Lecture 1: Noisy Cognition and Economic Decision Making

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A Short Course on Cognitive Imprecision
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The Random Element in Economic Decisions

- Standard theory implies that a given DM's choice should be a perfectly **predictable** function of the distribution of returns associated with alternative options

  — they should with certainty choose the option that implies the highest expected utility (or at any rate, the distribution of returns that is most preferred under some well-defined ordering)

The Random Element in Economic Decisions

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  — hard for an observer to be sure exactly how the possible returns are understood by a given DM, or what their personal preferences may be

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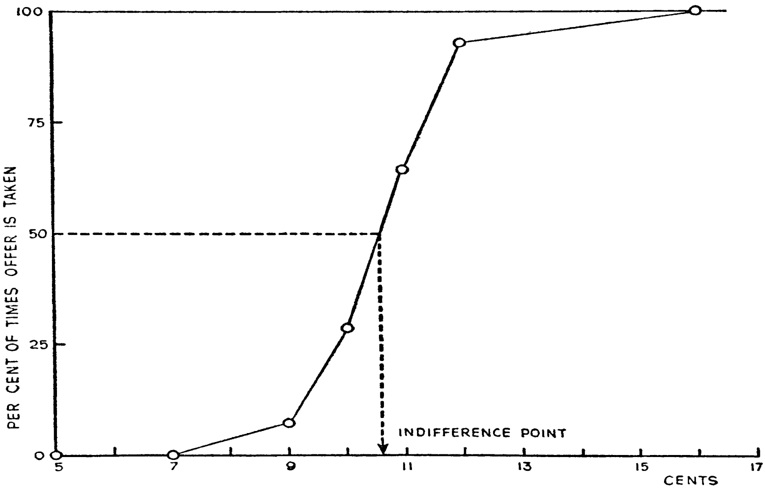
- But it **can** be tested in the case of laboratory experiments, in which both possible payoffs and their probabilities are **stated** by the experimenter, and the same choice problem can be **repeated** multiple times

  — and there choices are observed to be **random,** though with **probabilities** that vary systematically with the properties of the gambles offered

Mosteller and Nogee (1951)



Understanding Randomness of Choice

- A common interpretation of such observations: people **have** a well-defined valuation for each possible option, which depends only on its features (and hence is invariant across contexts)

  — but instead of choosing the highest-valued option with certainty, the probability of choosing a given option depends on **how great the difference in value** relative to the alternatives

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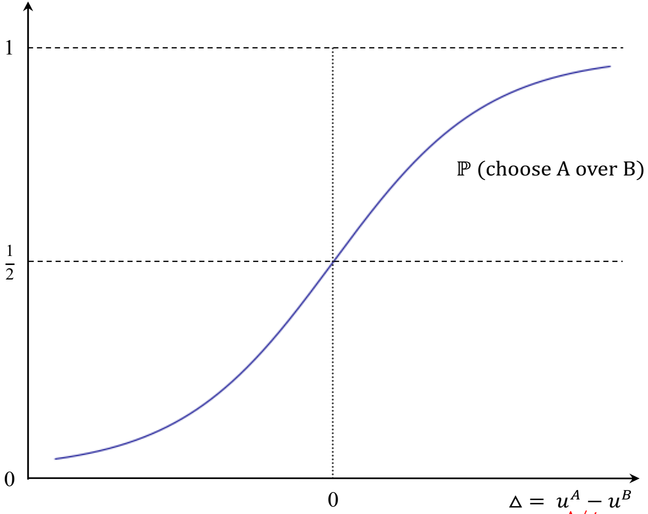
- This explains Mosteller and Nogee's method: they expect vonN-M utility to explain when two lotteries are **equally valued,** as revealed by 50-50 choice frequency

Stochastic Choice From Comparison Noise



common functional form: $\Phi(\Delta) = \frac{e^{\Delta/\phi}}{e^{\Delta/\phi}+1}$

Understanding Randomness of Choice

- This kind of model of choice can be justified in terms of an **additive random utility model:**
  - choices based not on u^A, u^B, but instead on occasion-specific values
    $$\tilde{u}^i \;=\; u^i + \epsilon^i,$$
    where random term ϵ^i is an independent draw (for each good, and on each occasion) from some distribution $F(\epsilon)$
  - the good i that is chosen is the one with the highest value of $\tilde{u}^i$ on that occasion
  - the nature of the distribution $F(\epsilon)$ determines the function $\Phi(\Delta)$ [e.g., probit or logit model]

