PhD course: Subjective Beliefs in Macroeconomics and Household Finance

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Introduction

Belief Formation

Broad question: What determines beliefs?

- General goal: Understand how people form beliefs
- Benchmark for information processing: Bayesian updating
- People frequently seem to deviate in systematic ways from Bayes' rule
- But what exactly do they do?

Hope of this agenda: Develop psychologically realistic, yet (hopefully) generalizable notions of what people actually do when forming beliefs

Determinants of Beliefs

On a very broad level, there are two basic forces that shape the process of belief formation

- Motivated Cognition
- Cognitive limitations

In the following, we will carefully go through both of them...

Goals of these lectures

- Provide some background and a (selective) overview of economic literature on belief *formation*
- Focus on current research
- Suggest further readings
- Highlight open research questions and possibly fruitful research directions

Motivated Beliefs

Background/Motivation

- Human cognition not exclusively guided by goal to find out the truth.

- Desire to hold a positive self-view or to maintain a certain view of the world is pervasive...
  - See, e.g., Kunda (1990), Epley and Gilovich (2016), Tali Sharot's work.
  - Growing literature in economics: e.g., Koszegi (2006), Brunnermeier and Parker (2005), Benabou and Tirole (2002), Falk (2017), Exley (2015), Di Tella et al. (2015), Gneezy et al. (2015), Moebius et al. (2013), Chew et al. (2012), Eil and Rao (2011), Haisley and Weber (2010), Babcock et al. (1995).

- Generates strong motives to manipulate beliefs in a self-serving way $\Rightarrow$ Motivated Beliefs

Background/Motivation

Contexts

- Prosocial behavior
  - People bias their beliefs in order to facilitate moral transgression (Babcock et al. (1995), Haisley and Weber (2010); Gneezy, Saccardo, Serra-Garcia, van Veldhuizen (2015); Di Tella, Perez-Truglia, Babino, Sigman (2015)).
- Ego/Ability
  - Motivated reasoning key determinant of (over)confidence.
  - Widespread implications: Malmendier and Tate (2008); DellaVigna and Malmendier (2006); Camerer and Lovallo (1999); Dohmen and Falk (2010).
- Political/religious beliefs
  - Public opinion on various topics highly polarized.
  - Kahan (2013) and others point to motivated beliefs as key.
  - Nunn and de la Sierra (2017) on magical warfare technologies.

Background/Motivation

New perspective on beliefs...

- Beliefs can play important psychological and functional role
- People attach value to beliefs - “beliefs as assets”
- Creates a trade-off between accuracy and desirability

Background/Motivation

Important and very useful distinction between demand side and supply side (Benabou and Tirole (2002)):

- Demand side - Why?
  - Direct utility relevance, for instance due to anticipatory utility, ego utility, social identity (Koszegi (2006); Brunnermeier and Parker (2005)).
  - Motivational value of optimistic beliefs (Benabou and Tirole (2002)).
  - Convincing others (Trivers' book "The folly of fools"; Schwardmann and van der Weele (2018)).

Background/Motivation

- Supply side - How?
  - Asymmetric processing (Eil and Rao, 2011; Sharot et al., 2011 and Moebius et al., 2013) - See Moebius et al., 2013 also for a nice theoretical framework as well as evidence on conservatism in updating.
  - Memory (Benabou and Tirole (2002); Zimmermann (2020))
  - Information Avoidance (Dana et al. (2007); Sicherman, Loewenstein, Seppi and Utkus (2016); Oster et al. (2013); Ganguly and Tasoff (2020); Chopra, Haaland and Roth (2020)).

Outline for motivated beliefs

- Focus on supply side of motivated beliefs
  - Zimmermann (2020)

The Dynamics of Motivated Beliefs - Zimmermann (2020)

Motivation

Key puzzle

- How do individuals maintain their biased perception of themselves and the world in the presence of information? (supply side of motivated beliefs)

Example

- Suppose I think I am smarter than I am
- Now I receive a signal from my employer saying I am actually not so smart
- How do I maintain my (over)confidence?

Motivation

Research Questions

1. What are the motivated belief dynamics after obtaining (unbiased) feedback? How do these dynamics depend on whether the feedback was positive or negative?

2. What is the role of memory in the dynamics of motivated beliefs? Can we find evidence for selective memory driving dynamic belief patterns?

Design

Design Goals/Challenges:

- Context that is ego-relevant (i.e., causes motivated reasoning) and allows for provision of information/feedback in a controlled way.
- Find a set-up that allows the study of belief dynamics.
- Establish causality in the relation between feedback (positive or negative) and belief dynamics as well as in the relation between feedback and memory.

