Cognitive Biases

So far we've done:⇌

- "quasi-maximization" models that posit that at each moment in time a person is constrained-maximizing a well-defined utility function—just not the 'right' one.⇌

Now we'll do:⇌

- "quasi-Bayesian" models that posit a person is maximizing utility w.r.t. to beliefs that are in error, as modeled by some specific distortion of Bayesian information processing.⇌

What does the 'quasi' mean?⇌

- resembling; seeming; virtual; some, but not all, the features of

↬

- Before outlining errors, an aside ...

An aside on Managed Funds

- Suppose that you observed the following advertisement, in its entirety from a brokerage firm that will advise you on stocks:

"We value you, the client."

- What would you infer from this statement?

Cognitive Biases

- Without answering, let me make up some statistics (my version of empirical work ...) to make it clear.

Suppose 813 funds in U.S. in business at least the last 2 quarters, and

- .... 202 of them have ads saying
  - "We've beat the market average the last 2 quarters"
- .... 197 of them have ads saying
  - "We beat the market average the last quarter"
- .... 414 of them have ads saying
  - "We value you, the customer"

Now what do you think "We value you, the customer" means?

- It probably means that the mutual fund lost to the market last quarter.

Cognitive Biases

Was my question unfair?

- Maybe, maybe not.
- I didn't give you context/comparison.
- But not at all clear that the mutual fund would give you context.
- Without context, you don't know what to make of it.
  - Maybe salient if you see lots of the other ads; depends.
- Those that have something good to report, report.
- Those who don't, tell you how valuable you are to them.

Cognitive Biases

What signals people "pay attention to" may play a huge role in inference.

- But not just whether data hits your eyeballs,
  - or even your decisionmaking
- Do you absorb the *logical implications* of what you've seen?
- But whether you focus on all the questions you should focus on.
- We'll get at a bit at end.

Cognitive Biases

- But this wasn't really the topic I wanted to pursue

Suppose that all 414 of them saying they value you lost to the market average last quarter.

- An easy question to segue into next topic:

What obvious inference would you make from the three different ads.

- What is the quality of a fund that advertises it has beat the market two quarters in a row vs. the other two categories?

Probably ... they are of the same quality. They are all probably average.

- Why?

Very close to the distribution you'd get if they were all average.

- Randomly 25% would beat market twice in a row, 50% would lose the last quarter.

I haven't given much to go on, and probably there is a clever way to infer difference in quality.

- But I'd argue these statistics are suggestive that all funds are average.

Cognitive Biases

What if you did not easily know the distribution of performances?

- What should you infer from seeing good recent performance?
- Should you pay to get good evidence on recent performance?

We happen to know such distributions are true.

- But what if investors don't?

It could be argued (and it would be correct) that they *should* know

- Logic of financial markets should tell them not to search for patterns

Final lecture topics related to that.

- Will turn out (among other lessons):
  - Often see patterns where there are none (cognitive biases),
  - and where you should know a priori that there are none! (cursedness)

Enough of me doing finance. Matthew's Next 3 Lectures:

Cognitive Biases

1. Errors in Probabilistic Reasoning $\rightleftharpoons$
    1. The Great Under-Extractions $\rightleftharpoons$
    2. Some Basic Errors $\rightleftharpoons$
        1. LSN, NBLLN, and SSN $\rightleftharpoons$
        2. Base-Rate Neglect (and Confirmation Bias) $\rightleftharpoons$
        3. **Economic implications** (Hey! Loss aversion again!)
            1. The great incompletenesses of existing model/evidence
    3. Difficult features of non-Bayesian models
        1. Dynamic inconsistency, conjunction violations, "framing" $\rightleftharpoons$
        2. **Question-Dependent/Elicitation-Dependent Beliefs** $\rightleftharpoons$
    4. Features of Bayesian Reasoning (that may not hold) $\rightleftharpoons$
2. Inattention (notice the missing adjective...) $\rightleftharpoons$
    1. *Subjectively* rational inattention and **perceived benefits** of attention.
    2. **What are we thinking when we're not paying attention**