“Late Noise” vs. “Early Noise”

- Models of this kind can all be viewed as involving **only comparison noise**

  — models in which noise only enters at the **end** of the choice process, when the (accurately computed) values of the various choice options must be **compared** in order to choose between them

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- But there is an alternative possible source of randomness in responses: one might suppose that the **features** that define the available options are **corrupted by noise,** before they can be integrated to compute assessments of value

"Late Noise" vs. "Early Noise"

- This would then result in random choice [as a function of the **objective** features], even if the value estimates (and hence choices) are perfectly optimal, conditional on their being based on noisy representations

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- A common interpretation of randomness of **perceptual** judgments

    - early stages of processing of many sensory features are demonstrably random [random firing of cortical neurons can be measured, and can in some cases be shown to explain randomness of judgments: e.g., Newsome *et al.*, 1989]

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  - yet judgments may be modeled as **optimal,** conditional on noisy sensory data [e.g., signal detection theory, Bayesian models]

Imprecision in Numerical Cognition

- But does this really provide a possible explanation for the randomness of responses in experiments like that of Mosteller and Nogee?

- One may admit that when number information is presented **visually,** rather than symbolically, this results in **errors in perception**

  — but in experiments like that of M&N, the monetary amounts are described using **symbols**

  — shouldn't this allow **precise** recognition of the amounts offered?

Imprecision in Numerical Cognition

- In fact, evidence suggests that even when symbolic representations of numbers are presented [e.g., Arabic numerals], these activate an **internal representation** of the quantity indicated that is **imprecise in the same way** as with perception of sensory magnitudes (including numerosity) [Dehaene (2011), Grossberg and Repin (2003)]

- This "semantic" representation allows judgments of the **approximate magnitudes** of symbolically-presented numbers
  - when very rapid judgments must be made [next slide]
  - when information presented symbolically must later be recalled [e.g., Dehaene and Marques (2002)]
  - by patients with brain injuries that impair arithmetic ability [see Dehaene (2011)]

Imprecision in Numerical Cognition

- Example: Dehaene *et al.* (1990), Experiment 2:
  - subjects are presented with two-digit Arabic numerals [other than 65]
  - asked to press one of two keys to quickly indicate whether the number shown is **larger** or **smaller than 65**

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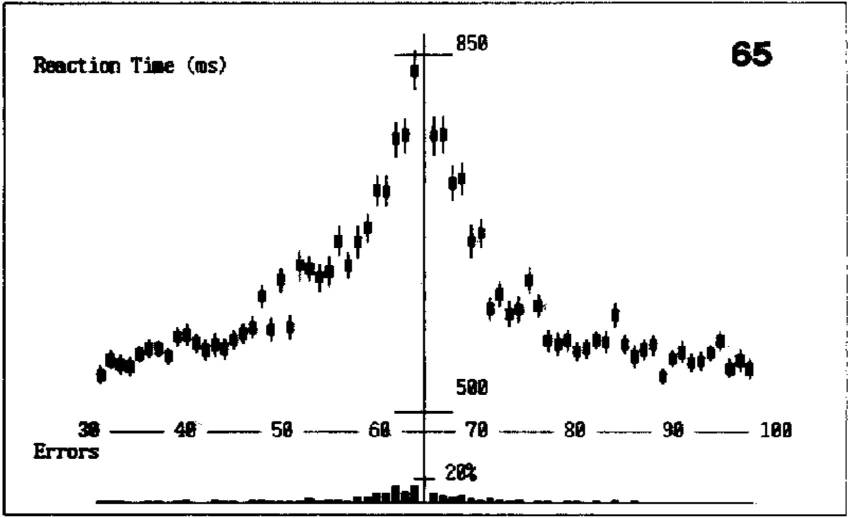
  - subjects are presented with two-digit Arabic numerals [other than 65]
  - asked to press one of two keys to quickly indicate whether the number shown is **larger** or **smaller than 65**

