Behavioral Finance at 40: Progress, Open Questions, and New Directions

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• the modern era in behavioral finance began in the 1980s

In today's talk, 40 years later:

- I review some important frameworks we have developed in behavioral finance
- I identify open questions
- and I discuss a recent shift in the field
 - the "cognitive turn"
 - i.e., the focus on cognitive foundations of beliefs and preferences

The talk is designed to be:

- accessible to all finance scholars, regardless of area of specialty
 - and even to non-academics
- mostly non-technical, focusing on intuition
- based on the work of many researchers

- behavioral finance has three main areas of application
 - asset pricing
 - corporate finance
 - household finance
- today, I will focus on asset pricing applications
 - because it is a context that helps to identify the most important investor biases
 - only biases that affect many investors in a correlated way have a chance of influencing asset prices

Major frameworks in behavioral asset pricing

• limits to arbitrage

Beliefs:

- disagreement in the presence of short-sale constraints
- (irrational, extrapolative) beliefs about returns *
- (irrational) beliefs about cash flows *

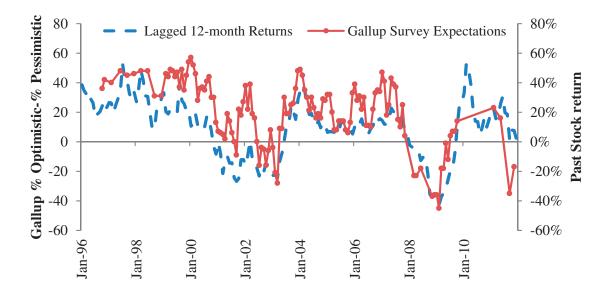
Preferences:

• gain-loss utility and prospect theory *

Roadmap

- beliefs
 - about returns
 - about cash flows
- preferences
 - gain-loss utility and prospect theory
- the cognitive turn in behavioral economics
 - cognitive foundations of beliefs and preferences

- the most prominent idea regarding beliefs about returns is that they are extrapolative
 - beliefs about future returns are a positive function of recent past returns
- this is motivated in part by survey evidence



Source: Greenwood and Shleifer (2014)

- return extrapolation has generated a lot of interest because it offers a simple explanation for several prominent asset pricing puzzles
 - excess volatility and predictability in the aggregate stock market (and other asset classes)
 - momentum and reversals in the cross-section of stocks
 - bubbles

- consider an economy with T+1 periods, $t=0,1,\ldots,T$
- and two assets
 - a riskless asset, with a constant return of zero
 - a risky asset that is a claim to a single, final cash flow \widetilde{D}_T

$$\widetilde{D}_T = D_0 + \widetilde{\varepsilon}_1 + \ldots + \widetilde{\varepsilon}_T$$

 $\widetilde{\varepsilon}_t \sim N(0, \sigma_{\varepsilon}^2) \text{ i.i.d.}$

• some investors have extrapolative beliefs about price changes

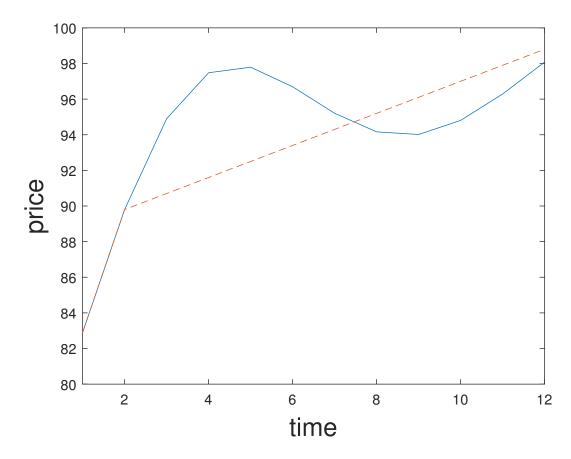
$$E_t^e(P_{t+1} - P_t) = X_t \equiv (1 - \theta) \sum_{k=1}^{t-1} \theta^{k-1} (P_{t-k} - P_{t-k-1}) + \theta^{t-1} X_1$$

- while other investors, "fundamental traders," buy when prices are low relative to expected cash flows
 - and sell when prices are high relative to expected cash flows
- equilibrium asset prices are given by

$$P_t = D_t + \frac{\mu^e}{\mu^f} X_t - \gamma \sigma_{\varepsilon}^2 Q(T - t - 1 + \frac{1}{\mu^f}), \qquad t = 1, \dots, T - 1$$

Source: Barberis (2018)