$\looparrowright$

Cognitive Biases

1. (3) Manski Mania! $\rightleftharpoons$
   1. Measuring Beliefs ... is obviously right right , starting (too slowly)$\rightleftharpoons$
   2. Do it *very* carefully (without nihilism or obstructionism)$\rightleftharpoons$
2. (4) Shortcomings in social inference$\rightleftharpoons$
   1. Inversion Neglect, Economics-Neglect, and Non-Structural Models$\rightleftharpoons$
   2. Redundancy Neglect

Cognitive Biases

- Relevant papers:
  - "Base-Rate Neglect" with Dan Benjamin and Aaron Bodoh-Creed (unfinished)
  - "Misconceptions of Chance: Evidence from an Integrated Experiment," with Dan Benjamin and Don Moore
  - "Belief Movement, Uncertainty Reduction, and Rational Updating," with Ned Augenblick
  - "Inference By Believers in the Law of Small Numbers"
  - "The Gambler's and Hot-Hand Fallacies" with Dimitri Vayanos
  - "A Model of Non-Belief in the Law of Large Numbers," with Dan Benjamin and Collin Raymond
- 1st Fundamental Theorem of my Working Papers:
  - Look on coauthors' websites!
- 2nd Fundamental Theorem of my Working Papers
  - They all build off of Kahneman and Tversky, and others! Read all of those
  - **Griffin and Tversky**, **Tversky and Koehler**

Cognitive Biases

Researchers have tended to neglect under-extractions/underconfidence, not realizing that it is variously a confound for, an enabler of, or the foundation for 'over-extraction' errors. $\rightleftharpoons$

- Over-infering from own ideas vs. under-infering from market prices. $\rightleftharpoons$
- Over-weighting your friend's auto mishaps vs. underweighting consumer reports. $\rightleftharpoons$

Researchers see over-interpretation of some focused-upon information rather than the under-interpretation of the unfocused-upon information. $\rightleftharpoons$

- Although now with so much attention to rational inattention, subculture of economists who do the opposite.

Deconstructing Overconfidence

Now I'm talking only about "over-certain beliefs"/over-precision

- Not other types in the Moore pantheon of overconfidences
  - E.g., Odean/Malmendier stuff of people thinking they are good.
  - Except insofar as it comes from over-certain beliefs
  - (Or generates over-certain beliefs?)

Arguments I would make

- Overconfidence is not a thing
  - As a general propensity

Arguments I would also make (not today)

- And even if it were a thing, it wouldn't be a thing.
- Overconfidence *can't* be a thing
- Well, it could be a thing
- And it's probably a very important thing

Overconfidence Isn't a Thing⇌

- Psychologists for 40 years and Economists for 20 years:⇌
  - A fixation on the (alleged) propensity for over-strong, relative to normative, beliefs.⇌
  - (Edwards $\longrightarrow$ Tversky?)⇌
  - Fair characterization? Seems so for BE-familiar JDM.⇌
- Although often little more than loose motivation, with definition differing paper to paper, economists often invoke notions of over-precision and over-inference-from-info, in many models.
  - Experimental economics & consumer contracts⇌
  - And in finance galore⇌ (where I believe neither as necessary, nor as sufficient, nor as meaningful as people think)⇌

But it is *not* universally true that people's beliefs, or interpretation of evidence, are non-normatively strong.⇌

- **Often non-normatively weak.**⇌

Many combos of circumstances and biases yield over-strong beliefs.

Deconstructing Overconfidence

I'll mention the formal models (that build from uncited Psych research) of updating in binary symmetric settings:

- Overconfidence/overstrong beliefs/over-updating from ...
  - Confirmation Bias (Rabin and Schrag, 1999)
  - Inference from LSN (Rabin, 2002, and Rabin-Vayanos, 2010)
  - Redundancy neglect in social inference/redundancy neglect (Eyster and Rabin, 2010, 2014)
- Underconfidence/understrong beliefs/under-updating from ...
  - "Cursedness"/disagreement neglect (Eyster and Rabin, 2005; Esponda, 2008; Eyster, Rabin, and Vayanos, 2016)
  - NBLLN (Benjamin, Rabin, and Raymond, 2015; Benjamin, Moore, and Rabin)
  - Base-rate neglect (Benjamin, Bodoh-Creed, and Rabin, "in progress")

Cognitive Biases

Approach building from research under the broad heading of “judgment and decisionmaking" (JDM)$\rightleftharpoons$