Design

- Subjects take an IQ test (Raven matrices)
- After taking the test, subjects are randomly paired with 9 other subjects that previously did a Raven test under the same conditions.
- Elicit subjects' beliefs about their rank in group using a quadratic scoring rule - prior belief.
  - Probability of ranking in upper half of the group
  - Full probability distribution over all ranks

Design

Feedback

- 3 other group members are randomly selected (Eil and Rao, 2011).
- Subjects learn - for the comparison with each of the 3 group members - if their rank was higher or lower:
  - Unbiased but noisy feedback about true rank
  - Noise component crucial to establish causality
- Subjects were asked to repeat the feedback once they saw it, to ensure that they realized it.
- After the feedback, beliefs about the likelihood of ranking in upper half of group of 10 are elicited $\Rightarrow$ *posterior belief*.
  - belief elicitation slightly different than in Eil and Rao...

Design

Key treatment variation

- Exogenously vary between-subjects the time between feedback and posterior beliefs:
  - "Immediate"
  - "1 month"

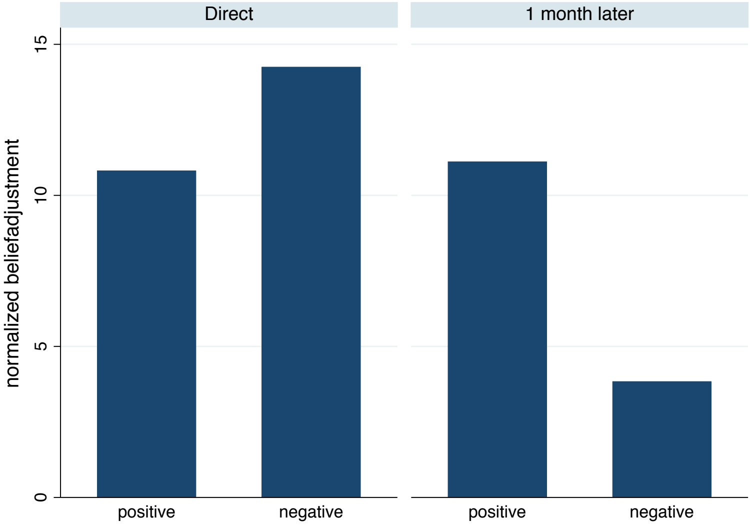
Results

Key outcome measure

- belief adjustment after feedback (posterior - prior).
  - Captures directly how people respond to feedback

- To make belief adjustments comparable between positive and negative feedback, I multiply adjustments after negative feedback by (-1).

Results


Direct
1 month later
normalized beliefadjustment
0
5
10
15
positive
negative
positive
negative

Results

	Positive Information		Negative Information		Diff-in-diff	
	(1)	(2)	(3)	(4)	(5)	(6)
1 if 1month	.301	1.504	-10.411***	-11.006***	.301	.392
	(3.564)	(3.062)	(2.540)	(2.539)	(3.564)	(3.907)
1 if negative information					3.436	2.403
					(2.328)	(2.847)
1 if 1 month negative information					-10.712**	-11.379***
					(4.377)	(4.144)
rank		1.416**		-.910		-.256
		(.645)		(.745)		(.484)
predicted belief adjustment		.674***		.252***		.391***
		(.071)		(.081)		(.055)
Constant	10.812***	-6.705**	14.247***	15.219***	10.812***	4.588**
	(1.604)	(2.762)	(1.687)	(5.600)	(1.604)	(2.217)
Observations	138	137	148	148	286	285
(R^2)	0.3081	0.3081	0.0965	0.1749	0.0443	0.1951

Linear estimates, robust standard errors in parantheses: $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

Results

Very robust pattern...

- Instead of controlling for rank in a linear way, include rank fixed effects.
- Robust to dropping most extreme ranks.
- Test performance fixed effects.
- Alternative definitions of positive and negative feedback.

Results

- Question: How can we explain the basic belief pattern we have seen?
- Candidate: Selective recall (key assumption in Benabou and Tirole (2002)).

Selective Recall

- Set-up identical to baseline design.

- But, instead of looking at beliefs after 1 month, I now look at recall accuracy of feedback after 1 month.

Outcome measure

- Recall of feedback:
  - After 1 month, subjects were reminded that they obtained feedback (3 direct comparisons)
  - Question was how many comparisons were positive
  - "3", "2", "1", "0", "I don't recall"
  - 2 euros if correct - "I don't recall" is dominated (to be discussed later)

Selective Recall

	Dependent variable:			
	Recall Accuracy		*"I don't recall"*	
	(1)	(2)	(3)	(4)
1 if negative information	-.407***	-.399***	.213***	.179***
	(.075)	(.114)	(.060)	(.068)
rank		.005		.002
		(.020)		(.013)
predicted belief adjustment		-.004*		.006***
		(.003)		(.002)
Constant	.907***	.962***	.037	-.061
	(.040)	(.081)	(.026)	(.055)
Observations	118	118	118	118
(R^2)	0.1914	0.2139	0.0871	0.1669

Selective Recall

Very robust pattern...

- Instead of controlling for rank in a linear way, include rank fixed effects.
- Robust to dropping most extreme ranks.
- Test performance fixed effects.
- Alternative definitions of positive and negative feedback.
- Similar evidence now in Huffman et al. (2019), Chew et al. (2019), Saucet and Villeval (forthcoming)

Summary

- Supply side paper
- People seem to be able to over time forget feedback that challenges their desired self-view
- Remainder of paper focuses on mechanisms
  - People seem to suppress rather than forget
  - Suppression is achieved by not thinking about the IQ test alltogether

Further Readings

Readings

- Chew, Soo Hong, Wei Huang and Xiaojian Zhao (2019). "Motivated False Memory."
- Huffman, David, Collin Raymond and Julia Shvets (2019) "Persistent Overconfidence and Biased Memory: Evidence from Managers."
- Schwardmann, Peter and Joel van der Weele (2019) "Deception and Self-deception."
- Exley and Kessler (2020) "Motivated Errors"
- Saccardo and Serra-Garcia (2020) "Cognitive Flexibility or Moral Commitment? Evidence of Anticipated Belief Distortion"

Open Questions / Research Directions

Open Questions

- Supply side on asymmetric updating: mixed evidence is puzzling - if you can reconcile this you have a great paper
- Very little on demand side: Schwardmann and van der Weele (2019) is a rare example
- Very little field evidence: Huffman et al. (2018) is a rare exception

Boundedly Rational Belief Formation

Background

Remember:

- Benchmark for information processing: Bayesian updating
- People are not Bayesian... but what are they?
- Develop psychologically realistic, yet (hopefully) generalizable notions of what people actually do
- **Now, focus on bounded rationality: people want to find out the truth, but make mistakes along the way...**

Bounded Rationality Research on Updating Biases

- 1970s / 1980s: Kahneman and Tversky's "heuristics and biases" program
- 1980s / 1990s: Economists catch up and replicate
- 1990 / 2000s: First models of heuristics (Rabin), applications in finance and other fields
- 2010s: Micro-foundations, in particular attention (but still new biases)

Several Problems with Biases Program

- Increasing frustration in profession about "accumulating biases" empirically . . .
- . . . as well as about "cherry picking model of certain bias to explain xyz" in theory (one separate model for each bias)
- Very limited understanding of *when* people exhibit *which* biases
- Calls for unification (e.g., Fudenberg, 2006)

$\Rightarrow$ Critique applies to behavioral economics more generally
$\Rightarrow$ Some disagreement about importance of this critique
$\Rightarrow$ In any case: Can only hope to unify (theory) and make sensible predictions (in applications) if understand micro-foundations of biases: what exactly is it that people do, and why?

Outline for this lecture

- “Neglect” in belief Formation

Correlation neglect in belief formation - Enke and Zimmermann (2019)

Motivation

- People often update from multiple signals
- Common source of information introduces correlations among signals:
  - News media: press agencies, influential journalists
  - Social networks: well-connected people
  - Akerlof and Shiller: "telling and re-telling of stories" induces exuberance

Motivation

- Common feature: double-counting problem; could induce overshooting
- Potential implications:
  - Excessive imitation and herding in networks, e.g., technology diffusion
    Eyster and Rabin (2010, 2014)
  - Ideological extremeness in political economy settings
    Ortoleva and Snowberg (2015), Levy and Razin (2015)

Motivation

Key research questions

- How do people update from correlated signals?
- What are the underlying mechanisms of correlation neglect?

Methodological Challenges

- Cleanly identify people's updating rules
- In the field, we often don't even know the signal-generating process, let alone people's priors
- How to investigate underlying mechanisms?

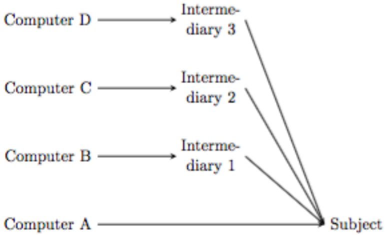
Experimental Setup for Correlation Neglect

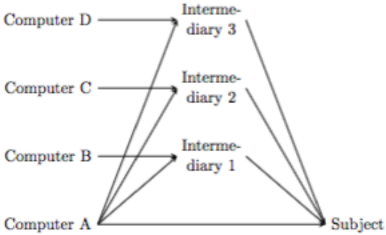
- Approach: Identify how people process correlated vs. uncorrelated signals, *holding everything else constant*

- Two treatments: *Correlated* and *Uncorrelated*
  - Key feature of between-subjects design: Construct two sets of signals (one with and one without correlation), which result in same Bayesian posterior
  - Simple correlation and *known* data-generating process

Experimental Setup for Correlation Neglect

- Subjects are asked to estimate true state ("number of balls in hypothetical urn")
- Participants receive computer-generated signals over true state





EXAMPLE:

	Uncorrelated	**Correlated**
Interm. 3	0	6
Interm. 2	10	11
Interm. 1	9	10.5
Computer A	12	12

Experimental Setup for Correlation Neglect

- Incentives for accuracy
- 10 different rounds with varying true state
- Between-subjects design

Prediction

- Computers generate signals $s_A, \ldots, s_D$
- Subjects in *Correlated* potentially naïve in extracting independent signals and instead treat messages of intermediaries as independent:
  - $\chi = 0$: rational; $\chi = 1$: full correlation neglect
- Stated belief $=$ Rational belief $+ \chi(s_A - \bar{s}_{-A})\frac{3}{8}$
- Relative magnitude of common source signal should predict direction of potential belief bias

Graphical Illustration of Results

- Stated belief $=$ Rational belief $+ \chi(s_A - \bar{s}_{-A})\frac{3}{8}$

- Normalize data by computing χ that is implied in stated belief

- To visualize results, distinguish between cases in which correlation neglect predicts inflated or deflated beliefs
    - Signal of A relatively high $\rightarrow$ inflated beliefs:

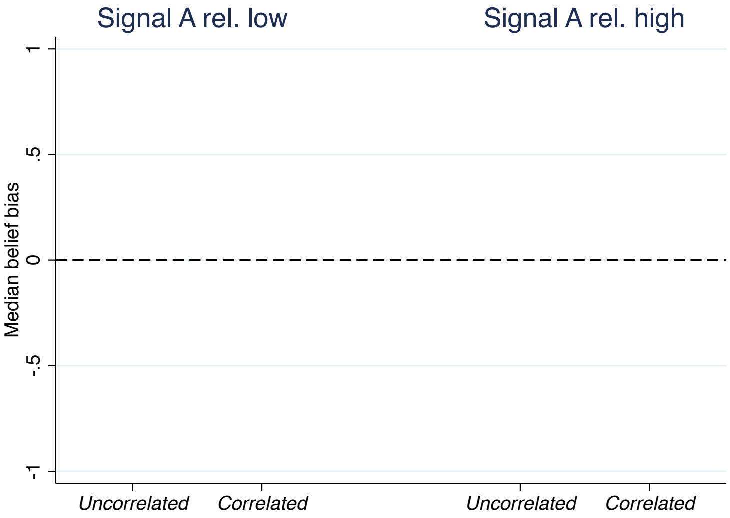
      $\chi = 0$ rational, $\chi = 1$ fully naïve

    - Signal of A relatively low $\rightarrow$ deflated beliefs:

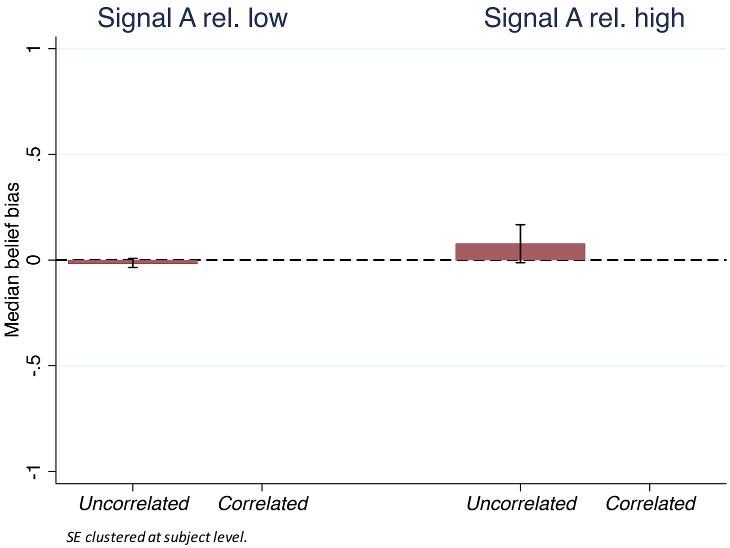
      $\chi = 0$ rational, $\chi = -1$ fully naïve

