Behavioral Finance 3.0

Nicholas Barberis

Yale University

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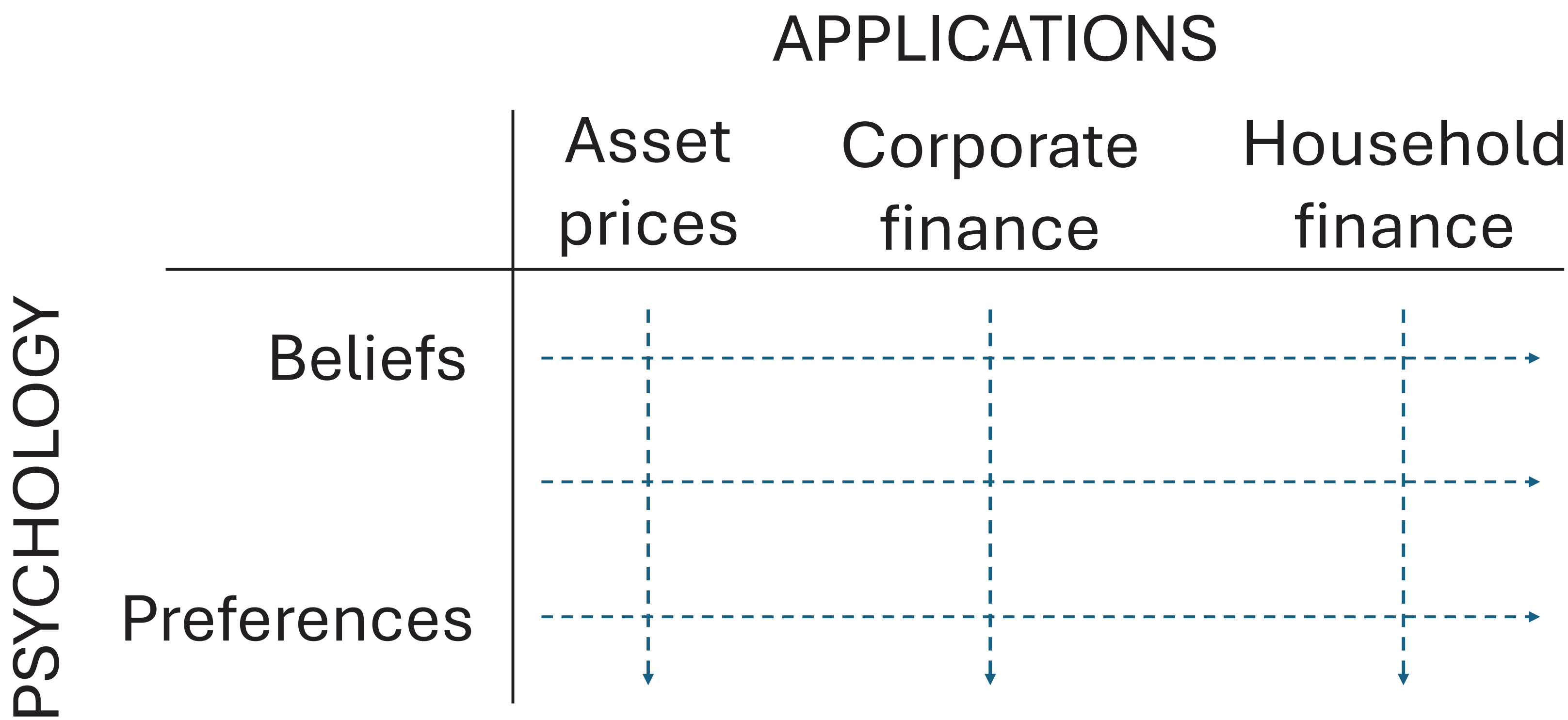
Overview

- the modern era in behavioral finance began in the 1980s
- the large body of work in the field since then can be summarized along two dimensions
  - the psychological assumption
  - the topic of application

Overview


APPLICATIONS
Asset prices
Corporate finance
Household finance
PSYCHOLOGY
Beliefs
Preferences

Overview

- there are three main areas of application
  - asset prices
  - corporate finance
  - household finance
- and two main types of psychological assumptions
  - about beliefs
  - about preferences
- I will briefly comment on each of these
  - and will then make some additional remarks on three topics of current interest
  - beliefs; cognitive foundations; AI and machine learning

Applications

Asset prices

- the first area of applications to be developed, starting in the 1980s and 1990s
  - many facts about prices were hard to understand in the traditional, rational paradigm
  - e.g., excess volatility and predictability, the cross-section of stock returns, tech-stock bubble, closed-end fund puzzle ...
- examples of early work
  - limits to arbitrage
  - noise-trader models
  - psychology-based models of asset prices
- this area has become much more active in the past decade
  - due to renewed attention to survey data

Applications

Corporate finance

- the second area of applications to be developed, in the 2000s
  - came later than asset pricing in part because of competition from rich, rational frameworks
- work includes:
  - rational managers responding to investor irrationality (Baker and Wurgler 2000, 2002, 2004)
  - irrational managers (Malmendier and Tate 2005, 2008)
  - behavioral credit cycles (Greenwood and Hanson 2013; Bordalo, Gennaioli, Shleifer 2018)
- recent research has branched out in new directions
  - social preferences of managers (Guenzel, Hamilton, Malmendier 2024)
  - health consequences for managers (Borgschulte, Guenzel, Liu, Malmendier 2024)

Applications

Household finance

- the last of the three areas of application to be developed, starting in the mid 2000s
  - due to the late arrival of large-scale datasets on household financial decision-making
- field was framed in John Campbell's 2006 Presidential Address
  - one exception: important earlier work by Brad Barber and Terrance Odean using brokerage data
- two lines of research
  - demonstrating the role of behavioral factors in several household decisions
  - prescriptive behavioral finance: helping people to make better decisions, e.g., through "Nudges"

Applications

Household finance, ctd.

- some have suggested that academics could do much more to help people make better decisions

  "How many people has [personal finance author] Dave Ramsey helped out of debt versus the average academic economist? It's a million to one."

Source: Personal finance author Morgan Housel, Freakonomics Radio, 2022

- one theme is that, when offering financial advice, academics should take more account of psychological factors that may impede adoption of the advice
  - Choi (2022)
- e.g., when giving advice on paying off debt

Psychological assumptions

Beliefs

- early models featured noise traders making random errors
  - De Long, Shleifer, Summers, Waldmann (1990)
- these were followed by explicitly psychological models of beliefs
  - Barberis, Shleifer, Vishny (1998), Daniel, Hirshleifer, Subrahmanyam (1998)
  - heavily inspired by the work of Daniel Kahneman and Amos Tversky
  - models of representativeness, overconfidence, ...
- beliefs have become a much bigger focus of research in the past decade
  - due to renewed attention to survey data
- progress has been rapid, but may be slower going forward
  - important questions remain, but the low-hanging fruit have been picked

Psychological assumptions

Preferences

- steady work on this topic starting in the 1990s
- due to the influence of Kahneman and Tversky, much of the focus has been on aspects of prospect theory
  - utility from gains and losses, loss aversion, diminishing sensitivity, probability weighting
- this line of research may be ready for "disruption"
  - the past few years have seen a lot of work on cognitive foundations of the elements of prospect theory
  - what we call "preferences" may not be true preferences

Specific topics

Additional thoughts on three topics of current interest:

- beliefs
- cognitive foundations
- artificial intelligence (AI) and machine learning (ML)

Beliefs

Two prominent ideas:

- extrapolative beliefs about returns
  - beliefs about an asset's future return are a positive function of its recent past returns
  - specifically, a weighted average of its past returns, with positive and declining weights on more distant past returns
  - after good (bad) returns, people over-estimate (under-estimate) future returns
- beliefs about future earnings growth that overreact to past news

Beliefs

Open questions about return extrapolation

- what is the source of return extrapolation?
- what determines the relative weight people put on recent vs. distant past returns when forming expectations?
  - do these weights vary over time, and why?
- what should we make of the evidence that portfolios are insensitive to beliefs?
  - Giglio, Maggiori, Stroebel, Utkus (2021)
- is this investor behavior really about beliefs?
  - or does it reflect a different, non-belief mechanism?
  - e.g., observational learning?