• the resulting price dynamics, following a positive cash-flow shock at time 2, are:



• the various asset pricing applications of return extrapolation can be seen in this figure

• there are now increasingly sophisticated models of return extrapolation and asset prices

Aggregate stock market

• Barberis, Greenwood, Jin, Shleifer (2015); Adam, Marcet, Beutel (2017); Jin and Sui (2022)

Cross-section of stocks

• Hong and Stein (1999); Barberis and Shleifer (2003); Da, Huang, Jin (2021)

Bubbles

• Barberis, Jin, Greenwood, Shleifer (2018); Bastianello and Fontanier (2024)

Real estate market

• Glaeser and Nathanson (2017)

This is promising, but there are many open questions:

- what is the source of return extrapolation?
 - and can knowledge of the source deepen our understanding of the empirical facts?
- what value of θ is consistent with observed prices, and is this value justified?
- does θ vary over time, and if so, why?
 - Cassella and Gulen (2018)

More open questions:

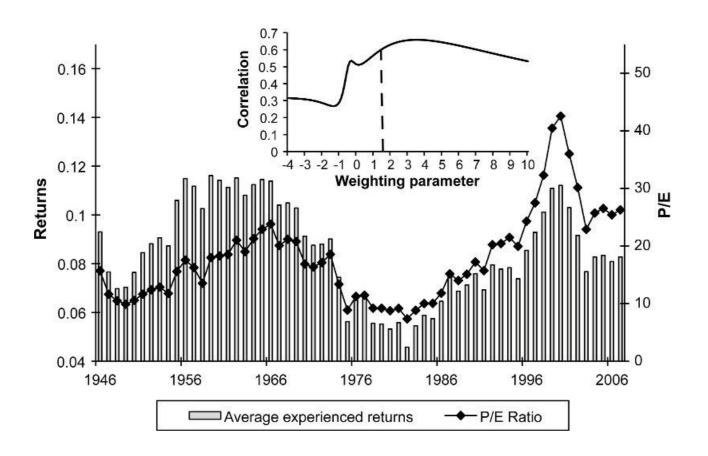
- are return extrapolation models consistent with the facts about investor portfolios?
 - who are the investors who are actually trading according to extrapolative beliefs?
- Giglio, Maggiori, Stroebel, Utkus (2021) find that investors' holdings are relatively insensitive to their beliefs
 - so can shifts in beliefs affect holdings enough to move prices?
- is this investor behavior really about beliefs?
 - or does it reflect a different, non-belief mechanism?
 - e.g., observational learning?

Sources of return extrapolation

- some are psychological in nature
 - representativeness, base-rate neglect
 - an incorrect belief in a law of small numbers
 - memory
- others focus on boundedly-rational inference about underlying fundamentals
 - Hong and Stein (1999), Andre, Shirmer, Wohlfart (2023), Bastianello and Fontanier (2024)

- the work on return extrapolation intersects in an important way with research on "experience effects"
 - Malmendier and Nagel (2011)
- in this context, the idea is that a person's demand for a risky asset will depend on a weighted average of the asset's returns over that person's lifetime
- Malmendier and Nagel (2011) present evidence that such a formulation may bring us closer to understanding both investors' portfolio holdings and stock market fluctuations

Experience effects and asset prices



Source: Malmendier and Nagel (2011)

Roadmap

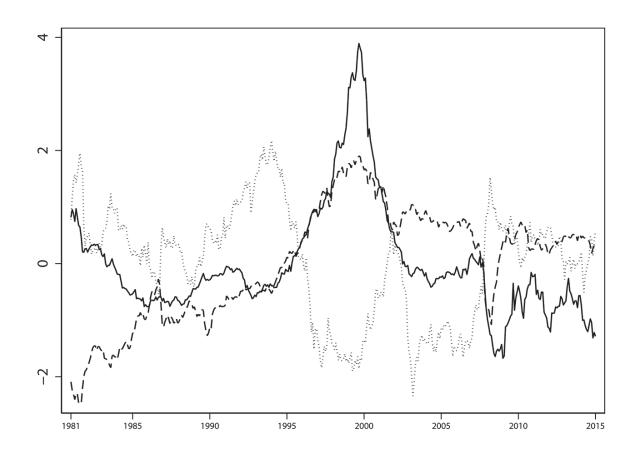
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- another line of research argues that important pricing puzzles are due to incorrect cash-flow forecasts that overreact to news
 - when prices are low, this is due to excessively pessimistic forecasts
 - when prices are high, this is due to excessively optimistic forecasts
- Barberis, Shleifer, Vishny (1998), Nagel and Xu (2022), Bordalo, Gennaioli, La Porta, Shleifer (2024a,b), De La O and Myers (2021)
- most papers use analyst forecasts to provide evidence for this view
 - specifically, forecasts of long-term earnings growth (LTG)