- Findings: **slowest** responses (and most **errors**) for numbers **near 65,** faster responses (and fewer errors) the more distant the number from 65, either below or above

Why **response time** is relevant:
In dynamic extension of model of noisy retrieval of information, noisier individual observations $\Rightarrow$ draw more before decision **and** decision less accurate

Dehaene, Dupoux and Mehler (1990)



top panel: distribution of response times for each number
bottom panel: error rate for each number

Imprecision in Numerical Cognition

- Note: slow response for numbers near 65 NOT simply due to fact that question can't be answered from first digit alone when first digit is 6
  - no discontinuity in response time when move from high 50s to low 60s, or high 60s to low 70s
  - slower response for high 50s than low 50s, for high 40s than low 40s; also for low 70s than high 70s, for low 80s than high 80s

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  - slower response for high 50s than low 50s, for high 40s than low 40s; also for low 70s than high 70s, for low 80s than high 80s
- Results suggest that presentation of Arabic numeral rapidly calls to mind a **semantic** representation of the number, as a quantity of a certain **size**

  — which representation is however **imprecise** (and random), just as with subjective representations of sensory magnitudes

Imprecision in Numerical Cognition

- Evidently, answer can be given more quickly when question can be answered using this quickly-available semantic representation, rather than having to consciously recall arithmetic meaning of numerals and exact order of precise numbers [though of course normal adults can do that, too]

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- Possible interpretation of experiments like Mosteller-Nogee: perhaps when subjects make **intuitive** judgments about choice between gambles [not resorting to any conscious arithmetic calculation], they consider whether the upside possibilities are **large enough** to outweigh the downside risk, using this fuzzy **semantic representation** of the magnitudes mentioned in the problem description

  — randomness in the semantic representation then gives rise to randomness in judgments of relative value of two options

Does the Nature of the Noise Matter?

- Yet one might wonder: is there any observationally distinguishable **difference** between models with

  - **noisy** evidence about the situation, but a **reliable** (perhaps optimal) response to the noisy data **["early noise"]**

  VS.

  - **reliable** recognition of the situation, and computation of the values of presented choices, but a **noisy** response on basis of that info **["late noise"]**?

Does the Nature of the Noise Matter?

Cases where the hypothesis of early noise + optimal decoding has different implications:

1. Biases in the estimation of individual **features** of a choice option, resulting from noisy encoding of the **individual features** of that option (rather only encoding its overall value), can result in estimates of its overall value that are not simply a function of the **true overall value** [i.e., the value that would be computed from the true features]

The Rabin (2000) Paradox

- People are observed in the laboratory to make risk-averse choices even when stakes are **quite small**

  — yet if one were to explain this as reflecting **diminishing marginal utility of wealth,** one would have to hypothesize such a **sharply decreasing** MUW as to imply extreme risk aversion in the case of **larger** gambles, that we don't see

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$$U(W_0 + 0.055) - U(W_0) \; < \; U(W_0) - U(W_0 - 0.05)$$
  - but this degree of curvature, if holding for all W_0, would imply that
$$U(W_0 + 1T) - U(W_0) \; < \; U(W_0) - U(W_0 - 1),$$
    so that the same DM should (more often than not) decline a bet that offers **50 percent chance of winning $\$1T$, but 50 percent chance of losing $\$1$**

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- The behavioral literature typically concludes from this that people **don't** care only about their utility $U(W)$ from overall wealth (integrating gains or losses from the experiment with their other sources of wealth)

  — instead, **"narrow bracketing"** of the prospective gains/losses from the individual gamble; and **"loss aversion"** in the consideration of gains and losses in isolation

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- If we instead suppose that decision must be based on a **noisy representation** of the terms of the gamble offered, can explain small-stakes risk aversion under hypothesis of a decision rule that **maximizes average** $U(W)$ across possible decision problems (Khaw *et al.*, 2021)

Noisy Representation of a Gamble

- Suppose that, as in the Mosteller-Nogee experiment, a DM must choose whether to pay C for a gamble that will pay X with probability $1/2$ (but zero otherwise); but suppose that the decision must be made on the basis of **noisy** retrieved representations of the quantities C, X specified on that trial

