transparent randomized experiments. We hold the evidence of Figure A.8 and Table A.14 as suggestive of history-dependent reference points.

Figure A.8: *Differences in Mean Investment Shares between Old and Young*

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

Panel A. Differences in Mean Shares in Stocks



Panel B. Differences in Mean Shares in Deposits

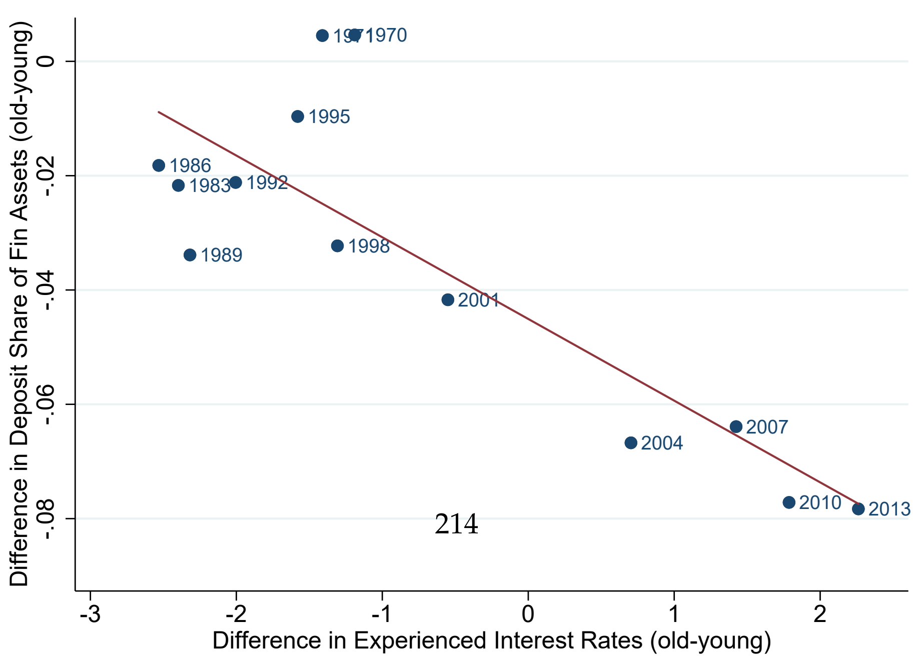


Table A.14: *Investment Decisions and Interest Rate Experiences*

Panel regressions using Survey of Consumer Finance data:

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

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

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

t-statistics in brackets, corrected for multiple imputation

A.4 Data

A.4.1 List of Experiments

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

A.4.2 Sources and Variable Definitions for Observational Data

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

Appendix B

Appendix to Chapter 2

B.1 Asset-Based Lending and Cash Flow-Based Lending

In this section, we explain in detail the categorization of asset-based lending and cash flow-based lending. We first lay out the main types of debt in each category. We then describe our categorization procedure in the aggregate and at the firm level.[1]

Asset-Based Lending

Asset-based lending consists of debt where creditors' claims are against specific physical assets, and payoffs in default tie to the liquidation value of the assets that serve as collateral. The debt has the following features: 1) it is secured by specific physical assets as collateral; 2) it restricts the size of the debt based on the value of the given collateral, and creditors focus on the liquidation value of the specific assets that serve as collateral; 3) the debt may also have some liquidity tests, but place less emphasis on the borrower's cash flow performance and related financial covenants.

To understand creditors' payoffs in bankruptcy, we briefly review US bankruptcy procedures. Creditors' claims are grouped into secured and unsecured claims, with secured claims having higher priority. The portion of an asset-based debt up to the liquidation value of its collateral is considered a secured claim, which is the primary source of recovery for asset-based lenders; the rest

[1] In the categorization, we do not include commercial papers, which are short-term unsecured debt for liquidity purposes.

("under-collateralized" portion) is treated as an unsecured claim. In Chapter 7, creditors' payoffs almost entirely come from the liquidation value of the assets; unsecured claims get no or minimal payments. In Chapter 11, creditors' secured claims (up to the collateral value of the assets) can be paid in full;[2] they may get some additional recovery if they are "under-collateralized" and unsecured claims get some payments, but this portion is typically small in comparison.

The main components of asset-based lending are commercial mortgages and business loans secured by specific assets such as inventory, accounts receivable, certain types of machinery and equipment, and sometimes oil and gas reserves (often referred to as asset-based loans). We also include capital leases, but the total amount is small.[3]

1. Commercial mortgages

   Commercial mortgages are corporate debt backed by real estate. For larger firms, the collateral is typically commercial real estate, mostly office buildings/corporate headquarters and sometimes retail properties like shopping malls and hotels. Very small firms may also use residential mortgages.

2. Asset-based loans

   Asset-based loans are business (non-mortgage) loans backed by physical assets as collateral, such as inventory, receivable, some machinery and equipment, and some specialized assets such as oil and gas reserves. Asset-based loans specify a "borrowing base," calculated based on the liquidation value of eligible collateral. Creditors regularly monitor the borrowing base and require that the loan size cannot exceed a fraction of the borrowing base. Asset-based loans can be originated by banks, as well as finance companies that specialize in lending against specific types of collateral.

3. Capitalized leases

[2]Section 1129(a)(7)(A) of the Bankruptcy Code requires that for a Chapter 11 reorganization to be approved, it must be established that each secured claim holder would receive at least the amount he/she would get if the borrower were liquidated under Chapter 7.

[3]The term "asset-based lending" is sometimes used narrowly to refer to asset-based loans with inventory and receivables as collateral. Here we use the term more broadly.

In a capital lease, the leased asset shows up on the asset side of the lessee's balance sheet, and the lease shows up on the liability side. Capital leases are often treated as debt (Compustat includes capitalized lease as part of the debt variable). This contrasts with operating leases (e.g. rent), in which case the lease and the lease asset do not appear on the lessee's balance sheet. A lease is recognized as a capital lease when the lessee has exposures to the ownership of the asset, e.g. the lease specifies a transfer of ownership from the lessor to the lessee at the end of the lease period, or that the lease period covers a substantial amount of the life of the asset. US GAAP specifies rules about recognizing capital leases. A well known example of capital lease is used in aircraft financing and studied in Benmelech and Bergman (2011). In this case, a trust purchases the aircraft, leases it to the airline, and finances the purchase by issuing secured notes backed by the aircraft. The trust is sometimes set up by the airline, but is bankruptcy remote. Because the financing of assets in capital leases is often tied to the assets' liquidation value, we categorize capital leases as asset-based lending. As the size of this portion is relatively small (about $70 billion among Compustat public firms), in the following calculations we merge capital leases with asset-based loans.

Cash Flow-Based Lending

Cash flow-based lending consists of debt where creditors' payoffs primarily come from the value of cash flows from firms' operations, rather than the liquidation value of physical collateral (both in ordinary course and in bankruptcy). The debt has several features: 1) it is unsecured, or secured by a lien on the entire corporate entity ("substantially all assets," excluding those pledged for asset-based loans) or by equity, rather than by specific physical assets; 2) they closely monitor borrower's cash flows (e.g. through financial covenants), rather than the liquidation value of physical assets.

To understand creditors' payoffs in bankruptcy, we again review the US bankruptcy procedures. For cash flow-based debt secured by the entire corporate entity or by equity, creditors' collateral value and payoffs in Chapter 11 are determined based on the cash flow value from continuing operations.[4] Payoffs in Chapter 7 may be affected by the liquidation value of physical assets, but

[4]Specifically, in Chapter 11 different parties settle on a reorganization plan under court supervision and approval, which is associated with a calculation of going-concern cash flow value of the firm. The value is then

they are generally small and Chapter 7 cases are rare for large firms that extensively use cash-flow based lending (according to CapitalIQ data, more than 90% of large firms' bankruptcies are resolved through Chapter 11). For unsecured claims, in both Chapter 11 and Chapter 7, the payoffs are not closely related to the liquidation value of physical assets (payoffs depend on the cash flow value from continuing operations in Chapter 11, and are generally minimal in Chapter 7).

There are two main components of cash flow-based lending: corporate bonds and cash flow-based loans.

1. Corporate bonds

   Corporate bonds are generally backed by borrowers' future cash flows and are commonly unsecured. FISD data shows that less than 1% of corporate debt issuance by US non-financial firms is asset backed. About 10% is secured; a very small portion (e.g. industrial revenue bonds) is secured by physical assets, while most secured bonds are cash flow-based (e.g. secured by liens on corporate entity).

2. Cash flow-based loans

   Cash flow-based loans comprise of commercial loans that are primarily backed by borrowers' cash flows. The prototypical cash flow-based loans do not use specific physical assets as collateral. Rather, the collateral is a lien on the entire corporate entity, and the collateral value is calculated based on the cash flows of the borrower. Creditors perform detailed cash flow analyses, and closely monitor borrowers' cash flows. These loans use earnings-based covenants extensively (e.g. debt to EBITDA ratio, interest coverage ratio). They typically take the form of a term loan and are widely used among large firms.

   Among large firms, revolving lines of credit (“revolver"), is a class of debt that can be in between cash flow-based lending and asset-based lending. For large firms with high credit quality, the revolvers are generally unsecured and fit into cash flow-based lending. For those with higher risks, the revolvers are typically secured by inventory and accounts receivable (and some other eligible assets). In these cases, the revolvers rely on physical assets as collateral, and specify

distributed to creditors according to priority.

borrowing limits of the revolvers that depend on the liquidation value of the physical collateral ("borrowing base," discussed more below). They fit into asset-based lending. However, due to institutional reasons the revolvers are often bundled together with prototypical cash flow loans (e.g. term loans) in a single loan package, and share the earnings-based covenants. For small firms, many revolvers are instead standalone asset-based loans.

B.1.1 Aggregate Composition

In the following, we estimate the share of cash flow-based and asset-based lending among aggregate US non-financial corporate debt outstanding. Here we primarily rely on aggregate sources, so the estimates are not confined to public firms.

Asset-Based Lending: around 20% of debt outstanding

1. Commercial mortgages

    - Share in total non-financial debt outstanding: 7%
    - Data sources: Flow of Funds
    - Calculation: We use commercial mortgage outstanding from the Flow of Funds, which is around $0.6 trillion.

2. Asset-based loans:

    - Share in total non-financial debt outstanding: 12%
    - Data sources: DealScan, ABL Advisor, SNC, SBA/Call Report
    - Calculation: We first estimate asset-based loans to large firms. For this part, we start with data from DealScan, ABL advisor, and SNC data, which proxies the portion of syndicated loans (representative of loans to large firms) that are asset-based. We use the procedure described above: we find that around 5% of syndicated loans are asset-based and multiply it with the size of the syndicated loan market (roughly $3 trillion).

      We then estimate asset-based loans to small businesses. For this part, we use debt outstanding of loans to small businesses compiled by the SBA based on Call Report data.

These are loans under $1 million, and we categorize all of small business lending as asset-based loans. A small fraction of small business lending can also be cash flow-loans, but detailed loan-level information is much harder to get and we take a conservative approach. Total loans outstanding to small businesses is about $0.6 trillion.

For asset-based loans originated by finance companies, we use the Flow of Funds data and estimate the outstanding amount to be about $0.3 trillion. For capitalized leases, the total amount in Compustat public non-financial firms is around $70 billion, and we estimate the total amount in all non-financial firms to be around $0.1 trillion.

Putting these parts together, we get an estimate of asset-based loans of around $1.2 trillion. There may be some commercial loans to medium sized firms missing (not covered by SNC/DealScan and finance company loans, but not necessarily small business loans). To the extent these loans are more likely to be asset-based, there might be potential under-estimation. At the same time, the small business loans can include many loans to non-corporate entities (sole proprietorship, partnership) or some mortgages, leading to potential over-estimation. Nonetheless, in either case the magnitude should be small.

Cash Flow-Based Lending: around 80% of debt outstanding

1. Corporate bonds

   - Share in total non-financial corporate debt outstanding: 49%
   - Data source: Flow of Funds, FISD, CapitalIQ
   - Calculation: According to Flow of Funds data, corporate bond outstanding by US non-financial firms is about $4.5 trillion. Based on FISD and CapitalIQ data, which provide more information on the structure of individual corporate bonds, only a small portion of corporate bonds are backed by specific physical assets (<2%). Thus in the aggregate, we categorize all corporate bonds into cash flow-based lending.

2. Cash flow-based loans

   - Share in total non-financial corporate debt outstanding: 32%

- Data sources: DealScan, ABL Advisor, Shared National Credits Program (SNC)
- Calculation: We approximate the volume of cash flow loans using the cash flow-based portion of syndicated loans, which cover the vast majority of cash flow loans by dollar volume. We proceed in two steps. We first estimate the share of cash flow loans versus asset-based loans in syndicated loans, using data from the DealScan and ABL Advisor. In particular, ABL Advisor reports the volume of issuance in DealScan that can be classified as asset-base loans, and we can compare this to the volume of all DealScan issuance to get the asset-based share, and the remainder is the cash flow-based share. We can alternatively calculate (directly using DealScan data) the share of DealScan loans that do not have borrowing base requirements, and the results are very similar. The estimated share of cash flow loans is roughly 95% (annual syndicated loan issuance is about $1,500B to $2,000B, of which $60B to $100B is asset-based). We then turn to the volume of syndicated loans outstanding. Volume outstanding in not included in DealScan. Thus we instead use data on syndicated loans outstanding from SNC, and estimate the amount to be about $3 trillion.

Table B.1: *Summary of Asset-Based Lending and Cash Flow-Based Lending*

Debt Type	Category	Amount ($ Tr)	Share
Commercial mortgages	Asset-based lending	$0.6	6.5%
Asset-based loans	Asset-based lending	$1.2	13%
Corporate bond	Cash flow-based lending	$4.5	48%
Cash flow loans	Cash flow-based lending	$3	32%

B.1.2 Firm-Level Composition

We now discuss the firm-level composition of cash flow-based and asset-based lending, based on debt-level data for public non-financial firms.

We begin with debt-level information from CapitalIQ, which is available starting in 2002. For each debt, CapitalIQ provides information about the amount outstanding, whether it is secured, and some basic descriptions of the debt (with more details about the debt type, collateral structure, lender, etc.). CapitalIQ is very helpful because it covers all types of debt and tracks the amount outstanding for each debt in each firm-quarter, which facilitates a comprehensive analysis. CapitalIQ assembles these data from many types of firm filings. It covers about 75% of Compustat firms and total debt value matches well with Compustat data. We supplement CapitalIQ data with additional information on debt attributes from DealScan, SDC, and FISD.