Aggregate market

- Bordalo, Gennaioli, La Porta, Shleifer (2024a) present several pieces of evidence consistent with this view
 - the P/E ratio is correlated with analysts' forecasts of aggregate LTG
 - LTG predicts future market returns with a negative sign
 - LTG also predicts forecast errors for subsequent realized earnings growth

Aggregate market



Source: Bordalo, Gennaioli, La Porta, Shleifer (2024a)

Individual stock level

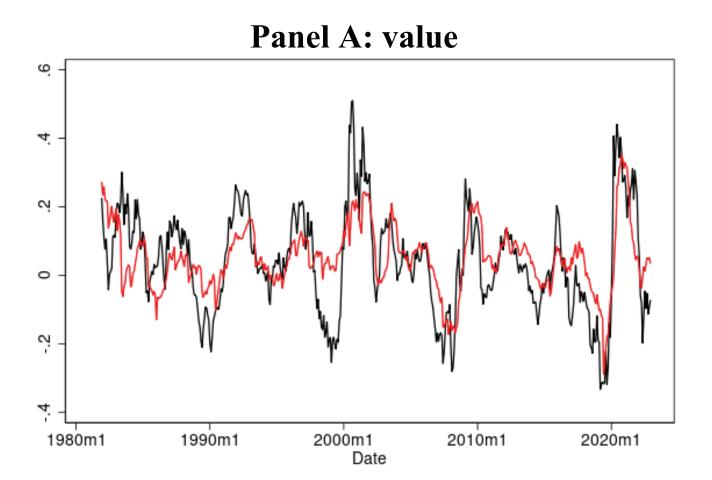
• we can approximate the return on a stock as:

$$r_{i,t+1} \approx r_i + \left[(g_{i,t+1} - E_t(g_{i,t+1})) + \sum_{s \ge 1} \alpha^s (E_{t+1} - E_t)(g_{i,t+1+s}) \right]$$

- Bordalo, Gennaioli, La Porta, Shleifer (2024b) compute the term in square parentheses using analyst forecasts of future earnings
 - use EPS forecasts up to two years out, and LTG forecasts from two to five years out
 - convert to dividend growth expectations using observed dividend payout ratios

- Bordalo, Gennaioli, La Porta, Shleifer (2024b) find that the expectationsbased component can explain the entirety of the value and size anomalies
 - and a substantial portion of the investment, profitability, and momentum anomalies
- e.g., the high returns to value are due to investors revising upwards their excessively pessimistic forecasts of future earnings growth

Earnings growth expectations and the value premium



Source: Bordalo, Gennaioli, La Porta, Shleifer (2024b)

- LTG forecasts are the expectations that appear particularly helpful for understanding asset prices
- the evidence above strongly suggests that LTG forecasts overreact to information
 - this is directly confirmed by Coibion-Gorodnichenko regressions for both individual and consensus LTG forecasts
- important open question: what is the source of the overreaction?
 - representativeness (e.g., "diagnostic expectations"), base-rate neglect
 - an incorrect belief in a law of small numbers
 - memory

Other open questions:

- which specific news are investors overreacting to?
- how does the overreaction in LTG forecasts fit with the observed *under*-reaction in short-term earnings forecasts?
- are cash-flow expectations driving prices, or are prices driving the cash-flow expectations?
 - Chaudhry (2023), but also Bordalo, Gennaioli, La Porta, Shleifer (2024a,b)

Which news are investors overreacting to?

- one view is that investors are overreacting to past tangible, i.e., accounting, information
 - e.g., overreacting to past earnings growth
- the evidence on this is mixed
 - Nagel and Xu (2022) find that a long-term weighted average of past fundamentals predicts stock market returns with a negative sign
 - Bordalo et al. (2024a) find that past earnings surprises lead to excessive revisions in consensus analyst LTG forecasts
 - but, in the cross-section, Daniel and Titman (2006) find that growth in past fundamentals has no predictive power for returns
- the last finding has led some researchers to argue that investors may be overreacting in part to intangible information