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- Then a decision rule that is optimal for the DM (that would maximize the average $U(W)$ resulting from decisions) would require acceptance of the gamble if and only if noisy representation $\boldsymbol{r}$ satisfies

$$\frac{1}{2}\mathrm{E}[U(W_0 + X - C)\,|\,\boldsymbol{r}] + \frac{1}{2}\mathrm{E}[U(W_0 - C)\,|\,\boldsymbol{r}] \;>\; \mathrm{E}[U(W_0)\,|\,\boldsymbol{r}]$$

Noisy Representation of a Gamble

- If C, X are both **small** relative to the curvature of $U(W)$, we can use the approximation

$$U(W_0 + \Delta) \;\approx\; U(W_0) \;+\; U'(W_0) \cdot \Delta$$

to conclude that (an approximately) optimal decision rule will accept the gamble if and only if

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- Thus decision depends only on inference about parameters of this gamble — as if "narrow bracketing," though decision rule actually optimized for an objective that assumes payoffs only matter due to their **effect on overall lifetime budget**

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- Only need for the condition

$$\mathrm{E}[X\,|\,\boldsymbol{r}] \;>\; 2\cdot\mathrm{E}[C\,|\,\boldsymbol{r}],$$

to be satisfied **with probability less than 1/2,** even when $X > 2C$ (though not larger by a factor much greater than 2)

— this can happen, if "regression to the mean" shrinks the estimated magnitude of the larger quantity X by a larger factor, on average [to discuss further in Lecture 2]

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   - for example, varying **time pressure**

     — if internal evidence is a stream of noisy signals [as for example in the DDM], then less time for collecting additional signals should mean **noisier cumulative evidence**

     — Bayesian decoding of the noisier internal representation can result not just in **more variable** estimates, but in larger **average bias** in valuations

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   - Polania *et al.* (2019) find that increased time pressure changes average ratings of food items

     — in a way consistent with Bayesian decoding of noisy internal representation of items' values

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  - Enke and Graeber (2023) elicit “certainty equivalent” values for simple lotteries [an amount X is paid with probability p; otherwise, payoff is zero]

    — look at how bias in valuation [CE/X different on average from p] varies with p

    — finding: $CE/X > p$ for small p, while $CE/x < p$ for large p, regardless of sign of X [replicating findings of Tversky and Kahneman, 1992]

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- As discussed further in Lecture 3, this can be interpreted as consequence of Bayesian decoding of a **noisy internal representation of p**

  — internal noise ["cognitive uncertainty"] $\Rightarrow$ estimates of p biased toward the **prior mean** [$\bar{p} = 0.5$ in symm. case]

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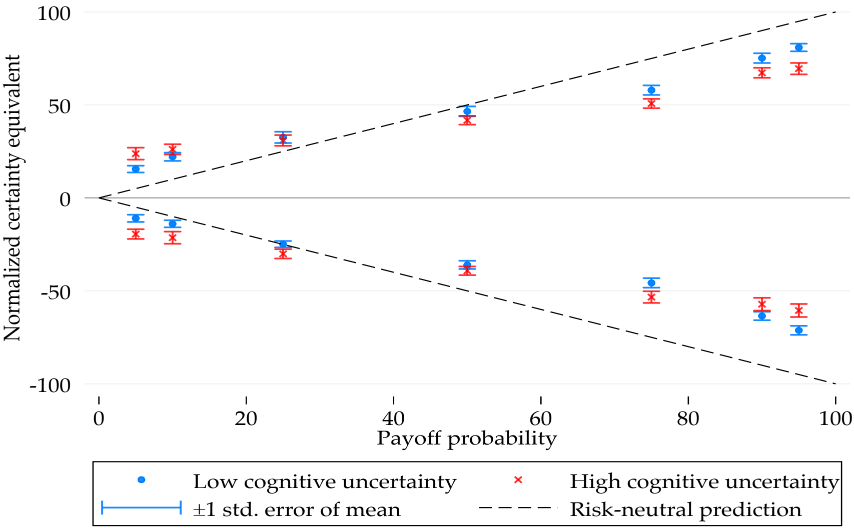
- Enke and Graeber (2023) manipulate the degree of noise in the internal representation by presenting the payoff probability in a more complex form [compound lottery, rather than simply stating the implied probability p of the non-zero payoff]