Evidence for Correlation Neglect – Pooled Data

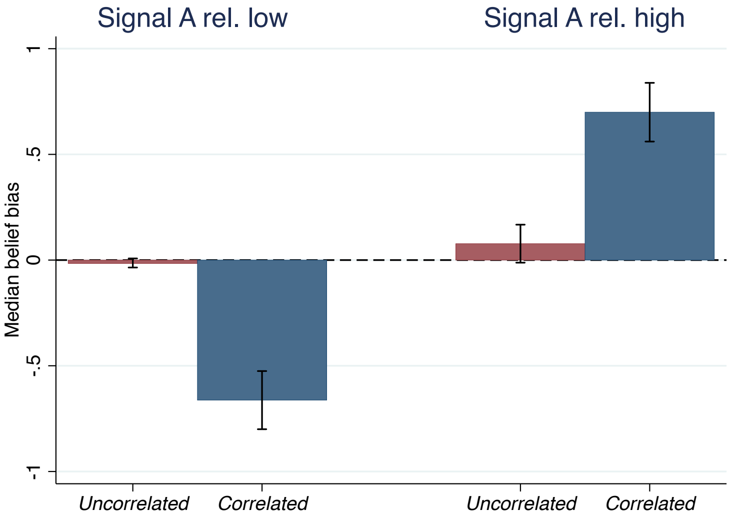
Evidence for Correlation Neglect – Pooled Data



Evidence for Correlation Neglect – Pooled Data



Evidence for Correlation Neglect – Pooled Data



95% CI. SE clustered at subject level.

People Neglect Correlations on Average

- Significant difference in beliefs across treatments (p-value < 0.001)
- No effect of magnitude of true state (significant treatment effect when true state was 23112, but also when it was 10)
- No order effect
- No learning
- Strong Impact on earnings

The Sources of Correlation Neglect

- What exactly are the cognitive mechanisms underlying correlation neglect?
- Important to know not just to de-bias people, but also to develop an empirical understanding of the potential ingredients (micro- foundations) of theories of boundedly rational updating
- Predictions where correlation neglect is likely (not) to occur

The Role of Complexity

- Recurring theme in literature is that prevalence of updating mistakes depends on complexity (Charness and Levin, 2009; Levin et al., forthcoming)
- Effect of reduction of complexity in our set-up?

The Role of Complexity

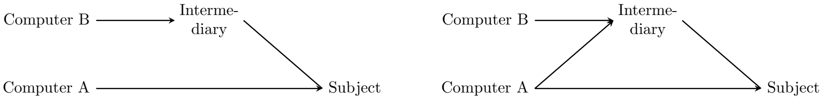


Figure: Simple uncorrelated (left panel) and correlated (right panel) information structure

- Nature of correlation identical, but complexity severely reduced

The Role of Complexity

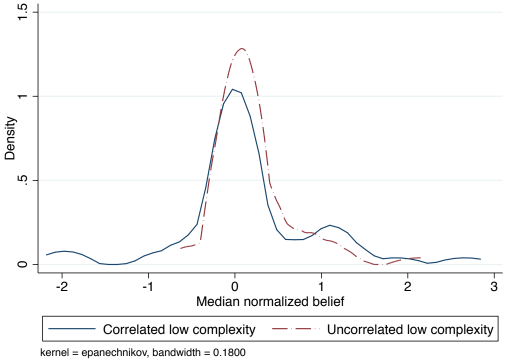


Figure: Kernel density estimates in low complexity treatments.

- Correlation neglect basically vanishes

The Role of Complexity

- Role of complexity noteworthy - in (admittedly extremely) simple informational environments subjects do grasp the implications of correlated information structures
- Suggests that correlation neglect depends not only on subject's updating type, but also on the environment
- At the same time, complexity manipulation is not suited to pin down mechanisms, because it changes a number of features at once ("size" of the problem, but also mathematical complexity)
- To organize discussion of the mechanisms underlying correlation neglect (and its dependence on complexity), adopt a simple framework akin to DellaVigna (2009).