We categorize firms' debt into four groups: 1) asset-based lending, 2) cash flow-based lending, 3) personal loans, 4) miscellaneous and unclassified borrowing. We proceed in several steps:

1. We classify a debt as asset-based lending if
   - the debt information contains the following key words (and their variants): borrowing base, mortgage, real estate/building/property, equipment, machine, receivable, inventory, working capital, automobile/vehicle, aircraft, asset-based, capital lease, SBA (small business administration), oil/drill/rig, reserve-based, factoring, industrial revenue bond, fixed asset, finance company, construction, project finance;
   - it is a revolver and is not explicitly unsecured or designated cash flow-based in debt documents.
2. We classify a debt as personal loan if
   - the lender is an individual (Mr./Ms., etc);
   - it is from directors/executive/chairman/founder/shareholders/related parties.
3. We assign a debt to the miscellaneous/unclassified category if it is
   - borrowing from governments (not specifically asset-based);
   - borrowing from vendor/seller/supplier/landlord;
   - insurance-related borrowing;
   - borrowing from parent or affiliates;
   - pollution control bonds.
4. We classify a debt as cash flow-based lending if it **does not belong to any of the categories above** and

- the debt is unsecured/un-collateralized, is a “debenture", or explicitly says “cash flow-based"/“cash flow loan";
- it contains the following key words and their variants, which are representative of cash flow-based loans: substantially all assets, first lien/second lien/third lien, term facility/term loan facility/term loan a, b, c..., syndicated, tranche, acquisition line, bridge loan;
- it is a bond or it contains standard key words for bonds, such as senior subordinated, senior notes, x% notes due, private placement, medium term notes;
- it is a convertible bond.

5. We assign all remaining secured debt to asset-based lending to be conservative.

In Table B.3 below, we show that the amount of asset-based lending a firm has is positively correlated with the amount of physical assets, while the amount of cash flow-based lending is not (generally negatively correlated with physical assets). The results confirm that cash flow-based lending does not appear to depend on the value of physical assets.

Table B.2: *Median Debt Share across Firm Groups*

	Large Firms	Rated Firms	Small Firms
Asset-Based Lending	12.4%	8.0%	61.0%
Cash Flow-Based Lending	83.0%	89.0%	7.2%

Table B.3: *Properties of Debt in Asset-Based Lending and Cash Flow-Based Lending*

Firm-level annual panel regressions of debt in each category on the amount of specific assets (all normalized by book assets). In Panel A, the right-hand-side variables include all asset-based lending, as well as mortgages and non-mortgage asset-based loans. In Panel B, the right-hand-side variables include all cash flow based lending, as well as cash flow-based loans in particular. Controls include size (log assets) and cash holdings. Columns (3) and (4) include firm fixed effects. Sample period is 2002 to 2015, and all public firms which have CapitalIQ debt detail data are included. Standard errors are clustered by firm and type. *t*-statistics in brackets.

Panel A. Asset-Based Lending and Physical Assets

	Asset-Based Lending/Assets			
Book PPE	0.126***		0.116***	
	(0.010)		(0.014)	
Market value real estate		0.036**		-0.006
		(0.018)		(0.021)
Book inventory	0.050***	-0.071**	0.085***	-0.037
	(0.018)	(0.036)	(0.031)	(0.070)
Receivable	0.061***	-0.134***	0.043**	-0.049
	(0.017)	(0.038)	(0.022)	(0.070)
Firm FE	N	N	Y	Y
Obs	45,830	6,359	44,803	6,266
R^2	0.077	0.146	0.025	0.017
	Mortgages/Assets			
Book PPE	0.038***		0.022***	
	(0.003)		(0.003)	
Market value real estate		0.017***		0.019***
		(0.004)		(0.006)
Book inventory	0.003	0.009	0.003	-0.020
	(0.003)	(0.008)	(0.004)	(0.017)
Receivable	-0.006***	-0.020*	-0.000	-0.009
	(0.002)	(0.011)	(0.002)	(0.011)
Firm FE	N	N	Y	Y
Obs	45,406	6,329	44,380	6,239
R^2	0.075	0.079	0.009	0.018
	(Non-Mortgage) Asset-Based Loans/Assets			
Book PPE	0.066***		0.081***	
	(0.009)		(0.013)	
Market value real estate		0.007		-0.026
		(0.017)		(0.021)
Book inventory	0.055***	-0.056*	0.082***	-0.011
	(0.016)	(0.032)	(0.029)	(0.070)
Receivable	0.074***	-0.083**	0.041*	-0.033
	(0.017)	(0.034)	(0.022)	(0.073)
Firm FE	N	N	Y	Y
Obs	45,798	6,358	44,772	6,266
R^2	0.059	0.106	0.020	0.018

t-statistics in brackets.

Panel B. Cash Flow-Based Lending and Physical Assets

	Cash Flow-Based Lending/Assets			
Book PPE	-0.100***		-0.057**	
	(0.013)		(0.024)	
Market value real estate		-0.019		-0.071**
		(0.020)		(0.028)
Book inventory	-0.240***	-0.203***	-0.135***	-0.135*
	(0.019)	(0.044)	(0.036)	(0.071)
Receivable	-0.328***	-0.230***	-0.127***	-0.087
	(0.024)	(0.052)	(0.032)	(0.069)
Firm FE	N	N	Y	Y
Obs	45,820	6,359	44,794	6,266
R^2	0.068	0.169	0.006	0.010
	Cash Flow Loans/Assets			
Book PPE	-0.055***		-0.026**	
	(0.009)		(0.010)	
Market value real estate		-0.021**		-0.002
		(0.010)		(0.019)
Book inventory	-0.089***	-0.096***	-0.051***	0.004
	(0.011)	(0.023)	(0.014)	(0.041)
Receivable	-0.092***	-0.016	-0.042***	-0.017
	(0.011)	(0.030)	(0.013)	(0.045)
Firm FE	N	N	Y	Y
Obs	45,773	6,354	44,746	6,261
R^2	0.037	0.036	0.007	0.008

t-statistics in brackets.

B.2 Earnings-Based Borrowing Constraints

B.2.1 Specifications of Earnings-Based Covenant

Table B.5: *Variants of Earnings-Based Covenants*

This table lists the main variants of earnings-based covenants and the construction using Compustat variables compiled by Demerjian and Owens (2016). The first column displays the covenant type, which is reported in DealScan data, and the second column describes the form of the covenant. The third column shows how to compute the metric used in each type of covenant using Compustat data. The fourth column tabulates the fraction of DealScan loans to US non-financial that have the specific type of covenant. The final column shows a check of the Compustat formula. For some types of covenants, the formula and details of the components may not be fully standardized across different debt contracts. Demerjian and Owens (2016) study a subset of DealScan loans where details of the covenant formula are provided by the Tearsheets dataset, and they calculate the frequency of cases where the Compustat formula listed is matches with details provided by the Tearsheets data.

Covenant Type	Standard definition	Compustat implementation	Fraction of loans	Exact match in Demerjian and Owens (2016)
Max. Debt-to-EBITDA	Debt/EBITDA	(DLTT+DLC)/EBITDA	29.7%	91.0%
Max. Senior Debt-to-EBITDA	Senior Debt/EBITDA	(DLTT+DLC–DS)/EBITDA	5.2%	89.4%
Min. Interest Coverage	EBITDA/Interest Expense	EBITDA/XINT	20.8%	76.3%
Min. Cash Interest Coverage	EBITDA/Interest Paid	EBITDA/INTPN	0.7%	76.8%
Min. Debt Service Coverage	EBITDA /(Interest Expense+ST Debt)	EBITDA/(XINT+L.DLC)	4.5%	37.9%
Min. Fixed Charge Coverage	EBITDA/(Interest Expense+ST Debt+Rent Expense)	EBITDA/(XINT+L.DLC+XRENT)	18.5%	2.7%
Min. EBITDA	EBITDA	EBITDA	5.0%	97.4%

B.2.2 Other Earnings-Based Constraints

This section provides more information about other forms of earnings-based borrowing constraints discussed in Section 2.2.2. As mentioned in Section 2.2.2, when a firm wants to raise debt, it can be hard to surpass a reference level of debt to EBITDA ratio. This type of credit market norms are most pronounced in the leveraged loan market and especially relevant for non-investment grade borrowers.

Figure B.1 below shows a time series of reference debt to EBITDA ratio in the leveraged loan market for large firms. It is an indicator of the mean debt to EBITDA ratio lenders are willing to allow when large firms raise debt. Unlike financial covenants, this is primarily a market reference, and not legally binding. Nonetheless, to the extent that firms need to comply to such norms when they borrow, their debt to EBITDA ratio may end up being sensitive to the market norm.

Table B.6 shows the sensitivity of firm-level debt to EBITDA to the reference level of Debt to EBITDA, based on a regression:

$$\text{Debt/EBITDA}_{it} = \alpha + \theta \text{Ref Debt/EBITDA}_t + X_{it}'\gamma + Z_t'\rho + v_{it} \tag{B.1}$$

where Debt/EBITDA$_{it}$ is firm i's debt to EBITDA at time t, Ref Debt/EBITDA is the reference debt to EBITDA at time t (which LCD compiles based on the mean debt to EBITDA ratio of firms completing leveraged loan deals during period t), X_{it} is firm-level controls, and Z_t is macro controls including interest rates and business cycle proxies (credit spread, term spread, GDP growth). The regressions are separately estimated for firms in different ratings categories: those below the investment grade cut-off (BB+ and below), and those above the investment grade cut-off (BBB- and above). We show the sensitivity to the reference debt/EBITDA at both annual and quarterly frequencies.

B.3 Classic Models of Corporate Borrowing

In this appendix, we further discuss several strands of literature on costly external financing and their predictions about how cash flows influence corporate borrowing and investment. We clarify the differences between predictions based on EBCs and predictions in these models. As discussed in

Figure B.1: *Debt/EBITDA Reference Level for Large Issuers*

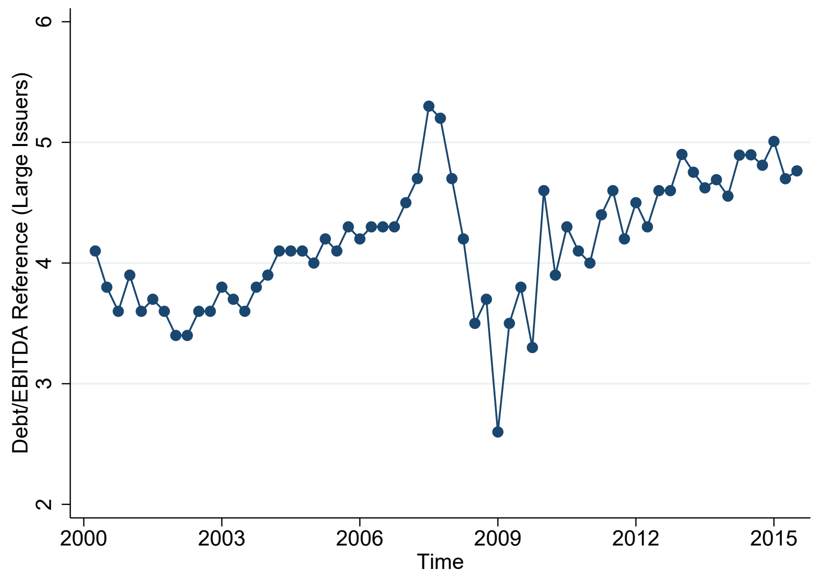


Table B.6: *Sensitivity to Reference Debt/EBITDA*

This table summarizes the regression coefficient θ from:

$$\text{Debt/EBITDA}_{it} = \alpha + \theta \text{Ref Debt/EBITDA}_t + X_{it}'\gamma + Z_t'\rho + v_{it}$$

where Debt/EBITDA_{it} is firm i's debt to EBITDA at time t, Ref Debt/EBITDA is the reference debt to EBITDA at time t. Firm level controls X_{it} include lagged debt/EBITDA, as well as Q, past 12 months stock returns, and book leverage (debt/asset), cash holdings, accounts receivable, inventory, book PPE, log assets at the end of time $t-1$. Macro controls include term spread (spread between 10-year Treasury and 3-month Treasury), credit spreads (spread between BAA bond yield and 10-year Treasury yield, as well as spread between high yield bond yield and 10-year Treasury yield), and real GDP growth at time t. For the annual regression, firm-level debt to earnings ratio is debt in year t over EBITDA in year t, and observations where EBITDA is negative are dropped; reference debt to EBITDA is the annual average in year t. For the quarterly regressions, firm-level debt to earnings ratio is debt in quarter t over total EBITDA in the past 12 months, and observations where past 12 month EBITDA is negative are dropped; reference debt to EBITDA is measured in quarter t. We also exclude firms that are in violation of earnings-based covenants (earnings-based covenant binding) at the beginning of time t. Standard errors are clustered by both firm and time.

	Non IG		IG	
	All BB	BB+	BBB-	All BBB
	Annual Frequency			
θ	0.55	0.61	0.47	0.48
s.e.	(0.242)	(0.274)	(0.250)	(0.483)
	Quarterly Frequency			
θ	0.15	0.10	0.06	0.06
s.e.	(0.049)	(0.044)	(0.035)	(0.040)

Section 2.3.1, in these other models, cash flows only affect corporate borrowing through the impact on internal funds; EBITDA does not have an independent role after controlling for internal funds. We summarize the detailed predictions below.

1. This paper

    - Determinant of cost/capacity for external borrowing: Operating earnings.
    - Formulation: $C(b, \pi)$; π is operating earnings (EBITDA).
    - How cash flows influence borrowing and investment: Cash flows in the form of EBITDA relax borrowing constraints/decrease cost of external borrowing, and crowd in borrowing and investment. Holding EBITDA constant, cash receipts increase internal funds, but do not relax borrowing constraints/decrease cost of external borrowing. They boost investment but substitute out external borrowing.
    - EBITDA plays an independent role controlling for internal funds.

2. Froot, Scharfstein and Stein (1993), Kaplan and Zingales (1997)

    - Determinant of cost/capacity for external borrowing: Exogenous (not dependent on financial variables).
    - Formulation: $C(b)$.
    - How cash flows influence borrowing and investment: Cash flows increase internal funds, but do not relax borrowing constraints/decrease cost of external borrowing. They boost investment but substitute out external borrowing.
    - EBITDA does not play an independent role controlling for internal funds.

3. Kiyotaki and Moore (1997), Bernanke, Gertler and Gilchrist (1999)

    - Determinant of cost/capacity for external borrowing: Liquidation value of physical assets.
    - Formulation: $C(b, qk)$. k is the amount of physical capital the firm owns, q is the liquidation value per unit of capital measured at the time of debt repayment.

- How cash flows influence borrowing and investment: Borrowing constraints/cost of external borrowing do not directly depend on cash flows. Higher cash flows may increase borrowing indirectly as they increase firms' internal funds ("net worth"), allow firms to acquire more physical assets, and relax firms' borrowing constraints/decreases cost of external financing.
- EBITDA does not play an independent role controlling for internal funds.

4. Holmstrom and Tirole (1997)

- Determinant of cost/capacity for external borrowing: Pledgeable income.
- Formulation: $C(b, P)$. P is the amount of pledgeable income a firm has.
- How cash flows influence borrowing and investment: Borrowing constraints/cost of external borrowing do not directly depend on cash flows. Higher cash flows may increase borrowing indirectly as they increase firms' internal funds ("net worth"), allow firms to acquire more projects, and therefore generate more pledgeable income and relax firms' borrowing constraints/decreases its cost of external financing.
- EBITDA does not play an independent role controlling for internal funds.