  — and show that increasing noise in this way leads to **increased bias** in the elicited certainty equivalents

Enke and Graeber (2023)



cognitive uncertainty increased by more complex presentation

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    - but not because of how the prior is used in **interpreting** noisy evidence; instead, the precision of the **encoding** can vary with the prior (and hence across contexts)

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   - but not because of how the prior is used in **interpreting** noisy evidence; instead, the precision of the **encoding** can vary with the prior (and hence across contexts)
   - predicted by theories of **"efficient coding"**

Efficient Coding

- Idea: the neural system used to produce internal representations of particular quantities has only a **finite capacity** to represent different amounts in sufficiently distinguishable ways

  — like the finite *capacity* of a communications channel, in Shannon's theory

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- **Efficient coding:** the hypothesis that external stimuli are mapped into the limited variety of possible internal states in such a way as to make decisions as accurate as possible

  — worse discrimination between some states may be accepted, as the price of allowing sharper discrimination between other states, that it matters more to be able to distinguish

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- This implies that the encoding scheme should depend on the **prior** (Payzan-LeNestour and Woodford, 2022)

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- Idea: the **accuracy of discrimination** between any two magnitudes will be **worse** when these two magnitudes are drawn from a prior distribution with a wider **range**
  - the larger range of objective magnitudes must be mapped into the **same** range of possible internal representations
  - hence the two magnitudes will be closer together in "psychological space" when the objective difference between them is a smaller **fraction of the overall range**
  - making the encoding noise more significant relative to the degree of difference in their internal representations

Range Normalization

- An illustration, where the internal representations can actually be observed:
  - Padoa-Schioppa (2009) measures the internal representation of the values of different choice options, by the rate of firing of certain cells in the macaque OFC ["offer cells"], when monkeys choose between offers of different quantities of two types of juice

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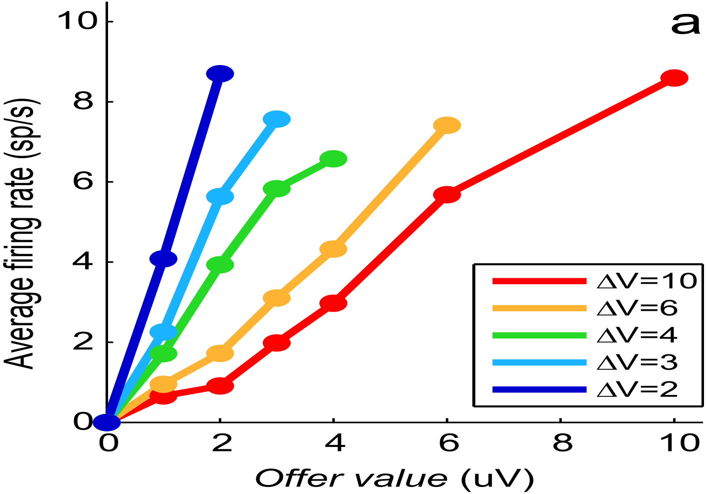
  - the firing rate is higher when the quantity of apple juice offered is higher [this is what identifies the cells as "offer cells"]
  - but the firing rate associated with a given quantity of juice is smaller, when the range of quantities of juice that occur on different trials [in that experimental session] is greater

Padoa-Schioppa (2009)



vertical axis = firing rate of "offer cell"

Range Normalization

- The fact that two drops of juice are differently encoded when 4 is the upper bound, than when 10 is the upper bound, doesn't mean that they are **valued more** (on average) in the former case
  - the "decoding" of the internal representation seems to adjust to the range in an efficient way as well (Rustichini *et al.*, 2017)

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  - the "decoding" of the internal representation seems to adjust to the range in an efficient way as well (Rustichini *et al.*, 2017)
- But the change in encoding when the range is 10 **does** mean that two drops are not as accurately distinguished from four drops, as is the case when the range is 4
  - resulting in less predictable choices