- How people’s probabilistic judgments might be distorted.$\rightleftharpoons$
- Probabilistic reasoning *not* random or totally irrational.$\rightleftharpoons$
- Human rationality, not superhuman rationality or subhuman idiocy.$\rightleftharpoons$

Types of formal bias models:$\rightleftharpoons$ “Misfunctional Bayesian”: $\rightleftharpoons$

- Use conditionals and priors, but with wrong functional form.$\rightleftharpoons$
    - Base-rate neglect.$\rightleftharpoons$

But many models of errors stick closer:$\rightleftharpoons$ Quasi–Bayesian Models$\rightleftharpoons$

- Assume people engage in putatively proper Bayesian updating.$\rightleftharpoons$
- But specify a precise way in which they either mis-observe or mis-understand how that evidence relates to the hypotheses.$\rightleftharpoons$
- Examine the implications of Bayesian updating given the error.

Cognitive Biases

- Two categories of quasi-Bayesian

Warped-Model Bayesian:

- False (but internally consistent) model of how signals are generated.
  - Barberis-Shleifer-Vishny (1998),
  - Rabin (2002), Rabin and Vayanos (2010),

Information-Misreading Bayesian:

- Right model, but misread signals.
  - Rabin and Schrag (1999)
  - Mullainathan (2002).

Cognitive Biases

Different combinations of bias and environment can lead to:$\rightleftharpoons$

- Overinference/overconfidence$\rightleftharpoons$ ... infer "too much" from information.$\rightleftharpoons$
- Underinference/underconfidence$\rightleftharpoons$ ... people infer too little$\rightleftharpoons$

These are **manifestations** of biases, not types of biases.$\rightleftharpoons$

- Psychologists first, now economists: talk like direction of beliefs vs. appropriate Bayesian are general tendencies.$\rightleftharpoons$
- Now too many researchers pitch generic "Overconfidence"/overinference$\rightleftharpoons$
- There is no general tendency towards over- or under-inference$\rightleftharpoons$
    - And no great definition outside of binary questions

Sampling Biases$_{\rightleftharpoons}$

Now review just subset of biases$_{\rightleftharpoons}$

- **The** (!) important biases in the simplest setting:$_{\rightleftharpoons}$
- Take an *i.i.d.* process *should* know is *i.i.d.*, or at some level *do* know.$_{\rightleftharpoons}$
- Prototype: (possibly biased) coin yields h in proportion $\theta \in (0, 1)$.$_{\rightleftharpoons}$
  - What are beliefs about samples given θ?$_{\rightleftharpoons}$
  - What do people infer about θ from samples?

$\looparrowright$

Cognitive Biases

In coins & urns, essentially 3 biases:

- Law of Small Numbers and Gambler's Fallacy:
  - Tversky and Kahneman (1971): exaggerated belief that small samples and short streaks will reflect population mean.
- Non-belief in LLN:
  - Very large psychology literature (1965ish-1975ish) on "conservatism."
  - BRR (2012) meta-analysis: under-inference from non-small samples.
- Base-Rate Neglect
  - Underweighting priors when processing new information

Cognitive Biases

LSN, GF, and NBLLN are, as primitives, distortions in beliefs about likelihood of different samples being generated from given θ.

- Bias: instead of Bayesian $p(s|\theta)$, some $\widetilde{p}(s|\theta)$.
  - Rabin (2002), RV (2010), & BRR (2012)
- These theories predict misinference from assuming

$$p(\theta|s) = \frac{\widetilde{p}(s|\theta)p(\theta)}{\sum_{\theta'} \widetilde{p}(s|\theta')p(\theta')}.$$

- Ignore BRN for now
- Seems like is close to true:
  - *Except* for BRN, inference errors more or less accord with Bayesian inference applied to sample-prediction errors.

Now: evidence on ways $\widetilde{p}(s|\theta) \neq p(s|\theta)$.

- GF/LSN, NBLLN $\rightarrow$ SSN
- We'll come back to inference problems.

Gambler's Fallacy

- Evidence in BMR (2013, 2016)
- But better evidence from earlier:
- Maryland State Pick-Three Lottery
    - Pari-mutuel Betting provides good data: Infer numbers from odds created, AND have people losing money from bad beliefs (many prediction tasks i.i.d. world means no wrong behavior).
    - Bet 50 cents on day's 3-digit draw, and winners get 52% of total bets (this is typical state cut).
    - If $\frac{1}{10}$% people bet on a number, it pays \$260. More than \$260 means $< \frac{1}{10}$% bet on it; less than \$260 means $> \frac{1}{10}$%.