5. Net worth channel

- The concept "net worth channel" is used in both the third case and the fourth case. "Net worth" is defined as the firm's maximum amount of funds available that can be used to acquire new assets and projects (Bernanke, Gertler and Gilchrist, 1999). This is equivalent to internal funds w in our framework.
- In the case of Kiyotaki and Moore (1997) and Bernanke, Gertler and Gilchrist (1999), the net worth channel means that an increase in internal funds w allows firms to acquire more physical assets and relax its borrowing constraints. In the case of Holmstrom and Tirole (1997), the net worth channel then means that an increase in internal funds w allows firms to acquire more projects, generate more pledgeable income and relax its

borrowing constraints. The concept “net worth channel" can be consistent with both asset-based lending and cash flow-based lending.

- In the models above, the net worth channel is focused on the role of internal funds. All components of internal funds have the same positive impact on borrowing; EBITDA does not play an independent role after controlling for internal funds.

B.4 Accounting

B.4.1 EBITDA and OCF

Definition and Construction

1. EBITDA
   - Compustat variable: EBITDA (equivalently OIBDP)
   - EBITDA is a measure of operating earnings
   - EBITDA = revenue - operating expenses = sales (SALE) - cost of goods sold (COGS) - selling, general and administrative expense (XSGA)
   - Does not include capital expenditures (CAPX), which is separately accounted as cash flows from investment activities. Does include R&D expenses, which count towards operating expenses (included in COGS and XSGA); R&D spending is required to be immediately expensed.
2. OCF
   - Compustat variable: OANCF + XINT
     - XINT: Interest Expenses. The Compustat variable OANCF subtracts interest expenses. We add them back to avoid mechanical correlations with debt issuance.
   - OCF is a measure of the net cash receipts (inflows minus outflows) a firm gets from operating activities (as opposed to investing activities or financing activities).

- OCF is typically calculated via the indirect method, i.e. starting with earnings and add back/subtract non-cash components. Based on Compustat variable definitions, the following relation holds:

$$\begin{aligned} \text{OCF} = \ & \text{EBITDA} \underbrace{+(\text{NOPI}+\text{SPI})+\text{SPPE}}_{\text{non-operating \& other income}} \underbrace{-(\text{TAX}-\text{DTAX}-\Delta\text{ATAX})}_{\text{cash taxes paid}} \\ & \underbrace{+\Delta\text{AP}-\Delta\text{AR}-\Delta\text{INV}}_{\Delta\text{NWC}} + \underbrace{\Delta\text{UR}-\Delta\text{PX}}_{\substack{\text{cash income/cost} \\ \text{not in earnings}}} +\text{OCFO} \end{aligned} \tag{B.2}$$

  - NOPI: Nonoperating Income (e.g. dividend, interest, rental, royalty income).
  - SPI: Special Item (e.g. windfalls, natural disaster damages, earnings from discontinued operations, litigation reserves). Based on the Compustat definition, variables XIDOC (cash flows from extraordinary items & discontinued operations) and MII (noncontrolling interest) are also added back.
  - SPPE: Sale of Property, Plant and Equipment.
  - TXT: Total Income Taxes; TXD: Deferred Taxes; ΔTXA: Changes in Accrued Taxes. TXT $-$ TXD $-$ ΔTXA is cash payment of taxes.
  - ΔAP: Changes in Accounts Payable.
  - ΔAR: Changes in Accounts Receivable.
  - ΔINV: Changes in Inventory.
  - ΔUR: Changes in unearned revenue. For instance, if a firm receives cash for purchases of goods and services to be delivered in the future (e.g. membership, subscription, gift card), it does not record any earnings but gets more cash. This leads to an increase in unearned revenue. ΔPX: Changes in prepaid expenses. Similarly, if a firm pays for goods or services to be delivered to it in the future (e.g. insurance), it does not record an expense but has less cash. This leads to an increase in prepaid expenses. OCFO: other miscellaneous cash flows from operations. See Compustat definitions of OANCF.

- Does not include capital expenditures (CAPX), which is separately accounted in cash flows from investment activities. Does include R&D expenses, which count towards operating expenses (included in COGS and XSGA); R&D spending is required to be immediately expensed. Does not include the effect of payouts and securities issuance, which are separately accounted in cash flows from financing activities.

3. Difference between EBITDA and OCF

   - There are two main differences between the EBITDA and OCF variables.

     First, OCF takes into account the cash receipts due to non-operating income, asset sales, windfalls, minority interests, etc., which are items not included in EBITDA.

     Second, due to accounting principles, earnings recognition and cash payments may not happen concurrently. Cash payments may occur before, at the same time, or after earnings recognition. For instance, it is customary for companies to make sales and receive payments from customers later. Companies may also receive payments first before delivering goods and services (e.g. customers purchase gift cards and only use them later, or customers purchase membership/subscription that they use later).

Discussion

In the baseline regression of Section 2.3.2, we first have a specification where the right hand side is EBITDA (with other controls but no OCF). Variations in EBITDA come from sales and operating expenses: EBITDA is high either because sales are high or because expenses are low. When EBITDA is high, the firm may also receive more cash. Suppose firm A has EBITDA 20 and firm B has EBITDA 10. With EBC, firm A's debt capacity expands more than firm B, helping firm A to borrow more and investment more. But firm A may also receive more cash than firm B: more cash may lead to less borrowing and more investment spending (using the cash) based on the traditional mechanisms in Froot, Scharfstein and Stein (1993). Accordingly, the positive comovement between EBITDA and cash receipts may push the EBITDA coefficient downward when the outcome variable is debt issuance; it may push the EBITDA coefficient upward when the outcome variable is investment.

Thus we then use a specification where the right hand side includes EBITDA, and we also control for OCF to take into account the impact of literal cash receipts on debt issuance/investment. Given that EBITDA and OCF are related (as shown by Equation (B.2), below we discuss how to understand variations in each of the two variables.

1. Coefficient on EBITDA

   - Based on the definition of EBITDA discussed above, variations in EBITDA come from either sales or operating expenses. Whether cash associated with sales/expenses comes in advance, concurrently, or later does not affect EBITDA.
   - If two firms end up with same OCF, but have different EBITDA, there will be accompanying differences in the second to last terms of Equation (B.2). But they do not *cause* differences in EBITDA.
     - For example, consider firm A with EBITDA 20, NOPI 0, and OCF 20, and firm B with EBITDA 10, NOPI 10, and OCF 20. They happen to have the same OCF and different EBIDA because they have different NOPI. The different NOPI does not cause differences in EBITDA, because by the definition of EBITDA, it is not affected by NOPI.
     - For another example, consider firm A with EBITDA 20 and firm B with EBITDA 10. Firm B happens to receive payments of 10 from customers for previous purchases. In this case, both firms have OCF 20: firm A has more EBITDA and firm B has some idiosyncratic cash receipts to get the same OCF despite lower EBITDA.
   - One question is whether some components of the second to last terms of Equation (B.2) may themselves cause variations in debt issuance/investment. In the example above, for two firms with *the same* OCF, would *lower* NOPI be a driver of *higher* debt issuance/investment?

     This type of issue does not seem obvious for NOPI. It could be more relevant in a few cases, which we discuss below.

     We first consider changes in accounts receivable ΔAR. Suppose firm A has EBITDA 20, ΔAR 0 (all the earnings are concurrently received in cash), and OCF 20, while firm B has EBITDA 30, ΔAR 10 (20 of the EBITDA is received in cash, while 10 is booked as receivable), and OCF 20. One concern is firm B expects to receive 10 in the next period, and it could pledge the receivable as collateral to borrow more. Even in the absence of EBCs, if firms borrow by pledging receivable, we may see firm B borrow more than firm A.[5] Such borrowing based on receivable is more likely to be short term, so we focus on the issuance of long-term debt. In addition, such borrowing is also secured debt, while our results also hold among unsecured debt.

Another case worth considering is changes in inventory. Changes in inventory ΔINV has several components: $\Delta\mathrm{INV} = (\mathrm{INVP}_t^{t+1} + \mathrm{INVP}_t^t) - (\mathrm{INVP}_t^t + \mathrm{INVP}_{t-1}^t)$.

- INVP_t^{t+1} denotes inventory purchased in period t for future production. It counts toward OCF in period t but does not affect EBITDA in period t.
- INVP_t^t denotes inventory purchased in period t for period t production. It affects both EBITDA and OCF by the same amount in period t.
- INVP_{t-1}^t denotes inventory purchased before period t use in period t production. It affects the EBITDA of period t (counts toward cost of goods sold in period t, but does not affect OCF in period t.
- The sum $\mathrm{INVP}_t^{t+1} + \mathrm{INVP}_t^t$ is inventory purchase in period t. The sum $\mathrm{INVP}_t^t + \mathrm{INVP}_{t-1}^t$ is reported as cost of goods sold in period t (a component of EBITDA).

As shown above, changes in the inventory balance can come from two sources: 1) usage of old inventory, and 2) purchase of inventory for future production. There are two corresponding situations to consider. The first situation focuses on usage of old inventory. Suppose firm A makes sales of 30, which uses *old* inventory (INVP_{t-1}^t) 10, and it purchases additional inventory of 10 for *future* production (INVP_t^{t+1}). Accordingly, firm A has EBITDA 20, OCF 20, and ΔINV 0. Firm B makes sales of 30, which used *old* inventory (INVP_{t-1}^t) 20, and it purchases additional inventory of 10 for *future* production (INVP_t^{t+1}). So firm B has EBITDA 10, OCF 20, and ΔINV -10. In this situation, firm A

[5]This issue with accounts receivable could exist even when we do not control for OCF. Consider a limiting case where all sales are paid by receivable rather then cash. Then variations in sales are entirely variations in receivable.

and firm B have the same OCF and different EBITDA. The difference in EBITDA is driven by the fact that firm A produced the same amount of goods using less (old) material. This variation in EBITDA is fine, except we need to be careful about the investment opportunity issue which was addressed extensively in Section 2.3.2.

The second situation focuses on purchases of new inventory. Suppose firm A makes sales of 30, which uses old inventory ($INVP^{t}_{t-1}$) 10, and it purchases additional inventory of 20 for future production ($INVP^{t+1}_{t}$). Accordingly, it has EBITDA 20, OCF 10, and ΔINV 10. Firm B makes sales of 20, which uses old inventory ($INVP^{t}_{t-1}$) 10, and it purchases additional inventory of 10 for future production ($INVP^{t+1}_{t}$). Thus firm B has EBITDA 10, OCF 10, and ΔINV 0. Now firm A and firm B have the same OCF, different EBITDA, and firm A purchased more inventory. To the extent that investment opportunities are well measured, inventory purchase would not add additional information about investment decisions. As we discuss below, inventory purchase is more likely to affect the OCF coefficient, so in the Internet Appendix Table IA4Debt Issuance and Investment Activities: Controlling for Inventory Purchasetable.caption.5, we also provide results controlling for inventory purchase.

2. Coefficient on OCF

- As shown by Equation (B.2), if two firms have the same EBITDA but different OCF, it would be due to the second term to the last term.
  - For example, suppose firm A and firm B both have EBITDA 20, while firm A has NOPI 10 and firm B has NOPI 0, then firm A will have OCF 30 and firm B will have OCF 20.
  - For another example, suppose firm A and firm B both have EBITDA 20, while firm A happens to receive payments of 10 from customers for previous purchases. In this case, firm A has OCF 30 and firm B has OCF 20; firm A has gets more OCF due to idiosyncratic cash receipts.
- In both of the above cases, firm A gets more internal funds at its disposal. It may borrow

less or invest more (using these internal funds), which reflect the mechanism of Froot, Scharfstein and Stein (1993). This would lead to a negative coefficient on OCF when the outcome variable is debt issuance, and a positive coefficient on OCF when the outcome variable is investment, as predicted by Froot, Scharfstein and Stein (1993).

- There are several cases where we need to be more careful about movements in OCF, which we discuss below.

  First, consider a case about accounts receivable: suppose firm A and firm B have the same EBITDA, and firm A receives cash while firm B gets receivables. In this situation, firm A gets more internal resources than firm B. Firm A may use the internal resources and borrow less than firm B, as predicted by Froot, Scharfstein and Stein (1993). A caveat is firm B, which has less OCF, may pledge its receivables as collateral to borrow more. This can attenuate the predictions of Froot, Scharfstein and Stein (1993). As discussed above, we focus on long-term debt and also study unsecured debt to minimize potential issues related to receivables.

  Second, consider a case about accounts payable: suppose firm A and firm B have the same EBITDA, but firm A decides to pay its suppliers more slowly. In this case, firm A will have an increase in ΔAP as well as more OCF. Effectively firm A is borrowing from suppliers; it now has more internal cash and may raise less money from capital markets. To the extent that borrowing from suppliers is less costly than external financing in capital markets, stretching accounts payable is one way of generating internal funds and using them as substitutes for external financing. This is consistent with the mechanism of Froot, Scharfstein and Stein (1993).

  Finally, consider a case related to inventory purchases: suppose firm A and firm B have the same EBITDA, but firm A purchases more inventory for future production (INVP_t^{t+1}), then firm A will have lower OCF. These purchases of inventories may require more external financing and are associated with more debt issuance. Thus we also present results controlling for inventory purchases.

B.4.2 Earnings Management

In the baseline regressions in Section 2.3.2, one driver of variations in EBITDA could be earnings management. For example, when EBCs become binding, firms may recognize earnings more aggressively (e.g. under-estimate operating expenses, or over-estimate sales or accounts receivable) so they can keep more debt. The survey of managers by Graham, Harvey and Rajgopal (2005) suggests such earnings management can happen when firms are close to violating debt covenants.

How does the possibility of earnings management affect the interpretation of the baseline regressions in Section 2.3.2? The objective in these tests is to study the sensitivity of external borrowing to accounting EBITDA. Whether the EBITDA comes from "true" operating earnings or from earnings management, both affect accounting EBITDA and can help us estimate the sensitivity of borrowing to accounting EBITDA.

The earnings management motive also speaks directly to the impact of accounting earnings on borrowing. Due to EBCs, current EBITDA plays a key role in firm's ability to borrow. Thus managers sometimes resort to earnings management to boost EBIDA and debt capacity.

B.5 Estimates of Market Value of Firm Real Estate

Because accounting data only report the value of firm properties at historical cost, not market value, we need to estimate or collect additional data to know the market value of firm real estate. We use three different methods, which are described in detail below.

B.5.1 Method 1: Traditional Estimates

The first estimate we use builds on Chaney, Sraer and Thesmar (2012). Firm real estate include buildings, land and improvements, and construction in progress. The steps to estimate market value are as follows:

1. We estimate the market value of firm real estate in 1993 RE_i^{93}. After 1993, the net book value and accumulated depreciation of real estate assets (buildings, land and improvements, and construction in progress) are no longer reported.