Beliefs

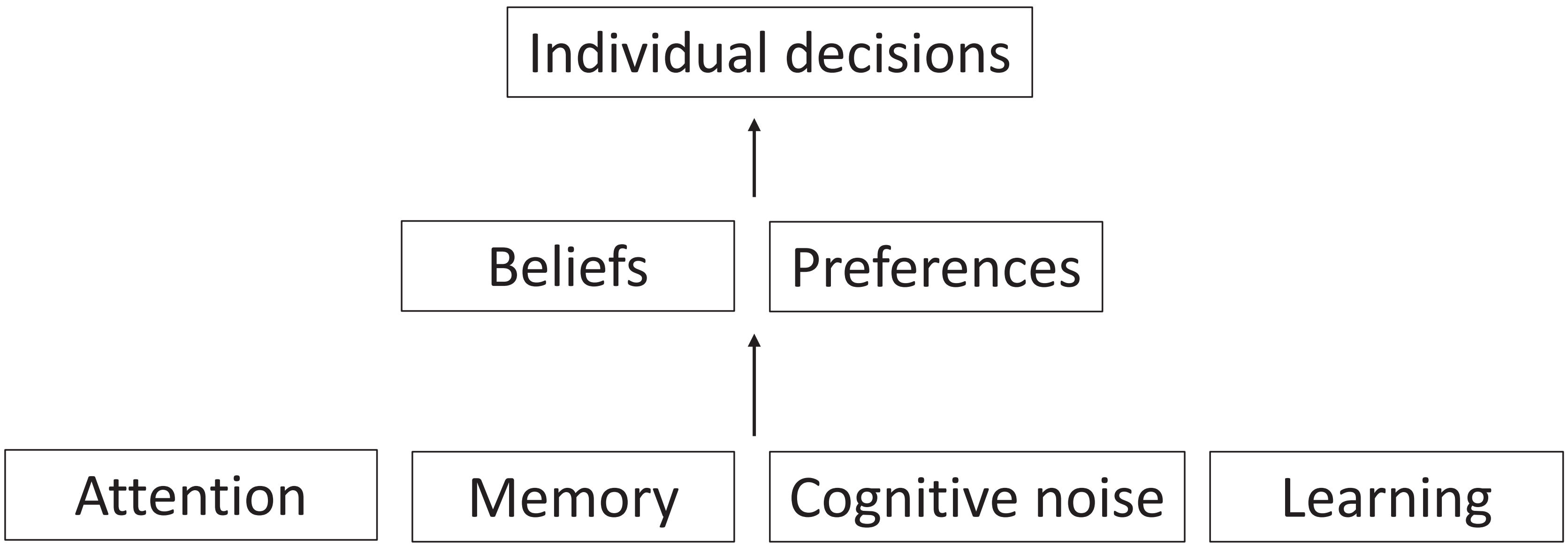
Open questions about earnings growth expectations that overreact

- which news are people overreacting to, and why?
- how does the overreaction seen in *long*-term earnings growth forecasts fit with the apparent underreaction in *short*-term earnings forecasts?
- are earnings growth expectations driving prices, or are prices driving the earnings growth expectations?

Cognitive foundations

- for the past 30 years, we have tried to make sense of financial phenomena by applying the psychology of *beliefs* and *preferences*
- in the past five years, a new line of research has sought to understand the cognitive foundations of these beliefs and preferences
- there are several strands to this work
  - cognitive uncertainty
  - memory
  - attention
  - complexity
  - reinforcement learning

Cognitive foundations



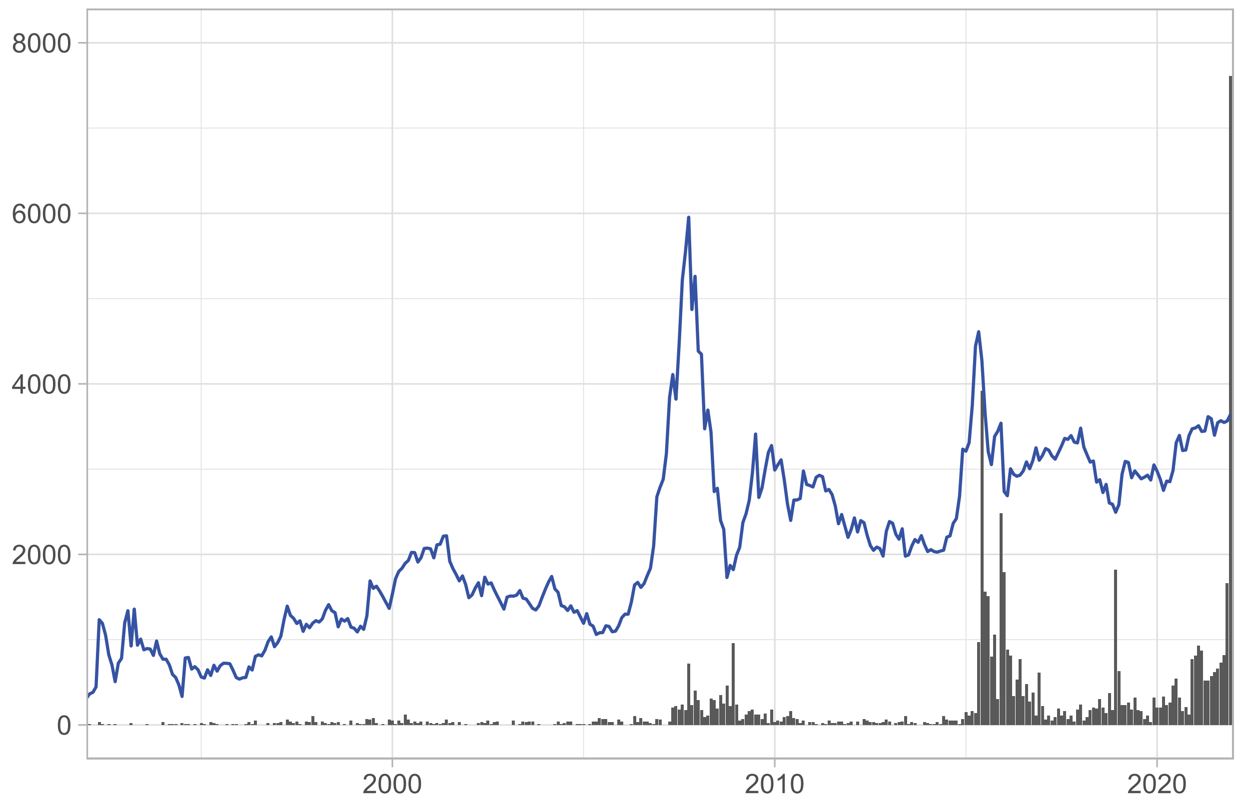
Cognitive foundations

Memory

- 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

Cognitive foundations

Recalled episodes



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

Cognitive foundations

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

Cognitive foundations

Benefits to studying foundations

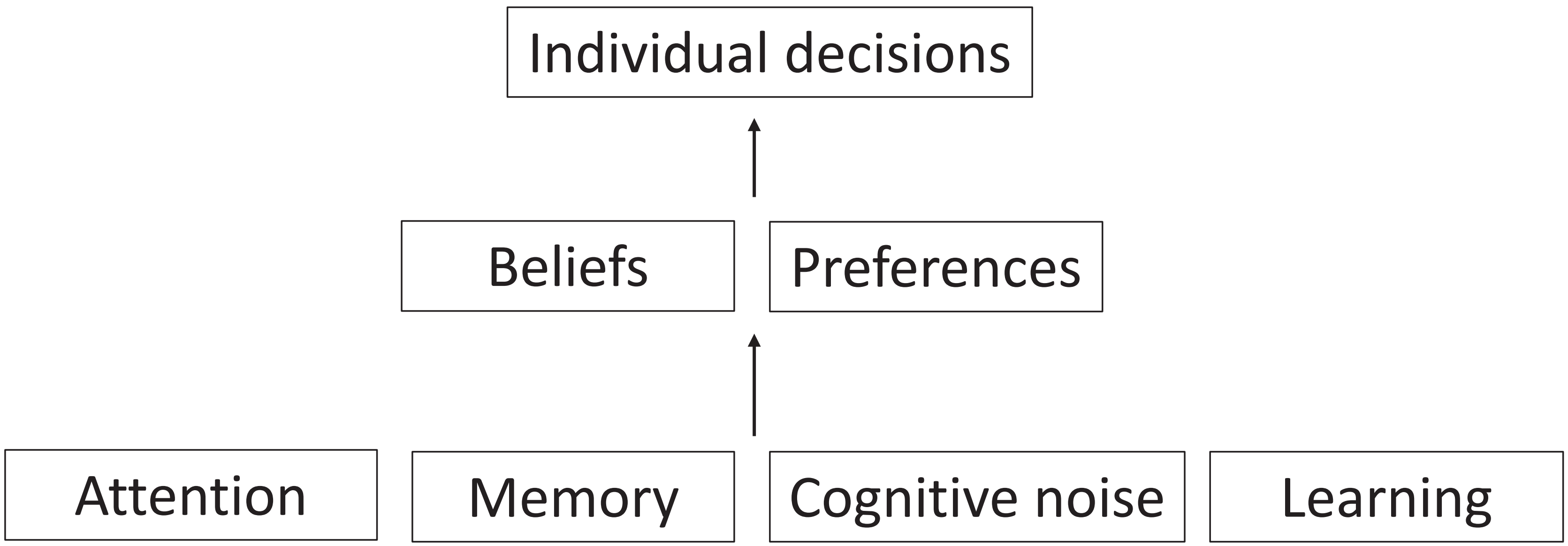
- they lead to a deeper understanding of several financial applications
- they offer a way of unifying an otherwise scattered set of assumptions about beliefs and preferences

Cognitive foundations

Challenges to studying foundations

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

Cognitive foundations



Cognitive foundations

- does the work on cognitive foundations 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

AI and machine learning

Four types of applications:

1. Use ML to uncover new patterns of return predictability

Example: *Gu, Kelly, Xiu (2020)*

AI and machine learning

2. Use AI to generate a proxy for people's expectations

Example: *Bybee (2024), "The Ghost in the Machine..."*

- inputs a large number of Wall Street Journal articles to ChatGPT and, for each one, asks it:
  - "*Do you think this news will increase or decrease [economic variable]*"
- uses the responses to construct time series of economic expectations
- finds that these series share the properties of human expectations from surveys

AI and machine learning

3. Use AI to summarize complex information sets

Example: *Zhou (2024), "Active Mutual Funds and Media Narratives"*

- examines how investors respond to news
- inputs 1.5 million Wall Street Journal articles into ChatGPT and asks it to boil them down to a few dozen topics, associating each article with a topic
  - can then measure the attention given to each topic at each moment of time
  - also ask ChatGPT to rate the "sentiment" of each article