Under- and over-reaction

- thus far, we have focused on *over*-reaction in beliefs about cash flows and returns
- \bullet yet, some phenomena strongly suggest under-reaction
 - e.g., post-earnings announcement drift (PEAD)
- more generally, all three of experiments, surveys, and markets display instances of both under- and over-reaction
- reconciling this evidence remains an important open challenge
 - recent work has made progress
 - Bordalo, Gennaioli, Ma, Shleifer (2020), Augenblick, Lazarus, Thaler (2024), Ba, Bohren, Imas (2024), Kwon and Tang (2024)

Under- and over-reaction

	Experiments	Surveys	Markets
Underreaction	Conservatism	(IND.) Near-term earnings and interest rates (CNS.) Most economic variables	Price reaction to earnings news
Overreaction	Representative- ness; time-series forecasts; overconfidence	(IND.) A majority of variables (CNS.) Long-term earnings growth	Excess volatility; value premium

Roadmap

- beliefs
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- preferences
 - gain-loss utility and prospect theory
- the cognitive turn in behavioral economics
 - cognitive foundations of beliefs and preferences

Gain-loss utility and prospect theory

- traditional models assume that investors make decisions under risk according to the Expected Utility framework
- however, decades of laboratory research has found that Expected Utility is not a very accurate description of choice under risk
- many "non-EU" models try to capture people's decisions more accurately
 - prospect theory, due to Kahneman and Tversky (1979, 1992), is by far the most influential

Prospect theory

Four elements:

Reference dependence

• people derive utility from gains and losses

Loss aversion

• they are much more sensitive to potential losses than to potential gains

Diminishing sensitivity

- people are risk averse over moderate-probability gains
 - e.g., prefer \$500 to a 50% chance of \$1000
- but risk-seeking over moderate-probability losses
 - e.g., prefer a 50% chance of losing \$1000 to losing \$500 for sure

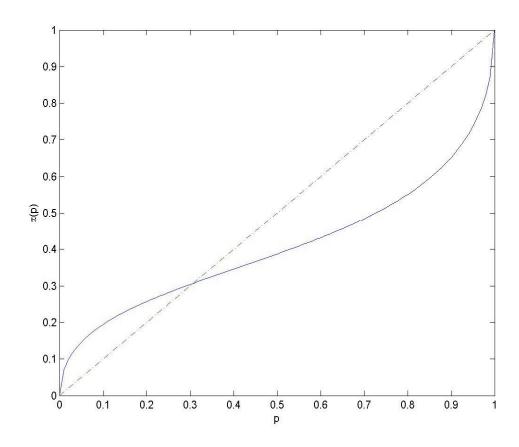
Prospect theory

Probability weighting

- people weight outcomes not with objective probabilities but rather with transformed probabilities that overweight low-probability outcomes
 - e.g., for the gamble "win \$100 with probability 5%," the typical person states a certainty equivalent higher than \$5

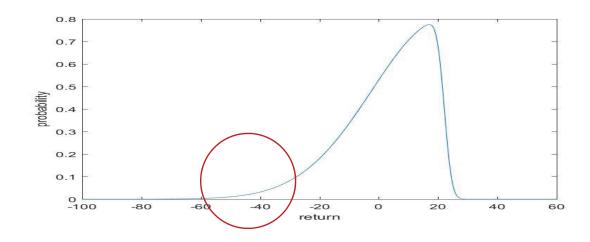
Prospect theory

Probability weighting



Prospect theory: Aggregate stock market

- here, the "gains" and "losses" are typically taken to be annual changes in financial wealth
- prospect theory then predicts a very substantial equity premium
 - due to loss aversion (Benartzi and Thaler, 1995; Barberis, Huang, Santos, 2001)
 - but also due to probability weighting, as the returns of the aggregate stock market are negatively skewed (De Giorgi and Legg, 2012)



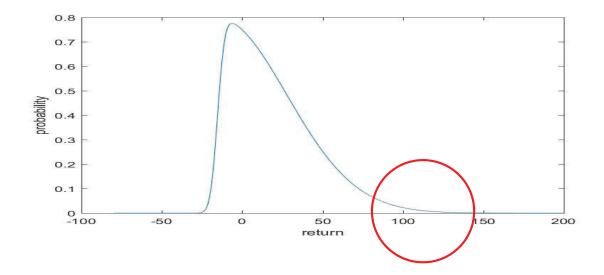
Prospect theory: The cross-section

- here, the "gains" and "losses" are typically taken to be gains and losses in the value of individual stock positions
 - defining them instead as changes in financial wealth leads to qualitatively similar results
- prospect theory then predicts that the average return of a stock will be determined by:
 - its return volatility, including idiosyncratic volatility
 - its return skewness, including idiosyncratic skewness
 - the average capital gain or loss across investors holding the stock (the "capital gain overhang")

average return = f(volatility(+), skewness(-), gain overhang(+))