- We calculate the net book value of firm real estate (sum of the net book value of buildings, land and improvements, and construction in progress). Net book value is equal to gross book value minus accumulated depreciation.
- We estimate the average purchase year of firm real estate as in Chaney, Sraer and Thesmar (2012). We compare accumulated depreciation and gross book value to estimate the fraction depreciated by 1993. Assuming linear depreciation and a 40 year depreciation horizon, we estimate the purchase year to be 1993 minus (percent depreciated times 40).
- We estimate the market value in 1993 by inflating the net book value in 1993 (which is assumed to reflect the nominal value benchmarked to the purchase year) by the cumulative property price inflation between the purchase year and 1993. The cumulative property price inflation is calculated using state-level residential real estate index between 1975 and 1993 and CPI inflation before 1975 as in Chaney, Sraer and Thesmar (2012).
- If the book value of real estate or the net book value of PPE is zero in 1993, we enter zero as the market value of firm real estate in 1993.

2. We estimate the market value of firm real estate for each year after 1993.
   - Starting from 1994, we estimate the market value of firm real estate from two parts: appreciation of existing holdings and acquisition/disposition of holdings. Specifically we calculate $\text{RE}_{i,t+1}$ as $\text{RE}_{i,t} \times P_{it+1}/P_{it} \times 97.5\%$ plus change in the gross book value of real estate, where P_{it} is the property price index in firm i's headquarters county in year t and real estate is assumed to depreciate at 2.5% per year (again following a depreciation horizon of 40 years).
   - If in a given year, the firm's gross book value of real estate or net book value of PPE becomes zero, we assume the firm no longer owns real estate and reset the market value of real estate to zero.

By using P_{it} as the property price index in firm i's headquarter county, this method assumes that most of the real estate owned by a firm is near its headquarter county. The premise of this assumption is that corporate offices or properties near the headquarter are the most common type of owned real estate. Chaney, Sraer and Thesmar (2012) verify that this is not an unreasonable assumption. As discussed in Section 2.4, we also find this assumption to be plausible for most US non-financial firms.

B.5.2 Method 2: Property Information from Firm 10-K Filings

In US non-financial firms' annual report filings (form 10-K), Item 2 is called "Properties" where firms discuss property holdings and leases. A number of firms provide detailed information about the location, size, ownership, and usage of their properties.

For example, AVX Corporation's 2006 10-K filing provides the following table of properties in the US (a large international manufacturer of electronic connectors with 10 thousand employees, headquartered in Myrtle Beach, SC):

Properties of AVX Corporation

Location	Size	Type of Interest	Usage
Myrtle Beach, SC	535,000	Owned	Manufacturing/Research/HQ
Myrtle Beach, SC	69,000	Owned	Office/Warehouse
Conway, SC	71,000	Owned	Manufacturing/Office
Biddeford, ME	73,000	Owned	Manufacturing
Colorado Springs, CO	15,000	Owned	Manufacturing
Atlanta, GA	49,000	Leased	Office/Warehouse
Olean, NY	113,000	Owned	Manufacturing
Raleigh, NC	203,000	Owned	Manufacturing
Sun Valley, CA	25,000	Leased	Manufacturing

For another example, Starbucks' 2006 10-K filing writes:

The following table shows properties used by Starbucks in connection with its roasting and distribution operations:

The Company leases approximately 1,000,000 square feet of office space and owns a 200,000 square foot office building in Seattle, Washington for corporate administrative purposes. As of October 1, 2006, Starbucks had more than 7,100 Company-operated retail stores, of which nearly all are located in leased premises. The Company also leases space in approximately 120 additional locations for regional, district and other administrative offices, training facilities and storage, not including certain seasonal retail storage locations.

For a final example, Microsoft's 2006 10-K filing writes: *Our corporate offices consist of approximately*

Properties of Starbucks Corporation

Location	Size	Owned or Leased	Purpose
Kent, WA	332,000	Owned	Roasting and distribution
Kent, WA	402,000	Leased	Warehouse
Renton, WA	125,000	Leased	Warehouse
York County, PA	365,000	Owned	Roasting and distribution
York County, PA	297,000	Owned	Warehouse
York County, PA	42,000	Leased	Warehouse
Carson Valley, NV	360,000	Owned	Roasting and distribution
Portland, OR	80,000	Leased	Warehouse
Basildon, United Kingdom	141,000	Leased	Warehouse and distribution
Amsterdam, Netherlands	94,000	Leased	Roasting and distribution

11.0 million square feet of office building space located in King County, Washington: 8.5 million square feet of owned space that is situated on approximately 500 acres of land we own in our corporate campus and approximately 2.5 million square feet of space we lease. We own approximately 533,000 square feet of office building space domestically (outside of the Puget Sound corporate campus) and lease many sites domestically totaling approximately 2.7 million square feet of office building space...We own 63 acres of land in Issaquah, Washington, which can accommodate 1.2 million square feet of office space and we have an agreement with the City of Redmond under which we may develop an additional 2.2 million square feet of facilities at our campus in Redmond, Washington. Microsoft is headquartered in Redmond (King County), WA.

We train assistants to read the 10-K filings and record the location, size, and usage for owned properties in the US; we also record whether the firm owns other properties for which these information are not available. We then match the properties with median property price per square footage in their respective counties using data from Zillow (we first try matching based on county, then city/metro area, and finally state if none of the previous matches were available). We use Zillow price if the property is commercial or retail (office, store, restaurant, hotel, casino). We multiply the Zillow price by 0.85 if the property is a mixture of manufacturing and office (often happens to headquarters of manufacturing firms); by 0.7 if it is manufacturing (facilities, warehouse, distribution center). For firms' owned land, we use state-level land price estimates.

B.6 Borrowing Constraints and Financial Acceleration

This appendix analyzes how financial acceleration dynamics are influenced by the form of firms' borrowing constraints. We consider an environment similar to Kiyotaki and Moore (1997). We study both collateral-based constraints (a firm's borrowing capacity depends on the liquidation value of physical assets) as the original study, and earnings-based constraints (a firm's borrowing capacity depends a multiple of its earnings) analogous to the EBCs we document in Section 2.2. We compare the equilibrium impact of a shock to productive firms' net worth[6] in these two scenarios. The results show that earnings-based constraints lead to much more muted initial response in productive firms' capital and aggregate output, but may lead to slightly more persistence in the model.

B.6.1 Set-Up

Environment. The environment is similar to the baseline environment studied in Section 2 of Kiyotaki and Moore (1997). We maintain their assumptions about preferences, technologies and markets. The only difference is that we introduce a non-zero depreciation rate of capital.[7] This modification guarantees the existence of steady states in environments with different borrowing constraints; it is not critical to the equilibrium dynamics in response to the shock per se.

We consider a discrete-time, infinite-horizon, economy with two goods: a durable asset (land) and a nondurable commodity (fruit). The depreciation rate of land is δ and the total supply of land is $\bar{K}$. The fruit cannot be stored. There is a continuum of infinitely lived agents. Some are farmers and some are gatherers.

Farmers. There is a measure one of infinitely lived, risk neutral farmers. The expected utility of a farmer at date t is

$$E_t \left(\sum_{s=0}^{+\infty} \beta^s x_{t+s} \right),$$

where x_{t+s} is her consumption of fruits at date $t+s$, and $\beta \in (0,1)$ is the farmer's discount rate. Each farmer takes one period to produce fruits from the land she holds, with the following constant

[6]This is the same shock considered by Kiyotaki and Moore (1997).

[7]Section 3 of Kiyotaki and Moore (1997) also introduces depreciation.

returns to scale production function:

$$y_{t+1} = F(k_t) = (a+c)\,k_t,$$

where k_t is the farmer's holding of land at the end of period t, ak_t is the portion of the output that is tradable, while the rest, ck_t, is non-tradable and can only be consumed by the farmer. Similar to Assumption 2 in Kiyotaki and Moore (1997), we assume c is large enough so that, in equilibrium, farmers will not want to consume more than the non-tradable portion of the fruits and invest all their funds in land. Finally, we use K_t to denote the aggregate land holding of farmers.

Gatherers. There is a measure one[8] of infinitely lived, risk neutral gathers. The expected utility of a gather at date t is

$$E_t\left(\sum_{s=0}^{+\infty}\left(\beta'\right)^{s} x'_{t+s}\right),$$

where x'_{t+s} is his consumption of fruits at date $t+s$ and $\beta' \in (0,1)$ is gathers' discount rate. We assume $\beta' > \beta$ so that in equilibrium farmers always borrow up to the maximum and do not want to postpone production, because they are relatively impatient.

Each gatherer has an identical production function that exhibits decreasing returns to scale: an input of k'_t land at date t yields y'_{t+1} tradable fruits at date $t+1$, according to

$$y'_{t+1} = G\left(k'_t\right),$$

where $G' > 0$, $G'' < 0$ and $G'(0) > aR > G'(\bar{K})$. The last two inequalities are included to ensure that both farmers and gatherers are producing in the neighborhood of a steady-state equilibrium. Finally, we use $K'_t = \bar{K} - K_t$ to denote the aggregate land holding of gatherers.

Markets. At each date t, there is a competitive spot market in which land is exchanged for fruits at price q_t.[9] The only other market is a one-period credit market in which one unit of fruit at date t can be exchanged for a claim to R_t units of fruit at date $t+1$. In equilibrium, as farmers are more impatient, they borrow from gatherers up to their borrowing constraints, and the rate of interest is

[8]In Kiyotaki and Moore (1997), there is a measure m of gatherer. For simplicity, we consider the case that $m = 1$.

[9]Fruits are the numeraire throughout.

always determined by gatherers' time preferences: $R_t = \frac{1}{\beta'} = R$.

Each farmer and each gatherer's flow-of-funds constraint in each period t can then be summarized as

$$q_t \left(k_t - (1-\delta)\, k_{t-1}\right) + Rb_{t-1} + x_t - ck_{t-1} = ak_{t-1} + b_t,$$
$$q_t \left(k_t^{'} - (1-\delta)\, k_{t-1}^{'}\right) + Rb_{t-1}^{'} + x_t^{'} = G\left(k_{t-1}^{'}\right) + b_t^{'},$$

where b_t and $b_t^{'}$ are the amount of loan borrowed by the farmer and the gatherer at period t.

Equilibrium concept. Same as Kiyotaki and Moore (1997), we consider perfect-foresight equilibria in which, without unanticipated shocks, the expectations of future variables get realized. We then consider the equilibrium effect of a shock to farmers' net worth in the steady state (characterized later) and its transmission. As in Kiyotaki and Moore (1997), this shock is driven by an unexpected temporary aggregate shock to farmers' productivity.

Capital prices and user costs. As each gatherer is not credit constrained, his demand for land is determined so the present value of the marginal product of land is equal to the opportunity cost, or user cost, of holding land, $u_t = q_t - (1-\delta)\, q_{t+1}/R$:

$$\frac{1}{R} G'\left(k_t^{'}\right) = \frac{1}{R} G'\left(K_t^{'}\right) = u_t,$$

where the symmetric concave production function guarantees that each gatherer holds the same amount of land. Ruling out exploding bubbles in the land price as in Kiyotaki and Moore (1997), one can then express the land price as the present value of user costs,

$$q_t = \sum_{s=0}^{+\infty} \left(\frac{1-\delta}{R}\right)^s u\left(K_{t+s}\right) = u\left(K_t\right) + \frac{(1-\delta)}{R} q_{t+1}, \tag{B.3}$$

where $u\left(K_t\right) \triangleq \frac{1}{R} G'\left(\bar{K} - K_t\right) = u_t$ expresses the user cost in each period as an increasing function of *farmers'* aggregate land holding. The user cost is increasing in the farmers' landing holding because, if farmers hold more land, gatherers hold less land and their marginal productivity of the land is higher. From the perspective of *farmers*, the above expression can be viewed as the capital supply curve they face. An increase in q_t or a decreases in q_{t+1} will increase the user cost of land, and increase the amount of land gatherers "supply" to farmers. Log-linearizing around the steady-state, we can express the above supply curve as

$$\hat{q}_t = \frac{1}{\eta}\frac{\frac{1-\delta}{R}-1}{\frac{1-\delta}{R}}\hat{K}_t + \frac{\frac{1-\delta}{R}-1}{\left(\frac{1-\delta}{R}\right)^2}\hat{q}_{t+1} = \frac{1}{\eta}\frac{\frac{1-\delta}{R}-1}{\frac{1-\delta}{R}}\sum_{s=0}^{+\infty}\left(\frac{1-\delta}{R}\right)^{-s}\hat{K}_{t+s}, \tag{B.4}$$

where, for any variable X, $\hat{X}$ denotes the log-deviation from the steady and η denotes the elasticity of the residual supply of land to farmers, with respect to the user cost at the steady state.

B.6.2 Collateral-Based Constraints

In this part, we follow Kiyotaki and Moore (1997) and study the equilibrium impact of an aggregate shock to farmers' net wroth under collateral-based constraints.

Collateral-based constraints. Similar to Kiyotaki and Moore (1997), in period t, if the farmer has land k_t then she can borrow b_t in total, as long as the repayment does not exceed the market value of land (net of depreciation) at $t+1$:

$$Rb_t \leq q_{t+1}\left(1-\delta\right)k_t. \tag{B.5}$$

Their micro-foundation for such constraints is as follows. In Kiyotaki and Moore (1997), farmers' technology is idiosyncratic and they can always withdraw labor. As a result, fruits produced by farmers are not contractible. Creditors protect themselves by collateralizing the farmers' land. The liquidation value of land is then the market value of land (net of depreciation) in the next period, which gives rise to the borrowing constraint in (B.5).

Farmers' behavior. As discussed above, farmers borrow up to the maximum amount as they are impatient. They also prefer to invest in land, consuming no more than their current output of non-tradable fruits.[10] This means for each farmer, $x_t = ck_{t-1}$, $b_t = q_{t+1}k_t\left(1-\delta\right)/R$ and

$$k_t = \frac{1}{q_t - \frac{1-\delta}{R}q_{t+1}}\left[\left(a + q_t\left(1-\delta\right)\right)k_{t-1} - Rb_{t-1}\right],$$

where $n_t = \left(a + q_t\left(1-\delta\right)\right)k_{t-1} - Rb_{t-1}$ is the farmer's net worth (defined as the maximum amount of funds available that can be used to acquire new assets and projects) at the beginning of date t,

[10] This is because of a high enough c (non-tradable fruits), which guarantees the value of investing in land is high enough. Around the steady state, it suffices that $c < \frac{1-\beta}{\beta}a$, which is not restrictive when β is close to 1.

and $q_t - \frac{1-\delta}{R} q_{t+1} = u_t$ is the amount of down payment required to purchase a unit of land. In the case of collateral-based constraints, it coincides with the user cost of land at t.