Cognitive Biases

Terrel (1994) reported average winnings as function of when the last time that number won

Within Week:	*\$349*
1-2 Weeks ago:	*\$349*
2-3 Weeks ago:	*\$308*
3-8 Weeks ago:	*\$301*
Not Within 8 Weeks:	*\$260*
Overall:	*\$262*

E.g., 25% fewer bet on number if won in last 2 weeks. Expected return 34% higher betting on recent winners than recent losers.

What do people predict about samples?

KT (1973): How likely different proportions heads in a 50/50 coin?

		45-55%	75-85%
$N = 10$	true	25%	4%
	people think	20%	6%
$N = 100$	true	68%	$\approx 0\%$
	people think	22%	5%
$N = 1000$	true	$\approx 100\%$	$\approx 0\%$
	people think	21%	5%

Cognitive Biases

- Already by $N = 10$, distribution too dispersed.
  - By $N = 1000$, it is extreme.
- Now: BMR (2013,2016) replicate, get very similar results, but incentivized and frequentist.
- But we have design feature that changes interpretation of some
- Also, evidence for GF won't discuss today
  - (After 9 heads, people expect $\frac{2}{3}$ chance tails.)

Posted 2013 version, but now report updated data too.

- But first, aside central to our experiment

Cognitive Biases

Probabilities {0-909,910,911-1000}?$_{\rightleftharpoons}$ Mean {79%,7%,14%}, Median {91%,1%,6%}

$\rightleftharpoons$

- People don't realize that 911-1,000 never happens.

$\looparrowright$

Cognitive Biases

But do even *we* appreciated thinness of tails?$\rightleftharpoons$

- True fact: $p(910) > 5 \cdot p(911 - 1000)$.$\rightleftharpoons$ (Who knew?)$\rightleftharpoons$
- (Question to contemplate: is the bell curve as optical illusion?)$\rightleftharpoons$

How is our intuition on CLT/LLN?$\rightleftharpoons$

- Probability that
    - Exactly 60% of 40 flips heads? $\rightleftharpoons$
    - Exactly 90% of 40 flips?$\rightleftharpoons$
    - Both very small ...$\rightleftharpoons$ but how small? How compare?$\rightleftharpoons$
- Betting your intuition is bad / off. What is $\frac{prob(36/40)}{prob(24/40)}$? $\rightleftharpoons$
    - About $\frac{1}{680{,}000}$. $\rightleftharpoons$
    - Not knowing exact $\longrightarrow$ "bound error";$\rightleftharpoons$
    - finding this shocking $\longrightarrow$ "astray error".

Cognitive Biases

Also elicited beliefs about sample size 1,000,000

- First time ever such beliefs have been elicited?
- DB and MR astonished by results. **"Nuance"** not reporting today
- Non-belief in LLN we think is right, but vigorous disbelief less true than we thought?

Cognitive Biases

LSN, GF, and NBLLN as primitives in distortions in beliefs about likelihood of different samples being generated from given θ.

- These theories predict misinference from assuming

$$p(\theta|s) = \frac{\widetilde{p}(s|\theta)p(\theta)}{\sum_{\theta'} \widetilde{p}(s|\theta')p(\theta')}.$$

Now: evidence on LSN, NBLLN $\longrightarrow$ SSN in inference problems.

- Ignore BRN for now

Evidence on LSN, NBLLN, & SSN in Inference

Beautiful experiment: Griffin and Tversky (1992).

- "Imagine that you are spinning a coin, and recording how often the coin lands heads and how often the coin lands tails. Unlike tossing, which (on average) yields an equal number of heads and tails, spinning a coin leads to a bias favoring one side or the other because of slight imperfections on the rim of the coin (and an uneven distribution of mass). Now imagine that you know that this bias is $3/5$. It tends to land on one side 3 out of 5 times. But you do not know if this bias is in favor of heads or in favor of tails."

Tempting model to capture both: Sample-Size Neglect.

- Kahneman & Tversky (1973) and Griffin and Tversky (1992):
  - People attend to proportions, not sample size.
  - Intuitive model, **not far off**.