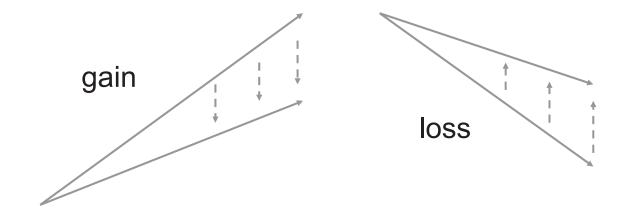
Prospect theory: The cross-section

- volatility matters due to loss aversion
- skewness matters due to probability weighting



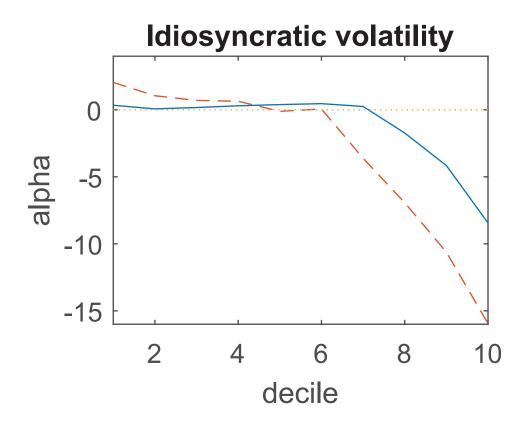
Prospect theory: The cross-section

- capital gain overhang matters due to diminishing sensitivity
 - Grinblatt and Han (2005)



Prospect theory: The cross-section

- Barberis, Jin, Wang (2021) show that this framework can help explain 14 of 23 prominent anomalies
- e.g., the volatility, distress, momentum, profitability, and issuance anomalies



Prospect theory: Open question

- the elements of prospect theory are increasingly being seen as reducedform ways of capturing risk attitudes that are actually driven by deeper psychological forces
 - e.g., loss aversion
 - e.g., probability weighting
- how does this change our interpretation of the various applications above, and the way we model them?

Overview

Major frameworks in behavioral asset pricing

• limits to arbitrage

Beliefs:

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Preferences:

• gain-loss utility and prospect theory *

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 - cognitive foundations of beliefs and preferences

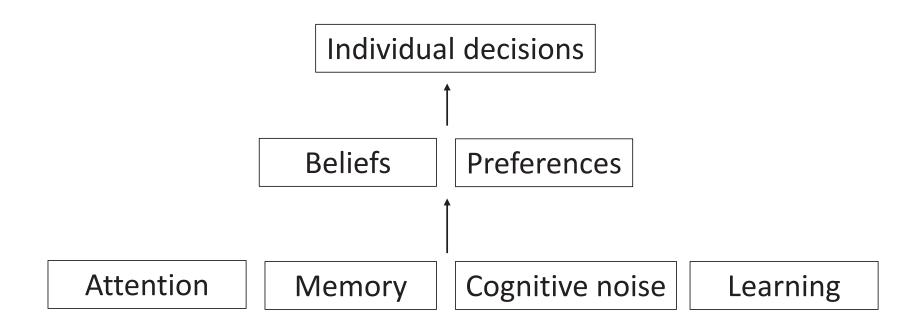
The cognitive turn in Behavioral Economics

- for the past 30 years, we have tried to make sense of financial phenomena by applying the psychology of *beliefs* and *preferences*
 - "high-level" psychology studied by Kahneman, Tversky, and others
- in the past five years, a new line of research has sought to understand the cognitive foundations of these beliefs and preferences
- in the remainder of the talk, I review some of this research, and comment on its potential

The cognitive turn in Behavioral Economics

- there are several strands to the work on cognitive foundations
 - cognitive uncertainty
 - memory
 - attention
 - complexity
 - reinforcement learning

The cognitive turn in Behavioral Economics



- cognitive uncertainty is a person's subjective uncertainty as to what decision is the right one, or what belief is the correct one
 - e.g., they don't know their true preferences, struggle to combine utils and probabilities, or imperfectly perceive the problem
 - e.g., they don't know Bayes' rule, or have trouble implementing it
- in this situation, Enke and Graeber (2023) propose that we can model a person's behavior as follows
 - they have a prior about the right action to take a "default action" they would take in the absence of any deliberation
 - they receive a noisy *signal* of the right action
 - and then combine the two in a Bayesian fashion