Since the optimal k_t and b_t are linear in k_{t-1} and b_{t-1}, we can aggregate across farmers to find the equations of the dynamics of aggregate land demand and borrowing of farmers, K_t and B_t:

$$K_t = \frac{1}{q_t - \frac{1-\delta}{R} q_{t+1}} \left[\left(a + q_t \left(1-\delta\right)\right) K_{t-1} - RB_{t-1} \right], \tag{B.6}$$

$$B_t = \frac{1-\delta}{R} q_{t+1} K_t. \tag{B.7}$$

Steady state. Based on conditions (B.3), (B.6) and (B.7), one can characterize the unique steady state, where

$$\left(1 - \frac{1}{R}\left(1-\delta\right)\right) q^* = u^* = a,$$

$$\frac{1}{R} G' \left[\left(\bar{K} - K^*\right) \right] = u^*,$$

$$\frac{B^*}{K*} = \frac{\left(1-\delta\right) a}{R \left(1 - \frac{1}{R}\left(1-\delta\right)\right)}.$$

Shock and transmission. As in Kiyotaki and Moore (1997), we consider the equilibrium response to an unexpected aggregate shock to farmers' net worth at $t = 0$. Specifically, suppose at date -1 the economy is in the steady state: $K_{-1} = K^*$ and $B_{-1} = B^*$. There is an unexpected and temporary shock to all farmers' productivity at period 0, which increases the fruits they harvest to $1 + \Delta$ times the expected level, at the start of date 0.[11] Such a shock will then increase farmers' net worth by $\Delta a K^*$. The production technologies then return to the pre-shock level thereafter. (For exposition, we use a positive shock $\Delta > 0$. The analysis of a negative shock $\Delta < 0$ is identical under log-linearization.)

Using conditions (B.6) and (B.7), one can then characterize farmers' land demand curve at $t = 0$ and $t \geq 1$. For period $t = 0$, farmers' land demand curves without and with log-linearization are:[12]

[11] Following Kiyotaki and Moore (1997), we take Δ to be small, so we can log-linearize around the steady state and find closed-form expressions for the new equilibrium path.

[12] In condition (B.9), $\frac{1}{1-\frac{1}{R}(1-\delta)} = \frac{q^*}{u^*}$ is the ratio between land price and down payment in the steady state and $\frac{1-\delta}{1-\frac{1}{R}(1-\delta)} = \frac{(1-\delta)q^* K^*}{aK^*}$ is the ratio between farmers' land holding collateral value and their net worth in the steady state.

$$u(K_0)K_0 = \left(q_0 - \frac{1-\delta}{R}q_1\right)K_0 = (a + \Delta a + (q_0 - q^*)(1-\delta))K^*, \tag{B.8}$$

$$\left(1+\frac{1}{\eta}\right)\hat{K}_0 = \frac{1}{1-\frac{1}{R}(1-\delta)}\hat{q}_0 - \frac{\frac{1}{R}(1-\delta)}{1-\frac{1}{R}(1-\delta)}\hat{q}_1 + \hat{K}_0 = \Delta + \frac{1-\delta}{1-\frac{1}{R}(1-\delta)}\hat{q}_0, \tag{B.9}$$

For a given down payment per unit of capital (in this case equal to the user cost, $u(K_0) = q_0 - \frac{1-\delta}{R}q_1$), an increase of land price q_0 increases farmers' net worth, $(a + \Delta a + (q_0 - q^*)(1-\delta))K^*$, and thus increases their land demand. Moreover, the net worth increases more than proportionately with q_0 because of the leverage effect of outstanding debt. Even though the down payment also increases with q_0, this is largely dampened as the down payment decreases with next period land price q_1. As a result, the total impact of land prices on farmers' land demand is highly positive (when $R \approx 1$ and $\delta \approx 0$, the coefficient on $\hat{q}_0$ in condition B.9 could be very large).

For period $t \geq 1$, farmers' land demand curves without and with log-linearization are

$$u(K_t)K_t = \left(q_t - \frac{1-\delta}{R}q_{t+1}\right)K_t = aK_{t-1}, \tag{B.10}$$

$$\left(1+\frac{1}{\eta}\right)\hat{K}_t = \frac{1}{1-\frac{1}{R}(1-\delta)}\hat{q}_t - \frac{\frac{1}{R}(1-\delta)}{1-\frac{1}{R}(1-\delta)}\hat{q}_{t+1} + \hat{K}_t = \hat{K}_{t-1}. \tag{B.11}$$

An increase in farmers' land holding in period $t-1$ increases their net worth in period $t-1$, aK_{t-1}, and in turn translates to an increase in farmers' land holding in period t.[13] Through the forward looking land pricing equation in condition (B.3), the persistent increase in farmers' land holding then increases land price in period 0, far more than what is driven by the increase in user cost in that particular period. The increase in land price then further increases farmers' net worth and capital demand in period 0 through condition (B.9), which in turn increases farmers' net worth and land holding in all periods and further pushes up the land price. This asset price feedback loop is the core of the financial acceleration mechanism in Kiyotaki and Moore (1997).

From conditions (B.4), (B.9), and (B.11), we can solve the the full equilibrium dynamics with

[13] However, farmers' period t net worth, aK_{t-1}, no longer depends on land price in t. This is because, for all $t \geq 1$, an increase in period t land price will be anticipated in period $t-1$, and allow farmers to borrow more. As a result, land price's impact on farmers' period t net worth is offset by the increase in debt payment in period t.

collateral-based constraints:

$$\hat{K}_t = \left(1+\frac{1}{\eta}\right)^{-t-1} \frac{\eta}{\eta + \frac{\delta}{1-\frac{1-\delta}{R}}} \left(1 + \frac{\frac{R}{1-\delta}}{\frac{R}{1-\delta}-1}\frac{1}{\eta}\right)\Delta, \tag{B.12}$$

$$\hat{q}_t = \left(1+\frac{1}{\eta}\right)^{-t} \frac{1}{\eta + \frac{\delta}{1-\frac{1-\delta}{R}}}\Delta.$$

When $R \approx 1$ and $\delta \approx 0$, the multiplier $1 + \frac{\frac{R}{1-\delta}}{\frac{R}{1-\delta}-1}\frac{1}{\eta}$ in farmers' land holding could be very large, summarizing financial acceleration driven by asset price feedback in Kiyotaki and Moore (1997).

B.6.3 Earnings-Based Constraints

In this part, we then consider the case of earnings-based constraints studied in this paper.

Earnings-based constraints. The constraint is specified as follows. If at period t, a farmer has land k_t, then she can borrow b_t in total, as long as the repayment does not exceed a multiple of her (tradable) earnings at $t+1$:[14]

$$Rb_t \leq \theta a k_t. \tag{B.13}$$

Such a constraint could arise if the bankruptcy court is able to and prefers to enforce the continuation of operation when the farmer fails to pay her debt.[15]

Farmers' behavior. Similar to the analysis in the previous subsection following Kiyotaki and Moore (1997), farmers prefer to borrow up to the maximum as they are impatient; they also prefer to invest in land, consuming no more than their current output of non-tradable fruits.[16] This means for

[14]Here we tie the farmer's borrowing capacity to her earnings at $t+1$, generated by current period land holding k_t. One could also tie the farmer's borrowing capacity to her earnings at t, generated by the past period land holding k_{t-1}. Such backward borrowing capacity will not change the key lesson about the attenuation of asset price feedback in this section. However, it would open the door for more deviations from the KM benchmark, such as path-dependence of firms' outcomes beyond their dependence on current net worth level.

[15]It must be that $\theta \leq \bar{\theta} \triangleq \frac{1}{1-\frac{(1-\delta)}{R}} = 1 + \frac{1-\delta}{R} + \left(\frac{1-\delta}{R}\right)^2 + \cdots$, which is the present value of tradable fruits generated by one unit of land held by the farmer. The ratio $\frac{\theta}{\bar{\theta}}$ could be thought of as the proportion of tradable fruits that can be produced with court involvement and continuing operations.

[16]This could be guaranteed with a high enough c (non-tradable fruits). Note that the farmer's utility from investing a dollar in land today is at least $\beta\frac{(a+c+(1-\delta)q_{t+1})}{q_t-\frac{\theta a}{R}}$, the utility of investing in land in this period and consuming fully in the next period. It is always bigger than one with a large c, as q_t is bounded above (gatherers' marginal product is bounded above).

each farmer, $x_t = ck_{t-1}$, $b_t = \theta a k_t / R$ and

$$k_t = \frac{1}{q_t - \frac{\theta a}{R}} \left[\left(a + q_t \left(1 - \delta \right) \right) k_{t-1} - R b_{t-1} \right],$$

where $q_t - \frac{\theta a}{R}$ is how much down payment is required to purchase a unit of land. In the case of earnings-based constraints, it does not depend on the land price in the next period q_{t+1} and does not coincide with the user cost u_t. This is because q_{t+1} does not directly enter the farmer's borrowing constraint (B.13) in the case of EBCs. As we elaborate later, this missing link from asset prices to farmers' borrowing capacity is key to dampening asset price feedback under EBCs.

Since the optimal k_t and b_t are linear in k_{t-1} and b_{t-1}, we can aggregate across farmers to characterize the dynamics of aggregate land demand and borrowing of farmers, K_t and B_t:

$$K_t = \frac{1}{q_t - \frac{\theta a}{R}} \left[\left(a + q_t \left(1 - \delta \right) \right) K_{t-1} - R B_{t-1} \right], \tag{B.14}$$

$$B_t = \frac{1}{R} \theta a K_t. \tag{B.15}$$

Steady state. We set $\theta = \frac{1-\delta}{1-\frac{1}{R}(1-\delta)}$. This guarantees that the economy under earnings-based constraints shares the same steady states as the economy under collateral-based constraints. This ensures that the difference in the two economies' responses to the shock we consider is driven by the form of borrowing constraints, instead of the steady state leverage ratio.

Shock and transmission. Similar to Kiyotaki and Moore (1997) and the analysis in the previous part, we consider the equilibrium response to an unexpected aggregate shock to farmers' net worth at $t = 0$. Specifically, suppose at date $t = -1$ the economy is in the steady state: $K_{-1} = K^*$ and $B_{-1} = B^*$. There is an unexpected and temporary shock to all farmers' productivity at period $t = 0$, which increases the fruits they harvest to $1 + \Delta$ times the expected level, at the start of date $t = 0$.[17]. Such a shock increases farmers' net worth by $\Delta a K^*$. The production technologies between 0 and 1 (and thereafter) then return to the pre-shock level.

Using conditions (B.14) and (B.15), one can then characterize farmers' land demand curve at

[17]Following Kiyotaki and Moore (1997), we take Δ to be small, so we can log-linearize around the steady state and find closed-form expressions for the new equilibrium path.

period $t = 0$ and $t \geq 1$. For period 0, farmers' land demand curves without and with log linearization are:[18]

$$\left(q_0 - \frac{\theta a}{R}\right) K_0 = \left(\left(1-\theta\right) a + \Delta a + q_0 \left(1-\delta\right)\right) K^*, \tag{B.16}$$

$$\hat{q}_0 \left(\frac{1}{1 - \frac{1}{R}\left(1-\delta\right)}\right) + \hat{K}_0 = \Delta + \frac{1-\delta}{1 - \frac{1}{R}\left(1-\delta\right)} \hat{q}_0, \tag{B.17}$$

$$\Longleftrightarrow \hat{K}_0 = \Delta - \frac{\delta}{1 - \frac{1}{R}\left(1-\delta\right)} \hat{q}_0.$$

For a given down payment per unit of capital ($q_0 - \frac{\theta a}{R}$), an increase of land price q_0 still increases farmers' net worth, $\left(1-\theta\right) a + \Delta a + q_0 \left(1-\delta\right)$. However, the down payment per unit of capital also increases with land price q_0. Different from the case under collateral-based constraints, as farmers' borrowing capacity under EBCs do not depend on the land price in the next period q_1, an increase of q_1 will not relax their borrowing constraints and decrease the down payment per unit of capital. As a result, the total impact of land prices on farmers' land demand is negative, as shown by the last expression above. This is in stark contrast with the case under collateral-based constraints. The asset price movement now dampens the financial shock's impact on farmers' land holding, instead of generating financial amplification.

For period $t \geq 1$, farmers' land demand curve is:

$$\left(q_t - \frac{\theta a}{R}\right) K_t = \left[\left(1-\theta\right) a + \left(1-\delta\right) q_t\right] K_{t-1}, \tag{B.18}$$

$$\hat{q}_t \left(\frac{1}{1 - \frac{1}{R}\left(1-\delta\right)}\right) + \hat{K}_t = \frac{1-\delta}{1 - \frac{1}{R}\left(1-\delta\right)} \hat{q}_t + \hat{K}_{t-1}, \tag{B.19}$$

$$\Longleftrightarrow \hat{K}_t = -\frac{\delta}{1 - \frac{1}{R}\left(1-\delta\right)} \hat{q}_t + \hat{K}_{t-1}.$$

Compared to the case under collateral-based constraints, condition (B.19), there are two differences. First, as discussed above, the down payment under EBCs does not depend on next period

[18] In condition (B.9), $\frac{1}{1-\frac{1}{R}(1-\delta)} = \frac{q^*}{q^* - \frac{\theta a}{R}}$ is the ratio between land price and down payment in the steady state and $\frac{1-\delta}{1-\frac{1}{R}(1-\delta)} = \frac{(1-\delta)q^* K^*}{(1-\theta)a + (1-\delta)q^* K^*}$ is the ratio between collateral value of farmers' land holding and net worth in the steady state.

land price, q_{t+1}, as q_{t+1} does not relax farmers' borrowing constraints. Second, current period net worth, $(1-\theta)\,a + (1-\delta)\,q_t$, now increases with land prices in period t. Specifically, in the case with EBCs, as an increase of land prices in period t does not allow farmers to borrow more in $t-1$, q_t's impact on farmers' period t net worth will *not* be offset by the increase in debt payment in period t. As we discuss more below, this may lead to a more persistent impact of the shock's impact on farmers' net worth, even though the initial impact is much more muted with EBCs.[19]

From conditions (B.4) and (B.19), we can then characterize the equilibrium dynamics under earning-based constraints:

$$\begin{pmatrix} \hat{q}_t \\ \hat{K}_t \end{pmatrix} = \begin{pmatrix} \frac{R}{1-\delta} & -\frac{1}{\eta}\left(\frac{R}{1-\delta}-1\right) \\ -\delta\frac{\frac{R}{1-\delta}}{1-\frac{1-\delta}{R}} & 1+\frac{\delta}{\eta}\frac{R}{1-\delta} \end{pmatrix} \begin{pmatrix} \hat{q}_{t-1} \\ \hat{K}_{t-1} \end{pmatrix} \quad \forall t \geq 1. \tag{B.20}$$

The matrix $\begin{pmatrix} \frac{R}{1-\delta} & -\frac{1}{\eta}\left(\frac{R}{1-\delta}-1\right) \\ -\delta\frac{\frac{R}{1-\delta}}{1-\frac{1-\delta}{R}} & 1+\frac{\delta}{\eta}\frac{R}{1-\delta} \end{pmatrix}$ has only one eigenvalue $\lambda \in (0,1)$ within the unique circle.[20] Let (q_λ, k_λ) be the corresponding eigenvector and $\alpha = \frac{q_\lambda}{k_\lambda} > 0$. Together with the initial condition (B.17), we have

$$\hat{K}_t = \frac{1}{1+\frac{\delta}{1-\frac{1}{R}(1-\delta)}\alpha}\lambda^t\Delta \quad \text{and} \quad \hat{q}_t = \frac{\alpha}{1+\frac{\delta}{1-\frac{1}{R}(1-\delta)}\alpha}\lambda^t\Delta. \tag{B.21}$$

B.6.4 Financial Acceleration: A Comparison

Now we can compare the equilibrium impact of the aggregate shock to farmers' net worth under these two forms of borrowing constraints. As mentioned above, since land price increases have a negative impact on farmers' land demand in the case of EBCs, financial acceleration due to asset price feedback is dampened. Indeed, one can prove analytically that the shock's initial impact on farmers' capital holding and aggregate output is stronger with collateral-based constraints.

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[19] As shown above, in farmers' land demand condition (B.19), the appearance of the term $\frac{1-\delta}{1-\frac{1}{R}(1-\delta)}\hat{q}_t$ increases the persistence of the shock. The disappearance of term $-\frac{\frac{1}{R}(1-\delta)}{1-\frac{1}{R}(1-\delta)}\hat{q}_{t+1}$ on the left hand side, meanwhile, decreases the persistence of the shock. However, as $\hat{q}_t - \frac{1}{R}\hat{q}_{t+1} > 0$ in the equilibrium (from condition (B.21)), the first effect nominates.

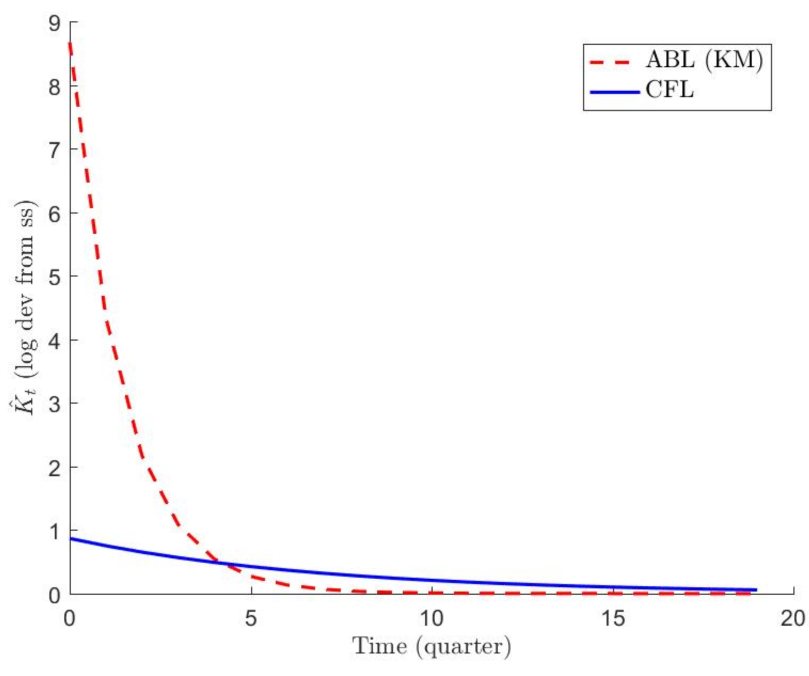
[20] Note that the land price is bounded as the gatherer's marginal product is bounded. As a result, explosive equilibrium can be ruled out. One can also prove the equilibrium uniqueness without the help of log-linearization.

Lemma 5. *When the shock to farmers' net worth hits, the impact on farmers' land holding and aggregate output is stronger with collateral-based constraints.*

To numerically illustrate the difference, we consider a standard parametrization. Specially, we let $R = 1.01$, $\delta = 0.025$ and $\eta = 1$. Figure B.2 shows the impulse response of farmers' land holding to the shock Δ. We find that the initial impact on farmers' land holding under collateral-based constraints is ten times as large as the one under earnings-based constraints. With EBCs, the dampening of financial acceleration driven by asset price feedback is quantitatively very important. As aggregate output $\hat{Y}$ is just a multiple of $\hat{K}$ (proved below), the initial impact on *aggregate output* under collateral-based constraints is also ten times as large as the one under earnings-based constraints. Nonetheless, the impact of the shock in the economy with EBCs can be more persistent. This is because, with EBCs, for each period $t \geq 1$, as borrowing in the previous period does not depend on current period asset prices, higher land value increases farmers' net worth and is not offset by higher debt payment.

Figure B.2: *Impulse Response of Farmers' Land Holdings*

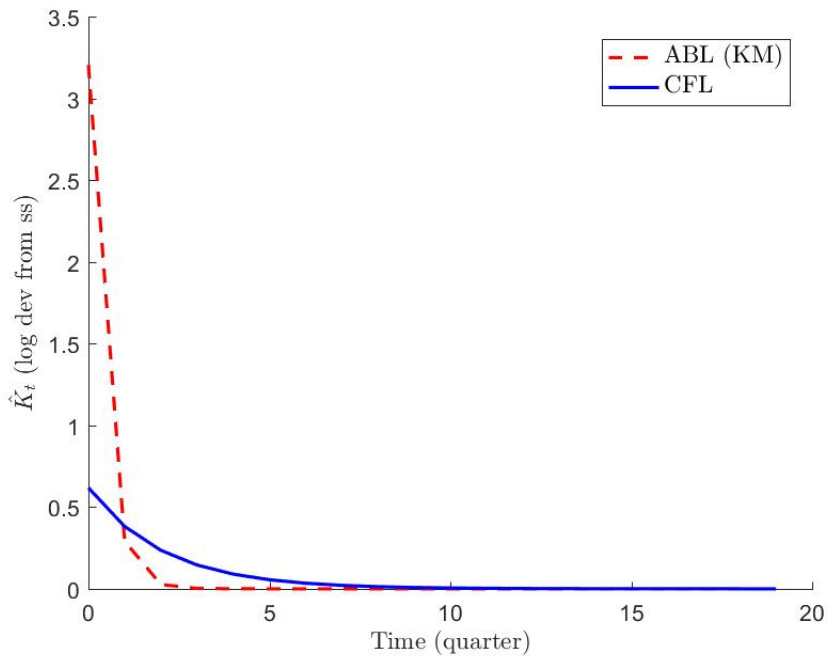
This plot shows farmers' land holdings (log deviations from steady state) after a small positive unexpected shock to their net worth (one log point).



Section 3 of Kiyotaki and Moore (1997) also considers a case in which the elasticity of land supply is low, $\eta = 0.1$ (shown in Figure B.3). Based on this parameter value, it is still the case that the initial impact on farmers' land holding and aggregate output under collateral-based constraints is way larger than that under earnings-based constraints, corroborating the robustness of the above finding.

Figure B.3: *Impulse Response of Farmers' Land Holdings,* $\eta = 0.1$

This plot sets $\eta = 0.1$, rather than $\eta = 1$ in Figure B.2.



B.7 Proofs

Proof of Proposition 4. In an internal solution, the optimal external borrowing must satisfy the following first order condition with respect to b:

$$F'(w + b^*) = C_b(b^*, \pi). \tag{B.22}$$

(i) We can then use the inverse function theorem to derive how optimal external borrowing b^* responds to π, for a given w: $\frac{\partial b^*}{\partial \pi}\mid_w = \frac{C_{b\pi}(b^*,\pi)}{-C_{bb}(b^*,\pi)+F''(w+b^*)}$. As $C_{b\pi} \leq 0$, $C_{bb} > 0$ and $F''(x) \leq 0$, for a given amount of internal funds w, optimal borrowing is weakly increasing in EBITDA $\frac{\partial b^*}{\partial \pi}\mid_w \geq 0$. For optimal investment, using $I^* = b^* + w$ we have $\frac{\partial I^*}{\partial \pi}\mid_w = \frac{\partial b^*}{\partial \pi}\mid_w$, and optimal investment is weakly increasing in EBITDA $\frac{\partial I^*}{\partial \pi} \mid_w \geq 0$.

(ii) Similarly, we can also use the inverse function theorem to derive how optimal borrowing b^* responds to w, for a given π: $\frac{\partial b^*}{\partial w} \mid_\pi = \frac{-F''(w+b^*)}{-C_{bb}(b^*,\pi)+F''(w+b^*)}$. As $C_{bb} > 0$ and $F''(x) \leq 0$, for a given amount of EBITDA π, borrowing is weakly decreasing in internal funds $\frac{\partial b^*}{\partial w} \mid_\pi \leq 0$. Moreover, when F is strictly concave, $\frac{\partial b^*}{\partial w} \mid_\pi < 0$. For optimal investment, using $I^* = b^* + w$, we have $\frac{\partial I^*}{\partial w} \mid_\pi = 1 + \frac{\partial b^*}{\partial w} \mid_\pi = 1 + \frac{-F''(w+b^*)}{-C_{bb}(b^*,\pi)+F''(w+b^*)} = \frac{-C_{bb}(b^*,\pi)}{-C_{bb}(b^*,\pi)+F''(w+b^*)} > 0$, and optimal investment is strictly increasing in internal funds.

Proofs for Appendix B.6

Characterization of the equilibrium dynamics under collateral-based constraints. From conditions (B.4) and (B.11), we have, for all t,

$$\hat{q}_t = \frac{1}{\eta} \frac{\left(\frac{R}{1-\delta}\right) - 1}{\left(\frac{R}{1-\delta}\right)} \frac{1}{1 - \left(1+\frac{1}{\eta}\right)^{-1} \left(\frac{R}{1-\delta}\right)^{-1}} \hat{K}_t = \frac{\left(1+\frac{1}{\eta}\right)\left[\frac{R}{1-\delta} - 1\right]}{\eta\left[\left(1+\frac{1}{\eta}\right)\left(\frac{R}{1-\delta}\right) - 1\right]} \hat{K}_t,$$

Substitute in period 0 farmers' land demand curve (condition (B.9)), we have

$$\begin{aligned}
\left(1+\frac{1}{\eta}\right)\hat{K}_0 &= \Delta + \frac{1-\delta}{1-\frac{1}{R}(1-\delta)} \left(\frac{\left(1+\frac{1}{\eta}\right)\left[\frac{R}{1-\delta} - 1\right]}{\eta\left[\left(1+\frac{1}{\eta}\right)\left(\frac{R}{1-\delta}\right) - 1\right]} \hat{K}_0 \right), \\
\hat{K}_0 &= \frac{1}{1+\frac{1}{\eta}} \left(1 + \frac{\frac{R}{1-\delta}}{\frac{R}{1-\delta} - 1} \frac{1}{\eta}\right) \frac{\eta}{\eta + \frac{\delta}{1-\frac{1-\delta}{R}}} \Delta, \\
\hat{q}_0 &= \frac{1}{\eta + \frac{\delta}{1-\frac{1-\delta}{R}}} \Delta.
\end{aligned}$$

Using conditions (B.11), we then have

$$\hat{K}_t = \left(1+\frac{1}{\eta}\right)^{-t} \hat{K}_0 \quad \text{and} \quad \hat{q}_t = \left(1+\frac{1}{\eta}\right)^{-t} \hat{q}_0.$$

Characterization of the steady state under earnings-based constraints. From conditions (B.14) and (B.15), the steady state can be characterized by

$$q^*\delta K^* + RB^* = aK^* + B^*,$$

$$RB^* = \theta a K^*,$$

$$q^* = u(K^*)$$

As a result,

$$q^* = a\frac{\left(1+\frac{\theta}{R}-\theta\right)}{\delta} \quad , \frac{B^*}{K^*} = \frac{\theta a}{R} \quad \text{and} \quad K^* = u^{-1}\left(a\frac{\left(1+\frac{\theta}{R}-\theta\right)}{\delta}\right).$$

When $\theta = \frac{1-\delta}{1-\frac{1}{R}(1-\delta)}$, the steady state will then be the same as the one under collateral-based constraints.

Characterization of the equilibrium under earnings-based constraints. $\lambda = \frac{\left(\frac{R}{1-\delta}\left(1+\frac{\delta}{\eta}\right)+1\right)-\sqrt{\left(\frac{R}{1-\delta}\left(1+\frac{\delta}{\eta}\right)+1\right)-4\frac{R}{1-\delta}}}{2} \in (0,1)$ is the only eigenvalue of $\begin{pmatrix} \frac{R}{1-\delta} & -\frac{1}{\eta}\left(\frac{R}{1-\delta}-1\right) \\ -\delta\frac{\frac{R}{1-\delta}}{1-\frac{1-\delta}{R}} & 1+\frac{\delta}{\eta}\frac{R}{1-\delta} \end{pmatrix}$ that is within the unit circle. Together with the fact that $\hat{q}_t$ is bounded, we have $\hat{q}_0 = \alpha\hat{K}_0$, $\hat{q}_t = \lambda^t\hat{q}_0$ and $\hat{K}_t = \lambda^t\hat{K}_0$, where $\alpha = \frac{q_\lambda}{k_\lambda} = \frac{\frac{1}{\eta}\left(\frac{R}{1-\delta}-1\right)}{\frac{R}{1-\delta}-\lambda} > 0$ and (q_λ, k_λ) is the eigenvector corresponding to λ. Using the farmers' capital holding at 0 in condition (B.17), we arrive at condition (B.21).

Proof of Lemma 5. From conditions (B.12) and (B.21), for the part of the Lemma about farmers' land holding ($\frac{d\hat{K}_0}{d\Delta}|_{KM} > \frac{d\hat{K}_0}{d\Delta}|_{EBC}$), we only need to prove that

$$\frac{1}{1+\frac{1}{\eta}}\left(1+\frac{\frac{R}{1-\delta}}{\frac{R}{1-\delta}-1}\frac{1}{\eta}\right)\frac{\eta}{\eta+\frac{\delta}{1-\frac{1-\delta}{R}}} > \frac{1}{1+\frac{\delta}{1-\frac{1}{R}(1-\delta)}\alpha}. \tag{B.23}$$

Let us first prove that

$$\frac{1}{1+\frac{1}{\eta}}\left(1+\frac{\frac{R}{1-\delta}}{\frac{R}{1-\delta}-1}\frac{1}{\eta}\right)\frac{\eta}{\eta+\frac{\delta}{1-\frac{1-\delta}{R}}} > \frac{1}{1+\frac{\delta}{\eta}}. \tag{B.24}$$

This is equivalent to proving that

$$\frac{\frac{\frac{R}{1-\delta}-1}{\frac{R}{1-\delta}}+\frac{1}{\eta}}{\frac{\frac{R}{1-\delta}-1}{\frac{R}{1-\delta}}+\frac{\delta}{\eta}} = \left(1+\frac{\frac{R}{1-\delta}}{\frac{R}{1-\delta}-1}\frac{1}{\eta}\right)\frac{\eta}{\eta+\frac{\delta}{1-\frac{1-\delta}{R}}} > \frac{1+\frac{1}{\eta}}{1+\frac{\delta}{\eta}},$$

which is true as $\frac{\frac{R}{1-\delta}-1}{\frac{R}{1-\delta}} > 1$ and $\delta < 1$.