Cognitive Biases

Two possible $i.i.d.$ coins each with prob $= .5$: $\rightleftharpoons$

- $\pi(h|\cdot) = \frac{3}{5}$ coin and a $\pi(h|\cdot) = \frac{2}{5}$ coin$\rightleftharpoons$
- Observe a set of flips h, t.$\rightleftharpoons$
- Bayes' Law says $\frac{\pi(\theta|h,t)}{\pi(1-\theta|h,t)} \equiv l(h,t) = \left(\frac{3}{2}\right)^{h-t}$.$\rightleftharpoons$
- So Bayesian inference from (h, t) depends solely on $h - t$.$\rightleftharpoons$
- That's all well and good ... but:$\rightleftharpoons$
  - Only geeks think that way.$\rightleftharpoons$
  - And only when paying attention.$\rightleftharpoons$
  - People in fact base beliefs on how close $\frac{h}{h+t}$ looks to $\frac{3}{5}$ vs. $\frac{2}{5}$.$\rightleftharpoons$

A tale of two tables **presenting the same data**:

$\hookrightarrow$

Over-infer from small samples, under-infer from large samples.

Sample of (h,t)	$h+t$	$h-t$	Median $P(\theta = \frac{3}{5} \| h, t)$	Proper $B(\theta = \frac{3}{5} \|$
5,0	5	5	.92	.88
7,2	9	5	.77	.88
11,6	17	5	.64	.88
19,14	33	5	.60	.88
3,0	3	3	.85	.77
4,1	5	3	.80	.77
6,3	9	3	.67	.77
10,7	17	3	.60	.77
2,1	3	1	.63	.60
3,2	5	1	.60	.60
5,4	9	1	.55	.60
9,8	17	1	.54	.60

Meta-Lesson: **proportional thinking**$_{\rightleftharpoons}$

Sample of (h,t)	% heads	Median $P(\theta = \frac{3}{5}\|h, t)$	Proper $B(\theta = \frac{3}{5}\|h, t)$
5,0	100%	.92	.88
3,0	100%	.85	.77
4,1	80%	.80	.77
7,2	78%	.77	.88
6,3	67%	.67	.77
2,1	67%	.63	.60
11,6	65%	.60	.88
3,2	**60%**	**.60**	**.60**
10,7	**59%**	**.60**	**.77**
19,14	**58%**	**.60**	**.88**
5,4	55%	.55	.60
9,8	53%	.54	.60

$\looparrowright$

Cognitive Biases

Meta-Lesson: **proportional thinking** $\rightleftharpoons$

- Basing on proportions leads to “Sample-Size Neglect”: $\rightleftharpoons$

Under-using sample size. $\rightleftharpoons$

- If double h and t, double $h - t$
- hence change a Bayesian's inference. $\rightleftharpoons$
- But you won't change $\frac{h}{h+t}$. $\rightleftharpoons$
  - So people infer same. $\rightleftharpoons$
- **Over-infer from small samples, under-infer from large samples.** $\rightleftharpoons$
- Discussion in BRR (2012) why don't model just as "SSN" $\rightleftharpoons$
- **Note:** sometimes underinference, underconfidence

Cognitive Biases

More attitude problem!

- Is thinking in terms of $h - t$ System 1 or System 2?
- Is thinking in terms of $\frac{h}{h-t}$ System 1 or System 2?
- And if we knew Sissy were using System X...
  - (whichever is the bad one)
    - Would we know how she uses sample size?

Whatever its conceptual usefulness and neuro-truth of system thinking...

- Severe danger of false consciousness.
- And empirical complacency.

Cognitive Biases

Some economic implications?

Implications of LSN?

- Rabin (2002) models: false belief by investors in the value of advice/managed funds may be LSN-related.
- People over-infer from short-run performance of mutual fund that its manager must be a genius.
- "Fictitious Variation":
  - When looking at global data, in fact might infer skill out there in investing when there is none.
- Rabin and Vayanos (2010) also explain other investment errors, such as under- and over-reaction and false belief in hot hands.
- More generally: How and when GF$\longrightarrow$ HH.