More formally:

- suppose that
 - the optimal action is $a^*(\theta)$, where θ is a payoff-relevant parameter
 - the prior about the right action is drawn from $N(a_d, \sigma_0^2)$
 - the noisy signal of the optimal action, $s(\theta)$, is drawn from $N(a^*(\theta), \sigma^2)$
- then, the action chosen is given by:

$$a(\theta) = \lambda s(\theta) + (1 - \lambda)a_d$$

$$E(a(\theta)) = \lambda a^*(\theta) + (1 - \lambda)a_d$$

$$\lambda = \frac{\sigma_0^2}{\sigma^2 + \sigma_0^2}$$

- this can provide a foundation for multiple aspects of beliefs and preferences
 - e.g., for evidence on belief updating
 - e.g., for probability weighting

Belief updating

• in the 1960s, psychologists began to do lab studies to see how people update their beliefs

Imagine two urns. Urn A has 700 blue chips and 300 green chips in it. Urn B has 300 blue chips and 700 green chips in it.

One of the urns is chosen at random and 12 chips are drawn from it; eight are blue and four are green.

What is the probability that the 12 chips were drawn from Urn A?

Belief updating

- people commonly give an answer in the range from 0.7 to 0.8
 - but the correct answer is 0.97!
- \bullet in this example, there is strong under-reaction to the signal
 - a finding known as "conservatism"
- but what is driving this phenomenon?

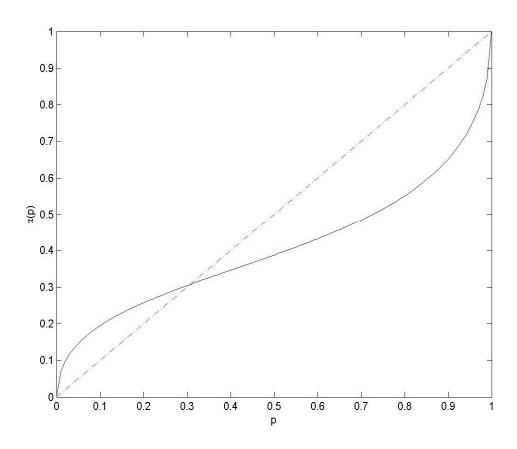
Belief updating

- under the cognitive uncertainty view, people are unsure what the right answer is and therefore cling to their prior the default probability estimate of 0.5
- Enke and Graeber (2023) run the updating experiment and record each participant's cognitive uncertainty
- they find that conservatism is present primarily when people report significant cognitive uncertainty

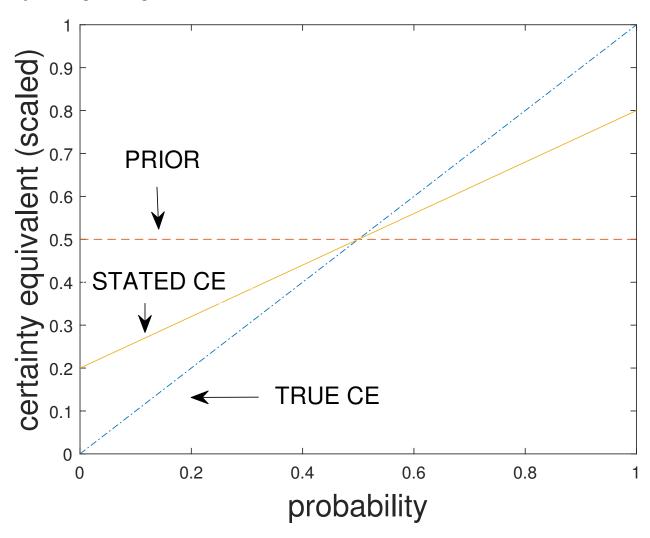
Probability weighting

- people weight outcomes not with objective probabilities, but rather with transformed probabilities that overweight low-probability outcomes
- the cognitive uncertainty view: people are unsure about their certainty equivalent for any gamble, and therefore shrink their stated equivalent toward a default value
- in an experiment, Enke and Graeber (2023) ask participants for their certainty equivalents for gambles, but also solicit levels of cognitive uncertainty
 - they find that probability weighting is much stronger when cognitive uncertainty is high

Probability weighting



Probability weighting



This framework has important implications: (1)

- the financial applications of probability weighting can be thought of, at a deeper level, as being driven in part by cognitive uncertainty
 - the overpricing of positively-skewed assets such as volatile stocks, distressed stocks, IPOs, and out-of-the-money options
- under cognitive uncertainty, probability weighting, and the preference for positive skewness it embodies, is not a *true* preference
 - but rather, a reflection of the brain's cognitive limits
- as a consequence, the buying of lottery-type assets is more of a mistake than previously thought

(2)

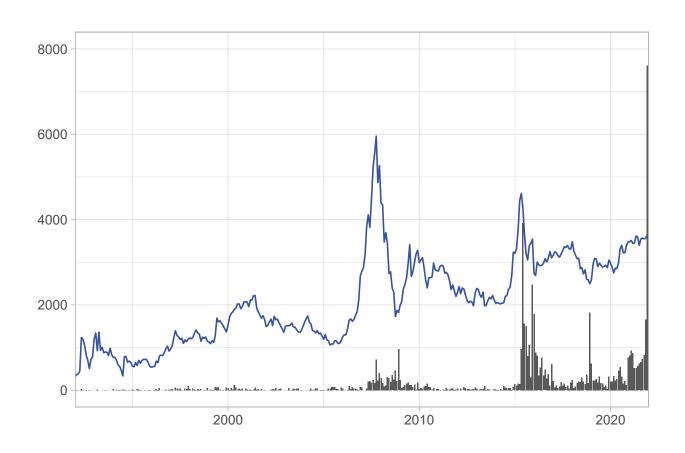
- cognitive uncertainty offers a deeper understanding of underreaction
- for years, we associated the apparent underreaction seen in post-earnings announcement drift with the evidence on conservatism in belief updating
 - but without knowing what drives conservatism, this does not give us a real understanding of PEAD
- if cognitive uncertainty is the root of conservatism, this immediately offers a concrete explanation for PEAD

(2), ctd.

- Barberis, Shleifer, Vishny (1998) present a model of under- and overreaction in financial markets based on "conservatism" and "representativeness"
- a more modern treatment would replace "conservatism" with "cognitive uncertainty"
 - Ba, Bohren, Imas (2024)

- a deeper study of human memory may help us better understand investor beliefs, e.g., about returns
- broad idea:
 - people recall past returns
 - and then simulate from the recalled returns to form expectations of future returns
 - Bordalo, Burro, Coffman, Gennaioli, Shleifer (2022); Jiang, Liu, Peng,
 Yan (2024)
- but which past returns do investors recall?
 - Jiang, Liu, Peng, Yan (2024) do a large-scale survey in China to find out
 - they find that investors recall *recent* episodes and *salient* episodes

Recalled episodes



Source: Jiang, Liu, Peng, Yan (2024)

This has two immediate implications:

- it offers a foundation for extrapolative beliefs about returns
- it suggests that our existing extrapolation and experience effect-based models of beliefs about returns are incomplete
 - they also need to account for a higher weight on *salient* past episodes

- to make additional progress, we can exploit the large scientific literature on memory
 - the book Foundations of Human Memory (Kahana, 2012) is a useful gateway to this research for economists
- Kahana, Diamond, Aka (2022) propose that there are five "laws" of human memory
 - law of recency
 - law of contiguity
 - law of similarity
 - law of primacy
 - law of repetition

- the law of similarity is particularly promising
- there is direct evidence for it in financial contexts
 - Jiang, Liu, Peng, Yan (2024) find that, following a good (bad) return, people are more likely to recall past episodes with good (bad) returns

Two implications:

(1)

- this further strengthens the memory-based foundation for extrapolative beliefs about returns
 - good recent returns will trigger recall of other episodes with good returns

(2)

- it also suggests that dramatic past episodes are more likely to be recalled when currently experiencing a dramatic event
- this points to a mechanism of overreaction to dramatic news
- Enke, Schwerter, Zimmermann (2024) provide experimental evidence for such a mechanism

Reinforcement learning

- thought to be one of the brain's fundamental learning mechanisms
 - take actions that have been rewarded in the past
 - don't take actions that have not been rewarded in the past
- three developments have made the framework ripe for use by economists
 - strong neural support for this learning mechanism
 - the emergence of computational models of reinforcement learning
 - the formulation of frameworks that combine reinforcement learning with economists' more traditional belief-based models