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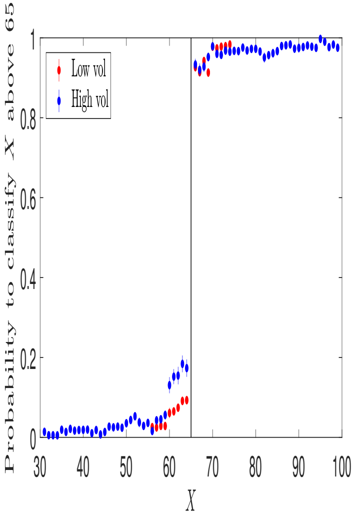
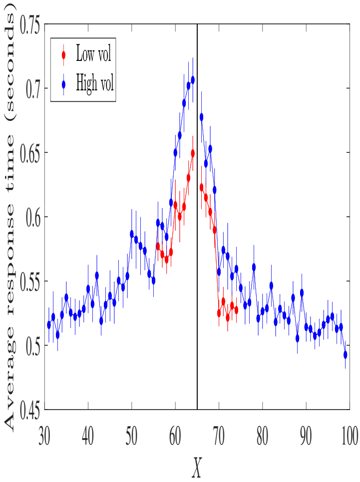
  - task: a two-digit Arabic numeral is presented, and the subject must (rapidly) say whether it is greater or less than 65
  - replicating the study of Dehaene *et al.* (1990), discussed above; but with numbers drawn from **two different distributions**
  - consequence: more mistakes (and slower responses) when the number presented is **closer** to 65
  - but for numbers near 65, responses are **slower** (and yet more mistakes) when the numbers are drawn from a wider **range**

Number Comparison [Frydman and Jin (2022)]





Range Normalization

- This suggests a model of noisy encoding of numerical magnitudes in which

$$r_x \sim p(r_x \,|m(X))$$

where $p(r_x \,|m)$ is the same across contexts, but the mapping $m(X)$ depends on the distribution of values of X used

  - $m(X)$ must adjust so that m has the **same bounded range,** regardless of the range over which X varies
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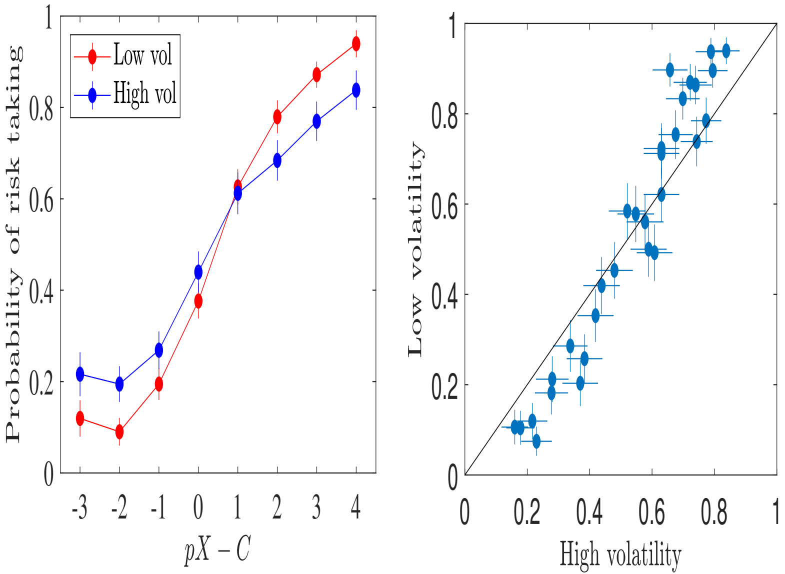
- Consequence: larger range of variation in X and C should result in noisier choice between lotteries

Lottery Choice [Frydman and Jin (2022)]



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- The hypothesis that decisions are based on **noisy internal representations** of the presented data can explain phenomena that a mere assumption of **comparison noise** (or more generally, response noise) cannot
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  — only that a hypothesis of comparison noise **by itself** doesn't adequately capture the role of cognitive noise in decision making
- Study of cognitive noise in other domains may help to improve economic modeling

The Remaining Lectures

- Lecture 2: Response bias as an optimal adaptation to cognitive noise

  — Enke *et al.*, "Behavioral Attenuation"

The Remaining Lectures

- Lecture 2: Response bias as an optimal adaptation to cognitive noise

  — Enke *et al.*, “Behavioral Attenuation”

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- Lecture 4: Cognitive noise in coordination games

  — Frydman and Nunnari, "Coordination with Cognitive Noise"

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