A Conceptual Framework

Arguably, solving our experimental task requires two steps of reasoning:

1. Subjects need to identify and think through the problematic feature of our updating environment, i.e., they need to *notice* that the workings of the intermediaries introduce a double-counting problem.

2. Subjects need to actually *solve* the problem mathematically, i.e., conditional on noticing and understanding the problem, they ought to execute the computations that are necessary to de-bias the messages of the intermediaries - this step is typically people's first guess of what goes wrong in updating...

Challenge to Notice the Problem

Concerning step 1, following DellaVigna (2009), two factors influence the probability of noticing:

- The *size* of the information structure, i.e., the number of signals and messages
- The *salience* of the double-counting problem

$\rightarrow$ Systematically manipulate both factors, *keeping the mathematical steps required to solve the problem constant*

Treatment Many Stimuli

- Recall that low complexity environments not only manipulated the size of the information structure, but also the required mathematical steps to solve the problem.
- Treatment Many Stimuli isolates the pure size effect
- Many Stimuli is identical to the low complexity correlated environment in terms of information content as well as math requirements, but the number of messages is higher

Treatment Many Stimuli

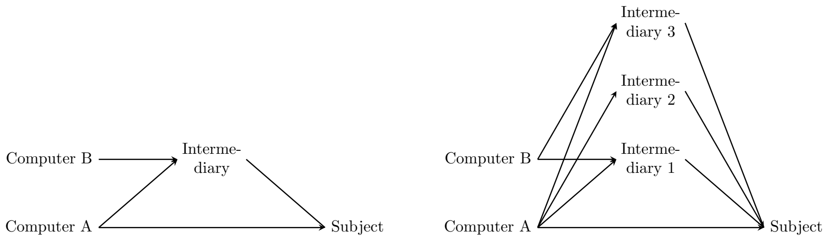


Figure: Low complexity correlated (left panel) and Many Stimuli (right panel) information structure

Treatment Alternating

- Goal was to increase the salience of double-counting problem, keeping everything else constant
- Within-subject - between rounds we alternated between correlated and uncorrelated information structure

Results

	Dependent variable: *Naïveté* χ					
	Low complexity & *Many Stimuli*				*Alternating*	
	(1)	(2)	(3)	(4)	(5)	(6)
0 if *Low complexity uncorr.*, 1 if *Low complexity corr.*	-0.14	-0.10				
	(0.10)	(0.08)				
0 if *Low complexity corr.*, 1 if *Many Stimuli*			0.34***	0.33***		
			(0.11)	(0.11)		
0 if *Correlated*, 1 if *Alternating*					-0.25***	-0.24**
					(0.08)	(0.09)
Constant	0.15***	0.18	0.0090	-0.55	0.54***	0.13
	(0.04)	(0.31)	(0.09)	(0.54)	(0.05)	(0.34)
Additional controls	No	Yes	No	Yes	No	Yes
Observations	884	874	891	881	681	687
R^2	0.01	0.05	0.03	0.06	0.02	0.09

Figure: Regression results from Many Stimuli and Alternating.

Results

Summary

- Both the size of the information structure and the salience of the double-counting problem are crucial factors (independent of mathematical difficulty)
- Suggests that correlation neglect is to a large extent driven by a failure to notice
- Noticing patterns depend on size of the problem, rationalizing the low complexity findings
- Mathematical difficulty does not seem to play a role

Further Readings

Readings

- Enke (2019) "What you see is all there is"
- Graeber (2019) "Inattentive Inference"
- Esponda and Vespa (2020) "Failures in Contingent Reasoning"
- Martinez-Marquina, Alejandro, Muriel Niederle, and Emanuel Vespa (2019) "Probabilistic States versus Multiple Certainties: The Obstacle of Uncertainty in Contingent Reasoning"
- Hartzmark, Samuel M, Samuel Hirshman, and Alex Imas (2019) "Ownership, Learning, and Beliefs"
- Enke and Graeber (2020) "Cognitive Uncertainty"
- Enke, Schwerter and Zimmermann (2020) "Associative Memory and Belief Formation"

Open Questions / Research Directions

Open Questions

- Unification: Still large number of biases to be explained
- Very little field evidence: finance is an exception but also there the evidence is limited
- Memory - intuitively crucial for belief formation, but little empirical work so far
- Is there a common thread between motivated and boundedly rational beliefs? Exley and Kessler (2019) is an attempt in this direction...