Reinforcement learning

- the reinforcement learning system computes $Q_t(s, a)$
 - the value of taking action a in state s and then continuing optimally from the next period on
- this quantity is updated through experience
 - take the action a in state s and observe what happens
 - if the reward is higher than expected, increase the estimate of Q(s,a)
 - if the reward is lower than expected, decrease the estimate of Q(s,a)

$$Q_{t+1}(s, a) = Q_t(s, a) + \alpha [r_{t+1} + \gamma \max_{a'} Q_t(s_{t+1}, a') - Q_t(s, a)]$$

Reinforcement learning

- Barberis and Jin (2023) implement this framework in the context of a simple portfolio allocation problem
- show that it can shed light on a range of observed investment behaviors
 - e.g., experience effects
 - e.g., the insensitivity of allocations to beliefs

The cognitive turn: Benefits

(1)

- it offers a deeper understanding of several financial applications
 - e.g., of financial phenomena previously associated with "conservatism" in belief updating
 - e.g., of phenomena associated with probability weighting

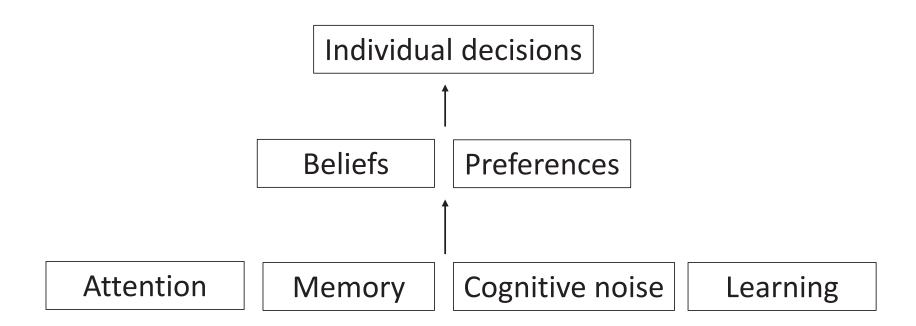
(2)

- the work on cognitive foundations offers a way of unifying an otherwise scattered set of assumptions about beliefs and preferences
 - seemingly different phenomena like conservatism and probability weighting can be traced to the same cognitive root

- work on cognitive foundations in behavioral economics has focused primarily on explaining beliefs and preferences
 - and less on applications
- an exciting agenda is to try to link the cognitive foundations to financial applications

But this agenda also faces some headwinds:
(1)

- by nature, the foundations involve low-level psychology that is further removed from applications in finance
- by contrast, the psychology of beliefs and preferences is easier to link to applications



(2)

- the lower-level psychology provides compelling foundations for beliefs and preferences
 - but the applications of these belief and preference assumptions are typically already known
 - as such, the low-level psychology can immediately offer a *re-interpretation* of these applications
 - but it would be more exciting to come up with new applications or new predictions

(3)

- as we work on cognitive foundations, we need to remain disciplined in our assumptions
- until five years ago, behavioral finance was quite disciplined
 - the center of gravity in the field was in a small number of concepts
 - over-extrapolation, overconfidence, prospect theory
- we need to make sure that the influx of many lower-level cognitive concepts into the field doesn't erode this discipline

The cognitive turn: A question

- does the cognitive turn in behavioral economics mean that we need to replace our models of investor behavior?
- in some cases, the answer is probably "yes"
- but even as we better understand cognitive foundations, we may sometimes still want to work with reduced-form models of beliefs and preferences
 - they are often easier to work with
 - they avoid taking a stand on which cognitive foundation is the right one
- examples:
 - return extrapolation
 - prospect theory

Roadmap

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Conclusion

- today, behavioral finance is a vibrant field
 - there is mounting evidence that behavioral finance mechanisms are central to many important financial phenomena
 - and more high-quality research in the area than ever before
- the outlook is promising for research in all three areas of application
 - asset prices
 - corporate finance
 - household finance
- and for research on both beliefs and preferences
 - with cognitive foundations playing an additional helpful role
- despite the progress, we have a long way to go
 - there are many important open questions

Resources

Readings

- Handbook of Behavioral Economics, 2018
 - "Psychology-based Models of Asset Prices and Trading Volume," (Barberis)
 - "Behavioral Corporate Finance" (Malmendier)
 - "Behavioral Household Finance" (Beshears, Choi, Laibson, Madrian)

Online videos

• American Economics Association Continuing Education, 2017, Lectures on Behavioral Finance (Malmendier, Barberis)

Resources

Summer schools

• Yale Summer School in Behavioral Finance

Conferences

- NBER Behavioral Finance Meeting (Fall and Spring)
 - live-streamed on Youtube