- then examine mutual funds' exposure to each topic over time

AI and machine learning

Example: *Ke (2024), "Analysts' Belief Formation in their Own Words"*

- seeks to understand how analysts form beliefs by way of the text in their reports
- uses a Large Language Model to summarize each of 1.2 million analyst reports
  - factual information about nine economic and financial variables
  - subjective beliefs about future firm performance
- looks at how quantitative forecasts and subjective beliefs depend on past factual information

AI and machine learning

Example: *Sarkar (2024), "Economic Representations"*

- wants to understand how people "think about" a firm, based on descriptions in the news
- uses news articles from Dow Jones Newswires, in combination with specially-trained language models, to obtain a representation of each firm
  - a vector that structures the information in language data
- finds that changes in valuation depend both on changes in valuation conditional on a representation
  - *and* on changes in representation
- also finds that changes in representation are mean-reverting
  - e.g., due to excessive attention to certain features, or to managerial persuasion

AI and machine learning

4. ML algorithms may overlap with those used by the human brain

Example: *Reinforcement learning*

- an ML algorithm that can solve complex dynamic problems
  - but also an algorithm that the human brain is thought to use
- economic applications are studied by Camerer and Ho (1999) and Barberis and Jin (2023)
- 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

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)

Summer schools

- Yale Summer School in Behavioral Finance

Resources

Conferences

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

And also:

- today, 2.30 pm in the Marriott Marquis!
  - "*Behavioral Finance at 40: Progress, Open Questions, and New Directions*"