We then prove that

$$\frac{1}{1+\frac{\delta}{1-\frac{1}{R}(1-\delta)}\alpha} < \frac{1}{1+\frac{\delta}{\eta}}. \tag{B.25}$$

Note that from the formula of λ above, we have

$$\begin{aligned}
\lambda &= \frac{\left(\frac{R}{1-\delta}\left(1+\frac{\delta}{\eta}\right)+1\right)-\sqrt{\left(\frac{R}{1-\delta}\left(1+\frac{\delta}{\eta}\right)+1\right)-4\frac{R}{1-\delta}}}{2} \\
&= \frac{2\frac{R}{1-\delta}}{\frac{R}{1-\delta}\left(1+\frac{\delta}{\eta}\right)+1+\sqrt{\left(\frac{R}{1-\delta}\left(1+\frac{\delta}{\eta}\right)+1\right)-4\frac{R}{1-\delta}}} > \frac{\frac{R}{1-\delta}}{\frac{R}{1-\delta}\left(1+\frac{\delta}{\eta}\right)+1} \\
\alpha &= \frac{\frac{1}{\eta}\left(\frac{R}{1-\delta}-1\right)}{\frac{R}{1-\delta}-\lambda} > \frac{\frac{1}{\eta}\left(\frac{R}{1-\delta}-1\right)}{\frac{R}{1-\delta}-\frac{\frac{R}{1-\delta}}{\frac{R}{1-\delta}\left(1+\frac{\delta}{\eta}\right)+1}} = \frac{\frac{1}{\eta}\left(\frac{R}{1-\delta}-1\right)}{\left(\frac{R}{1-\delta}\right)^2\frac{\left(1+\frac{\delta}{\eta}\right)}{\frac{R}{1-\delta}\left(1+\frac{\delta}{\eta}\right)+1}}.
\end{aligned}$$

We then have

$$\frac{1}{1+\frac{\delta}{1-\frac{1}{R}(1-\delta)}\alpha} < \frac{1}{1+\frac{\delta}{1-\frac{1}{R}(1-\delta)}\frac{\frac{1}{\eta}\left(\frac{R}{1-\delta}-1\right)}{\left(\frac{R}{1-\delta}\right)^2\frac{\left(1+\frac{\delta}{\eta}\right)}{\frac{R}{1-\delta}\left(1+\frac{\delta}{\eta}\right)+1}}} = \frac{1}{1+\frac{\frac{1}{\eta}\delta}{\frac{\frac{R}{1-\delta}\left(1+\frac{\delta}{\eta}\right)}{\frac{R}{1-\delta}\left(1+\frac{\delta}{\eta}\right)+1}}} < \frac{1}{1+\frac{\delta}{\eta}}.$$

Together, we prove condition (B.23). Finally, note that the aggregate output from period t land holding (which gets produced in period $t+1$) is

$$\hat{Y}_t = \frac{a+c-Ra}{a+c}\frac{(a+c)K^*}{Y^*}\hat{K}_t,$$

where $\frac{a+c-Ra}{a+c}$ reflects the difference between the farmers' productivity (equal to $a+c$) and the gatherers' productivity (equal to Ra in the steady state) and the ratio $\frac{(a+c)K^*}{Y^*}$ is the share of farmers' output. In other words, $\hat{Y}_t$ is just a multiple $\hat{K}_t$. The above result about $\frac{d\hat{K}_0}{d\Delta}$ then also applies to $\frac{d\hat{Y}_0}{d\Delta}$.

Appendix C

Appendix to Chapter 3

C.1 Additional tests

C.1.1 Formulation with lags

In this appendix, we explore the following alternative specification of our empirical model of expectation formation.

Firs, note that our recursive specification in equation (3.6) is equivalent to:

$$F_t x_{t+1} = (1-\lambda) \sum_{k\geq 0} \lambda^k E_{t-k} x_{t+1} + \gamma \sum_{k\geq 0} \lambda^k \left(x_{t-k-1} - E_{t-k-2} x_{t-k-1} \right) \tag{C.1}$$

Assume that $\gamma = .45$ and $\lambda = .2$ (this corresponds to average values from our main Table 3.4). In this case, we would expect to have:

$$\begin{aligned} F_t x_{t+1} \approx\ & .8 E_t x_{t+1} + .16 E_{t-1} x_{t+1} \\ & + .45 \left(x_{t-1} - E_{t-2} x_{t-1} \right) + .09 \left(x_{t-2} - E_{t-3} x_{t-2} \right) \end{aligned}$$

where we neglects the longer lags.

We thus run a regression using equation (C.1) and report the results in Table A.1. The coefficient on the first lag hovers between .64 and .8, which is consistent with our baseline results. The coefficient on the second lag (between .26 and .41) is –in some cases significantly - larger than the .16 we are expecting. The two coefficient on one- and two-period lagged extrapolation are very close –and statistically similar– to the .45 and .09 that we expected.

Table A.1: *Modeling Expectation Formation Model with lags*

	$F_t x_{t+1} - E_t x_{t+1}$			
	(1)	(2)	(3)	(4)
	3 lags	2 lags	$t \leq 20$	$t > 20$
$E_t x_{t+1}$	.69***	.69***	.58***	.79***
	(8.1)	(8.1)	(5.1)	(7.7)
$E_{t-1} x_{t+1}$	.29**	.39***	.46***	.33***
	(2.5)	(4.2)	(3.6)	(2.9)
$E_{t-2} x_{t+1}$	.094			
	(1.2)			
$x_t - E_{t-1} x_t$	.49***	.49***	.51***	.47***
	(12)	(12)	(9.1)	(9)
$x_{t-1} - E_{t-2} x_{t-1}$	.053**	.035*	.047*	.022
	(2)	(1.8)	(1.9)	(.91)
$x_{t-2} - E_{t-3} x_{t-2}$	.027			
	(1.6)			
N	6179	6346	3006	3340
r2	.45	.45	.45	.46

Note: On the panel of participants for which $\rho \in \{0, .2, .4, .6, .8\}$, we run the following regression:

$$F_t x_{t+1} = (1-\lambda) \sum_{k=0}^{n} \lambda^k E_{t-k} x_{t+1} + \gamma \sum_{k=0}^{n} \lambda^k \left(x_{t-k} - E_{t-k-1} x_{t-k}\right)$$

In column 1, we estimate the model assuming $n = 2$; in column 2, we stop at $n = 1$. In columns 3 and 4 we split the sample between the first and last 20 rounds of testing.

C.1.2 An alternative model: Adaptive expectations

An alternative formulation of sticky expectations is the traditional notion of adaptive expectations (Nerlove, 1958), which has been used in earlier experimental studies (Dwyer et al. (1993a), Hey (1994a)). Adaptive expectations also contain the notion that expectation formation incorporates new information more slowly than rational expectations, but the recursive formulation differs from specification (3.6):

$$F_t^i x_{it+1} - x_{it} = \lambda \left(F_{t-1}^i x_{it} - x_{it}\right) + \gamma (x_{it} - E_{t-1} x_{it}) + u_{it+1} \tag{C.2}$$

where this specification differs from our main specification in two respects. First, the benchmark with which we compare the forecast is the *past* realization of the signal x_{it} instead of the rational expectation about the future signal $E_t x_{it+1}$. These two formulations are equivalent only when $\rho = 1$, i.e. when the process is a random walk. Second, the past expectation component is not the past forecast of x_{it+1}, $F^i_{t-1} x_{it+1}$, but the past forecast over x_{it}, $F^i_{t-1} x_{it}$. Hence, the adaptive formulation does not make use of the term structure of expectations that our main specification exploits. Overall, this approach does *not* nest rational expectations as a particular case. Given that we can vary ρ, we are able to easily distinguish our formulation from the above adaptive-extrapolative model. To do this, we run regression (C.2) separately for each value of ρ, and ask whether the results are stable across specification.

We report the results in Table A.2, which exactly replicates Table 3.6 with the adaptive-extrapolative model. Clearly, the estimates of adaptiveness λ and extrapolation γ are quite unstable across values of ρ. For $\rho \in \{.6, .8\}$, none of the parameters is statistically significant. For all conditions except when $\rho = 1$ (in which case the new model is very close to our main specification), there is no trace of extrapolation, as γ is either negative, or negligible or insignificant, and in any case unstable. Similarly, the adaptiveness coefficient is positive and significant for $\rho = 0, .2, 1$ but differs widely. It is insignificant for the other values of persistence. It looks like incorporating rational expectation ρx_{it-1} instead of past realizations x_{it} has the virtue of stabilizing the model.

Table A.2: *Adaptive-Extrapolative Model*
Sample split by value of ρ

	$F_t x_{t+1} - x_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\rho =$	0	.2	.4	.6	.8	1
$F_{t-1}x_t - x_t$	.099**	.093**	-.0068	.12	.071	.53***
	(2.3)	(2.2)	(-.21)	(1.5)	(1.3)	(3.9)
$x_t - E_{t-1}x_t$	-.45***	-.27***	-.19***	.0074	.083	.7***
	(-6.7)	(-5.7)	(-4.7)	(.13)	(1.5)	(4.8)
N	1216	1216	1368	1482	1064	1520
r2	.22	.12	.027	.025	.0052	.3

Note: On the panel of participants for which $\rho \in \{0, .2, .4, .6, .8, 1\}$, we run the following regression:

$$F_t^i x_{it+1} - x_{it} = \lambda \left(F_{t-1}^i x_{it} - x_{it} \right) + \gamma (x_{it} - E_{t-1} x_{it}) + u_{it+1}$$

This model is the adaptive-extrapolative formulation in equation (C.2). In each column, we estimate the above equation for all participants with a given value of ρ. t-stats between brackets.

C.1.3 Estimate robustness across Realizations of the process

In this Appendix, we use the experiment where subjects are randomly sorted into 10 conditions. In each condition, the persistence parameter is $\rho = .6$. Within each condition, the path of realized innovations ϵ_{it} is the same for all participants, but it differs across conditions.

For each condition c separately, we run our main specification:

$$F_t^i x_{it+1} - \hat{E}_t x_{it+1} = \lambda_c \left(F_{t-1}^i x_{it+1} - \hat{E}_t^i x_{it+1} \right) + \gamma_c (x_{it} - \hat{E}_{t-1}^i x_{it}) + u_{it+1}$$

where we use the LS rational expectation $\hat{E}$. We then report these estimates in each column of Table A.3. Parameters are consistent with our main results in Table 3.4 and reasonably consistent with one another.

Table A.3: *Modeling Expectation Formation*
Model with lags

	$F_t x_{t+1} - E_t x_{t+1}$									
Realization	1	2	3	4	5	6	7	8	9	10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$F_{t-1}x_{t+1} - E_t x_{t+1}$	.18***	.17***	.18***	.27***	.22***	.21***	.19**	.19***	.005	.45***
	(6.7)	(5.8)	(5.7)	(4.3)	(5.3)	(5.9)	(2.1)	(4.4)	(.072)	(3.1)
$x_t - E_{t-1}x_t$	.41***	.64***	.42***	.54***	.46***	.31***	.32***	.46***	.13	.54***
	(9.3)	(15)	(7.5)	(7.7)	(8.8)	(9.1)	(3.6)	(7.6)	(1.2)	(8.1)
N	1369	1184	1369	1110	1184	1221	999	1221	962	1591
r2	.13	.35	.092	.18	.16	.1	.079	.16	.012	.27

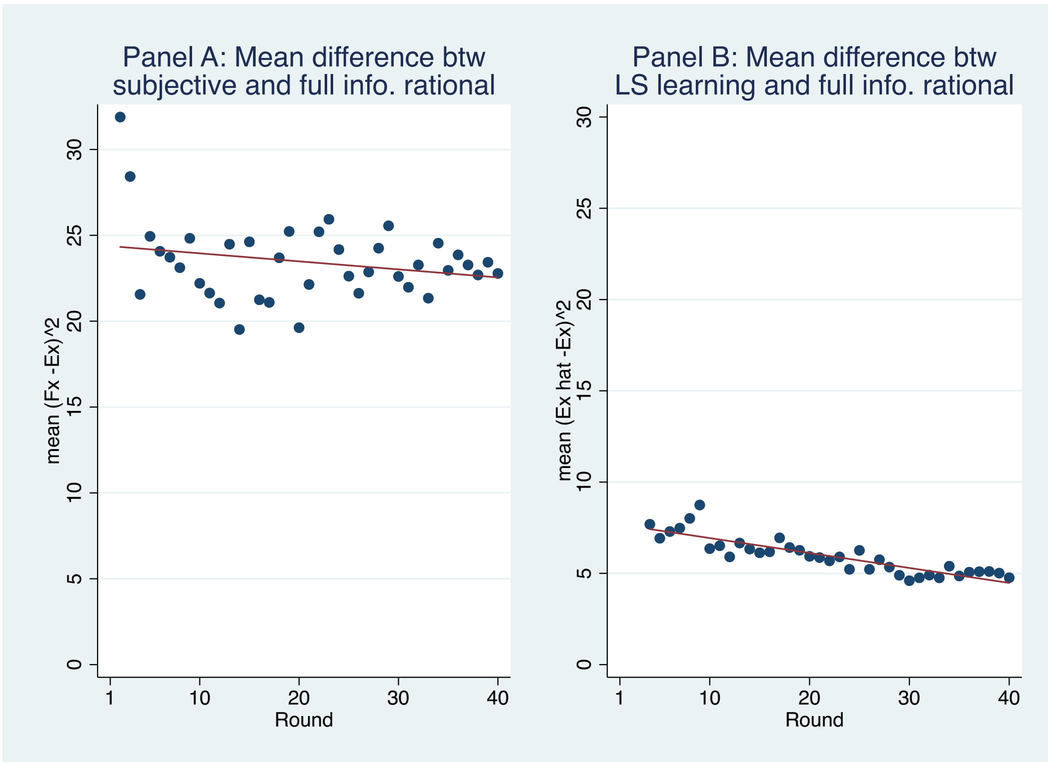
Note: There is only one process with $\rho = .6$. Subjects are randomly allocated to 10 different conditions where there is a single realization of innovation draws ϵ. Thus, within each conditions, all subjects forecast the "same" variable. For each condition c separately, we run our main specification:

$$F_t^i x_{it+1} - \hat{E}_t x_{it+1} = \lambda_c \left(F_{t-1}^i x_{it+1} - \hat{E}_t^i x_{it+1} \right) + \gamma_c (x_{it} - \hat{E}_{t-1}^i x_{it}) + u_{it+1}$$

where we use the LS rational expectation $\hat{E}$ instead of the full information rational expectation. We then report these estimates in each column of the table.

C.2 Appendix Figures

Figure A.1: *Mean Square Error in Least Square Learning as a Function of Time*



Note: Each period, for each participant, we compute the square of the difference $\left(E_{t-1}^{FI}x_t - E_{t-1}^{LS}x_t\right)^2$. We then take the average of this squared difference across participants, and plot it against time.

C.3 Survey Appendix

C.3.1 Sample Experiment

Below are the instructions for a sample experiment (Experiment 1, $rho = 0.6$, $\mu = 0$, $sigma = 20$). Participants first see a consent form with brief descriptions of the study. Once they agree to the consent, they will proceed to experimental instructions. The experiment starts with the forecasting task and is then followed by demographic questions. The demographic questions are the same for all of our experiments. The forecasting task may differ slightly depending on the treatment condition, as described in Section 3.4. We discuss these variants in the next subsection.

Consent Form

Purpose of research: The purpose of this research is to study how people make predictions.

What you will do in this research: You will make forecasts about future realizations of a random process on a web-based platform, followed by a few demographics questions. There are 40 rounds, and you will make 2 predictions per round. You may exit the platform at any time or skip some questions without penalty.

Time required: It takes about 20 minutes to complete the study. You are free to spend as much time as you like up to 60 minutes.

Risks: There are no anticipated risks associated with participating in this study.

Compensation: You will receive **base payment** of **$1.80**. You will also receive a **bonus payment**. The **bonus payment** will be on the scale of **$2.50**, but the precise amount will depend on the accuracy of your predictions.

Your **base payment** and **bonus payment** will be distributed together within one week via MTurk.

Please feel free to contact us with the contact information below or through MTurk if you have any questions about payments. A summary of your payments will be displayed at the end of the study. You may save that page for your records.

Confidentiality: The system allows us to see MTurk Worker IDs and IP addresses. We may use these information for handling payments and to verify data quality, for example that you are in the United States and have not taken our previous surveys. Please make sure to mark your Amazon Profile as private if you do not want it to be found from your MTurk Worker ID. If you communicate with us via email to discuss any issue related to your participation, we will keep your information confidential. All personally identifiable information will be handled in compliance with Harvard and MIT data security requirements, will not be accessible to anyone outside the study team, and will not be used in our data analysis. Data analysis will be based on de-identified data. Part or all of the de-identified data may be shared with other researchers or be made available publicly for academic replication after publication.

Benefits: Your input will help our research develop a better understanding about how people make forecasts. We appreciate your participation. We hope you will also find the survey questions to be interesting.

Contact: If you have any questions, concerns, or suggestions related to this study, the researcher can be reached at:

David Thesmar Sloan School of Management, Massachusetts Institute of Technology 30 Memorial Dr, Cambridge, MA 02142 Cambridge, MA 02139 Email: thesmar@mit.edu (617) 324-7023

This research has been reviewed by the Committee on the Use of Human Subjects in Research at MIT. They can be reached at 617-253-6787, 77 Massachusetts Avenue, Room E25-143B, Cambridge, MA 02139, or couhes@mit.edu. You can contact them for any of the following:

- If your questions, concerns, or complaints are not being answered by the research team,
- If you cannot reach the research team,
- If you want to talk to someone besides the research team, or
- If you have questions about your rights as a research participant.

Please print or screenshot this page for your records.

By selecting to continue, you indicate that you are at least 18 years old and you agree to complete this HIT voluntarily.

[I Give My Consent]

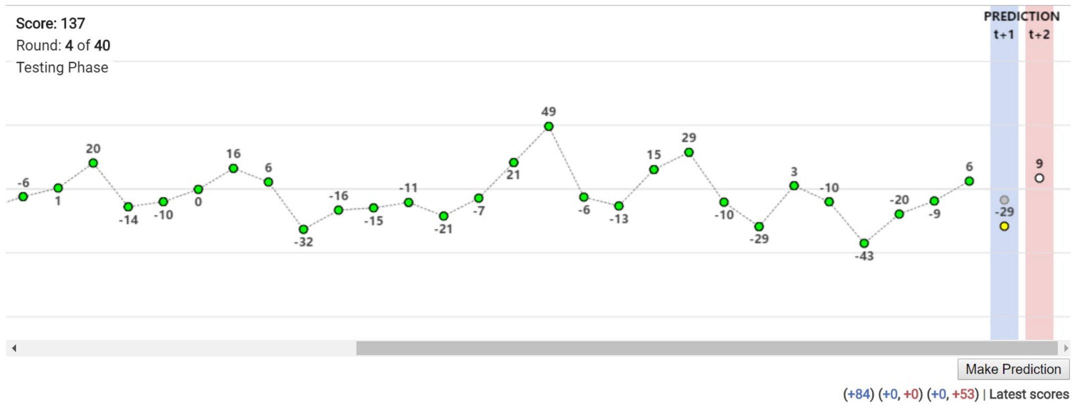
(page break)

Experimental Instructions

Thank you very much for your participation. This study will take you about 20 minutes to complete.

You will receive base payment of **$1.80**. You will also receive a **bonus payment**. The typical bonus amount will be around **$2.50**, but the precise amount will depend on the accuracy of your predictions.

In this study, we would like to understand how people make predictions about future realizations of random processes. We will first show you 40 past realizations of a process, and you will make predictions of its future value for 40 rounds.



You will receive a score for each prediction you make. The more accurate your predictions are, the higher your score will be. If your prediction is out of a certain neighborhood around the actual value, you may receive a score of zero. The specific formula for the score of each prediction is $100 \times \max\{0, 1 - |\Delta|/20\}$ where Δ is the difference between your prediction and the realized value. We estimate that the best performer will receive an average score of 36 per prediction.

In each of the 40 rounds, we will ask you to predict the next two values of the process. At the end of the experiment, we will calculate your total score in the 40 rounds of predictions. *You will receive the bonus payment in U.S. dollars which is equal to your total score divided by 600.*

[Start Experiment]

(page break)

(This plot is a screenshot of the interactive experimental interface. The green dots indicate past realizations of the statistical process. In each round t, participants are asked to make predictions about two future realizations $F_t x_{t+1}$ and $F_t x_{t+2}$. They can drag the mouse to indicate $F_t x_{t+1}$ in the purple bar and indicate $F_t x_{t+2}$ in the red bar. Their predictions are shown as yellow dots. The grey dot is the prediction of x_{t+1} from the previous round $F_{t-1} x_{t+1}$; participants can see it but cannot change it.

After they have made their predictions, participants click “Make Predictions" and move on to the next round.

The total score is displayed on the top left corner, and the score associated with each of the past prediction (if the actual is realized) is displayed at the bottom.)

Background Information

The prediction section is now over. We would now like to ask a few questions about yourself to help us in our research.

1. What is your gender?
   - Male
   - Female
2. What is your age?
3. What is the highest level of educational degree that you hold?
   - Graduate school (e.g. Masters, Ph.D., Post-doctoral degrees)
   - College
   - High school
   - Below high school
   - Other:
4. Have you taken statistics classes?
   - Yes
   - No
5. Do you have any experience investing in financial assets (e.g. stocks, bonds, mutual funds, pension funds, etc.)?
   - I have extensive experience investing in financial assets.
   - I have some experience.
   - I have very limited experience.
   - I have no experience at all.
6. What is the median of the following numbers? 10, 30, 60, 70, 90, 150, 220, 760

7. A town has two hospitals. The larger hospital has on average 35 babies born every day. The smaller hospital has on average 10 babies born every day. We know that about 50 percent of babies are boys. For a period of 6 months, the hospitals recorded the number of days when more than 70 percent of the babies born are boys, and called them “baby boy days." Which of the following do you think is most likely?

    - The larger hospital recorded more “baby boy days" than the smaller hospital.
    - The smaller hospital recorded more “baby boy days" than the larger hospital.
    - The two hospitals recorded the same number of “baby boy days."

8. A fair coin is tossed 6 times. What do you think about the likelihood of seeing Pattern A: H-T-H-T-T-H vs. Pattern B: H-H-H-T-T-T?

    - Pattern A is more likely than Pattern B
    - Pattern B is more likely than Pattern A
    - They are equally likely
    - None of the above

9. When would you say is a good time to invest in stocks:

    - If the stock market has been going up in the past two years
    - If the stock market has been going down in the past two years
    - I do not have an opinion

Feedback

The study is now completed. Do you have any comments and suggestions for the survey? Did you find anything to be unclear or confusing?

Submit Results

Click the button below to validate and submit your experiment data. This button will submit your HIT for approval and return you to Mechanical Turk.

[Submit Results]

(page break) **Almost done!**

The experiment is now completed. Thank you very much for your participation!

Your total score in the prediction section was [ ].

Base payment: [ ]

Bonus payment: [ ]

You will receive your payments within five days. Bonus payments may vary by +/- one cent due to rounding. Make sure to save this page for your records. If you have any questions, please feel free to contact us.

More Information

In case you are curious about the statistical questions at the end of the experiment, here are the answers. Your answers to these questions do not affect your payments or the quality of your performance in this HIT.

Q. What is the median of the following numbers: 10, 30, 60, 70, 90, 150, 220, 760?

A: The median is (70 + 90) / 2 = 80.

Q. A town has two hospitals. The larger hospital has on average 35 babies born every day. The smaller hospital has on average 10 babies born every day. We know that about 50 percent of babies are boys. For a period of 6 months, the hospitals recorded the number of days when more than 70 percent of the babies born are boys, and called them "baby boy days." Which of the following do you think is most likely?

A: The smaller hospital recorded more "baby boy days" than the larger hospital.

Q. A fair coin is tossed 6 times. What do you think about the likelihood of seeing Pattern A: H-T-H-T-T-H vs. Pattern B: H-H-H-T-T-T?

A: They are equally likely.

To help us with our research, please do not discuss or share these questions on public forums. Thank you very much for your cooperation!

[Submit HIT and Return to MTurk]

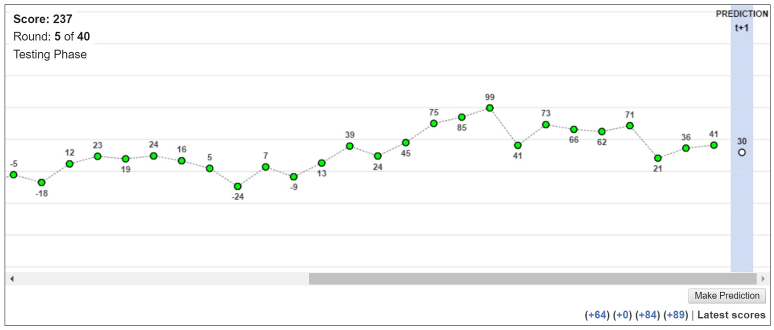
C.3.2 Variants

All experimental conditions in Experiment 1 and Experiment 2 described in Section 3.4 follow the sample experiment above, except they vary in the parameter ρ.

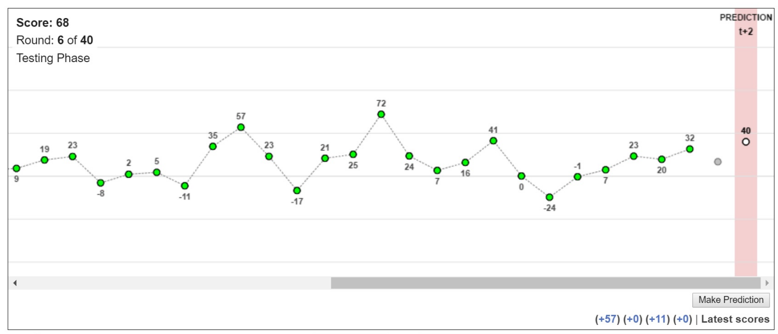
Several experimental conditions in Experiment 3 have some slight differences, which are explained below.

- Experiment C1 to C4 (context):
  - In third paragraph of experimental instructions, we explain the following

    "In this study, we would like to understand how people make predictions about future realizations of random processes. **The process you will see has the same property as quarterly real GDP growth/monthly inflation/monthly stock returns/monthly house price growth in the US in the last three decades.** We will first show you 40 past realizations of a process, and you will make predictions of its future value for 40 rounds."
  - The parameters *rho*, μ, σ are based on the properties of these actual processes.
  - Everything else is the same as the sample experiment above.
- Experiment C5 to C8 (no context, comparison):
  - The parameters *rho*, μ, σ correspond to those in Experiments C1 to C4.
  - Everything else is the same as the sample experiment above.
- Experiment C9 (comparison:
  - Everything else is the same as the sample experiment above. $\rho = 0.2$.
- Experiment C10 to C13 (forecast next realization F1 only):
  - Only forecast the next realization (instead of the next two realizations. Below is a screenshot.
  - Everything else is the same as the sample experiment above.
- Experiment C14 to C17 (forecast two step ahead realization F2 only):



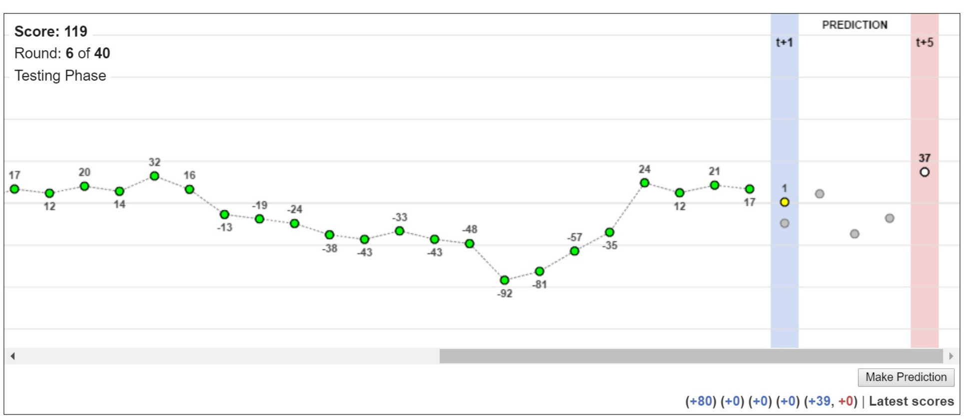
– Only forecast the two step ahead realization (instead of the next two realizations. Below is a screenshot.



– Everything else is the same as the sample experiment above.

- Experiment C18 to C21 (forecast F1 and F5):

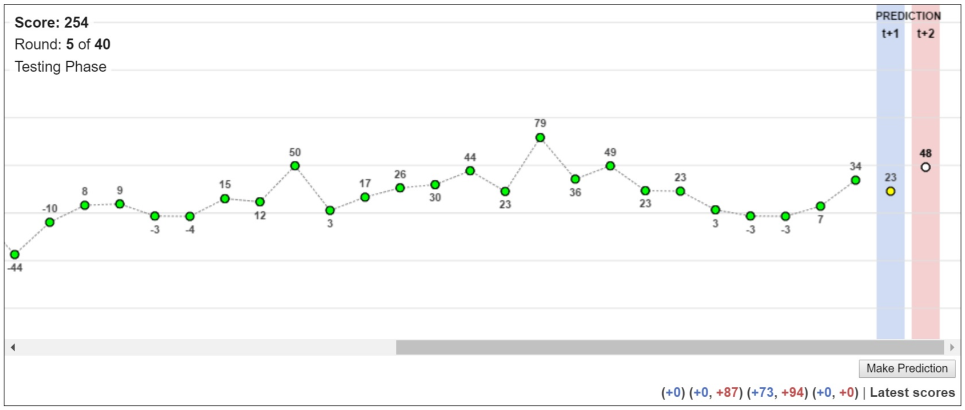
  – Forecast the next realization and the five step ahead realization. Below is a screenshot.



  – Everything else is the same as the sample experiment above.

- Experiment C22 to C25 (no gray dot):

  - Forecast the next two realizations, but remove the gray dot indicating $F_{t-1}x_{t+1}$. Below is a screenshot.



  - Everything else is the same as the sample experiment above.