Implications of NBLLN? $\rightleftharpoons$

- People unconvinced by statistics. $\rightleftharpoons$
- And: NBLLN is underemphasized as a *necessary* enabler and almost-sure confound for "over-extraction" biases. $\rightleftharpoons$
    - NBLLN says under-infer from Consumer Reports data sets. $\rightleftharpoons$
    - Salience/vividness: infer too much from friend's bad (& costly) experience. $\rightleftharpoons$
    - But: even if over-weighted your friend by 500 times, still follow *Consumer Reports* if believe in LLN. $\rightleftharpoons$
    - Even the greats have been sort of mis-emphasizing their own results. $\rightleftharpoons$

I can't go a whole lecture without ... $\rightleftharpoons$ Loss Aversion!
$\looparrowright$

Cognitive Biases

Despite spotty presentation, big punchline from Projection Bias and Narrow Bracketing/Decision Neglect ...$\rightleftharpoons$

- Those two errors exacerbate loss aversion$\rightleftharpoons$

I would now add NBLLN as the

- Exacerbates risk/loss aversion:$\rightleftharpoons$
  - People exaggerate chance of losing from large number of better-than-fair bets.$\rightleftharpoons$
  - Not just about narrow bracketing.

$\looparrowright$

Applying NBLLN to Compound Risk

- Samuelson's colleague said he would reject a 50/50 bet to gain \$200/lose \$100, but accept 100 independent repetitions.
- Samuelson's (1962) theorem: Absent implausible wealth effects, a Tommy with expected-utility preferences over wealth takes $N \geq 1$ repetitions of a bet if and only if he will take one.
  - Intuition: If no wealth effects, EU/DMU(W) says prefer $k+1$ over k iff prefer 1 to 0. So iff prefers 1 to 0 he prefers 2 to 1 and 3 to 2... so prefers 100 to 0.
- NBLLN does **not** explain Samuelson's colleague.
  - Samuelson's theorem *does* extend to Barney! An EU/DMU(W) Barney who rejects one gamble will reject many independent plays. Probably more so than Tommy!

- Indeed, the point lies elsewhere ...
- Of course Samuelson's colleague was *not* an EU/DMU(W) guy.
  - A trait he shares with billions ...
  - Calibrationally, that degree of risk aversion must be about *loss aversion* or some other reference-dependent cousin of loss aversion.
- He was also clearly right to want to take the 100 bets: it has expected gain of $5,000, the chance of a net loss is only 1/700, and the chance of losing more than $1,000 was only 1/26,000.
- Most people would take the 100 independent bets.
  - Loss aversion plus narrow bracketing together can explain SC
  - You'd have to be insane not to take that cumulative bet.
  - And yet ...

Cognitive Biases

- Many people also turn down 100 repetitions!

For the same (hypothetical) question, Benartzi and Thaler (1999) find:

- Evening MBA students: 64% take single, only 75% take 100 repetitions.
  - Huh?
- Coffee shop visitors: 43% take single, only 66% take 100 repetitions.
  - Huh?
- Undergraduates: 77% take single, only 50% take 100 repetitions.
  - Huh???

So why do so few people agree with Samuleson's Colleague?

- Answer: they're not as smart as Samuelson's Colleague

Cognitive Biases

Enter Barney... people massively overestimate chance of losing money.

- 49% of undergrads take 150 repetitions of real-stakes gamble of 90% win 10 cents, 10% lose 50 cents.
- This has expected gain of \$6. And less than 1/300 chance of losing money.
- But: B&T asked subjects likelihood of losing money.
  - Answer: 24%!
  - not because exaggerating bad outcomes ... similar results when reverse.
- Mis-estimation of probabilities appears to drive behavior:
  - when shown the histogram, proportion of undergrads taking the repeated bet goes from 49% to 90%.
- We think it is clear that this isn't "narrow bracketing" in way usually thought of. It is all about Barney.

Cognitive Biases

Calibrationally, Barney goes much of the way toward explaining why 25-57% of people turn down 100 repetitions of 50/50 bet to gain \$20/lose \$10.

- But not far enough: 100 repetitions yields exp(gain)/exp(loss) $>$ 32,000.
- Tommy realizes this.
- But 10-Barney thinks exp(gain)/exp(loss) $>$ 15. So with reasonable loss aversion would also take.
- (Fatter tails would reduce the favorability further.)
- Analogously, NBLLN leads people to overestimate the likelihood of equities losing money in the long run, and why people prefer to invest more in equities when shown the true distribution of returns.