Alex Imas and Richard Thaler
Behavioral Economics Anomalies: Then and Now

On Thursday, October 9, Alex Imas and Richard Thaler joined Markus' Academy for a conversation on their new book, The Winner's Curse. Imas is the Roger L. and Rachel M. Goetz Professor of Behavioral Science, Economics and Applied AI at the University of Chicago Booth School of Business. Thaler is the 2017 recipient of the Nobel Memorial Prize in Economic Sciences for his contributions to behavioral economics. Introductory remarks by Markus Brunnermeier.

A few highlights from the discussion.[1]

- [0:00] **Introduction**
  - There are two strands of literature within behavioral economics. The first emphasizes biases in preferences (e.g. reference dependence, loss aversion or hyperbolic discounting) and beliefs (e.g. probability weighting, overconfidence or confirmation bias)
  - The second emphasizes the cognitive origin of noise, modeling the information acquisition of agents that are self-aware of this noise
  - Thaler contributed the idea of nudging people to overcome biases, exposing them to information, providing default options (Thaler, 2004), or using one bias against another
  - Thaler's original *The Winner's Curse*, was published in 1992 and was based on a series of columns in the Journal of Economic Perspectives (e.g. Thaler, 1988). With the new edition they look back and assess the field's progress

- [3:50] **Economists should listen to Kahneman**
  - Economists should listen to Kahneman's advice in *Thinking, Fast and Slow*: before you do something rash, check in with System 2
  - There has been progress since the 1980s, when economists thought there was no alternative to expected utility. There is a large literature on loss aversion, reference dependence, fairness, salience, hyperbolic discounting…
  - However the textbooks and standard principles have barely changed
  - Economists should think twice about whether the models they write down are normative or descriptive
  - von Neumann explicitly formulated expected utility as a normative model, but economists use it as the workhorse model of how people make decisions
  - Together with the study of markets, what distinguishes us from other social sciences is that we model "agents" maximizing an objective function
  - However we should think twice about the difficulty of the problem we are modeling. Take for example the complex problem of saving over the life-cycle. Keynes' maxim that people spend a fraction of their income is not the right model, but it is probably closer to reality than the life-cycle models of Modigliani and Brumberg (1954) and Barro (1974)

[1] Summary produced by Pablo Balsinde (PhD student, Stockholm School of Economics)

- We should also think twice when we assume that people maximize utility. There is lots of evidence suggesting people are not good at making the forecasts required for doing so, while there is a long literature on preference reversals
- One alternative could be Herbert Simon's idea of satisficing: when you find the first option that feels good enough, you quit searching. However we don't have good satisficing models, and so we don't know how they differ from maximization models
- Expected utility or the efficient market hypothesis are benchmarks; a null hypothesis. Prospect theory couldn't exist without expected utility. But this does not mean we should write down rational expectations models where the market's expectations are assumed to be in line with those of the best econometrician
- Will AI end behavioral economics if humans outsource all of their decisions, making us all hyperrational? Two points: it is unlikely that AI models themselves are hyperrational, while it is also unlikely that humans will adopt them everywhere (for example in their marriage decisions)
- In ongoing work with Sanjog Misra and Kevin Lee, Imas experimented with humans giving agents their preferences to an AI and having AI agents negotiate outcomes. Not only did people's prompts inject their biases into their preferences, but they were less happy with the result because it came from a black box
- It is a 50-year-old result that simple linear models for decision-making most often do better than humans. Yet we did not switch to decision-making based on linear regression

- [33:08] **Progress in behavioral economics**
  - Early work documenting behavioral anomalies relied mainly on low-stakes, often hypothetical, lab experiments. The pushback was: "We don't care about what college students do in the lab"
  - Part of the reason behavioral econ has succeeded is that, since then, it has shown that the anomalies arise in real world settings, among professional investors, athletes, CEOs…
  - Neuroeconomics was especially exciting around the mid-2000s, hoping to achieve an Edgeworth-style "hedonometer" to measure utility
  - Although the use of fMRI data did not take off (it has become controversial even in the neuroscience community), using non-choice data to study decision-making is at the frontier of behavioral econ
  - What are the cognitive foundations of the anomalies? Are loss aversion and narrow bracketing just parameters in the utility function, or do they arise from cognitive constraints? Can we understand them as the result of a maximization problem constrained by limited attention and memory? This is the frontier of behavioral economics research.
  - Yet, there is always a risk that the new neural approaches feel novel without actually teaching us anything new
  - Context effects matter, but we lack theory for them. For example the data shows heterogeneity in loss aversion but we do not yet understand its drivers.

The new cognitive approach to behavioral economics has the potential to help us understand context effects better.
  - Behavioral finance has been one of the most successful subfields because people make frequent, high-stakes decisions and get rapid feedback. Much of its evidence comes from the field rather than the lab; for example, the disposition effect (Odean, 1998) and overconfidence (Odean, 1999).

- **[40:12] Selling fast and buying slow**
  - The pushback against behavioral finance has been that the evidence of biases comes from non-experts
  - To address it, Akepanidtaworn et al. (2023) study the buying and selling decisions of long-only institutional investors
  - They show that these two decisions are different and not just two sides of the same coin, benchmarking investors' performance against random strategy alternatives
  - To assess buying performance, they compare what investors bought against comparable alternatives they could have (randomly) bought. They find that investors outperform the random strategy, and so display skill. There is no correlation between prior returns and what they buy
  - To assess selling performance, they compare sales to a conservative "randomly sell an alternative holding" benchmark. Investors do drastically worse than the random strategy
  - The natural explanation is limited attention. Two aspects predict whether a holding will be sold: (1) the salience of past returns (sell extreme winners and losers), and (2) within these salient buckets, investors sell the holdings they are least attached to
  - That is, in line with the endowment effect, they sell stocks they have held for shorter periods of time. The problem is that the recent buys are the ones that are generating alpha

- **[48:00] The robustness and future of behavioral econ**
  - Behavioral econ has been largely spared from the replication crisis in the social sciences because it adopted the methods of experimental economics, which were different from those of psychology
  - Going back to Vernon Smith's work, papers have included the required instructions and data, while a condition for publication has been that papers replicate the relevant prior result (a good example is the classic asset-market bubble experiments; Smith et al., 1988)
  - In their book, they replicated the main lab or field experiment of each chapter, and effectively found that all of Thaler's (1988) anomalies hold: preference reversal, the dictator game, the ultimatum game, the endowment effect…
  - All of the required instructions and data are available at thewinnerscurse.org. Teaching slides are also available
  - Looking to the future, we need to think about the relationship between noise in observational data and the difficulty of the decisions studied. One answer is that difficulty brings noisier behavior, but often, as environments get more

complex, people rely more heavily on heuristics, so behavior can actually look less noisy

- We also need more research to measure complexity. Defining what counts as "difficult" is itself difficult. Do computer science's measures map to the ecologically valid response to complexity or the perception of complexity?
- Behavioral economics has become mainstream in departments and journals, yet, despite some texts adding behavioral flavors (Acemoglu et al., 2021), it is still underrepresented in the core textbooks
- The impact of AI is uncertain. It won't make behavioral questions disappear any time soon; we will not all become hyperrational
- The intersection between cognitive science and AI is booming. Particularly with small and interpretable models, AI could help elicit people's mental models and help represent parts of the judgment process

Timestamps: