Price Obfuscation, Ease of Comparison, and Salience

Silvio Ravaioli
Columbia University

Cognition & Decision Lab Meeting

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Motivation

- **Firms can manipulate consumers' ability to compare the final prices between *bundles* of products**
- Example: prices divided into a large number of contigencies, Banking services, insurance plans, grocery stores...
- Apparently inconsistent preferences may emerge from inability to make accurate comparisons
- Possible ways to obfuscate the total price may include:

1. Combine several cheap products, and few (very) expensive ones
2. Use the pricing strategy to differentiate from the competitors
3. Put a low price on a product that is *usually* expensive

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Motivating Example

A busy graduate student wants to buy the ingredients listed below to prepare a pizza. He can choose one among the nearby stores, but he does not have enough time to do shopping in more than one.

Ingredients	**Store A**	**Store B**	**Store C**
Flour			
Tomato			
Mozzarella			
Mushrooms			
Sausage			
Pineapple			
Total			

Motivating Example

A busy graduate student wants to buy the ingredients listed below to prepare a pizza. He can choose one among the nearby stores, but he does not have enough time to do shopping in more than one.

Ingredients	Store A	Store B	Store C
Flour	\$3.00	\$2.90	
Tomato	\$2.50	\$2.40	
Mozzarella	\$8.00	\$7.90	
Mushrooms	\$3.00	\$2.90	
Sausage	\$6.00	\$5.90	
Pineapple	\$2.50	\$2.40	
Total			

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Pineapple	\$2.50	\$2.40	
Total	\$25.00	\$24.40	

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Flour	\$3.00		\$1.30
Tomato	\$2.50		\$5.10
Mozzarella	\$8.00		\$6.50
Mushrooms	\$3.00		\$4.10
Sausage	\$6.00		\$4.00
Pineapple	\$2.50		\$4.60
Total			

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How is consumer's (aggregate) price perception systematically affected by the context?

Requires a definition of *context*. Choice set? Expectations?

Main hypothesis

1. **Diminishing sensitivity** (concavity): small advantages surpass big disadvantages
2. **Ease of comparison** (similarity): choices are more accurate when prices are similar
3. **Salience** (surprise): excessive sensitivity with respect to unusual, extreme values

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Background Literature

- **Price Obfuscation**
  - Strategic sellers: Spiegler (2006), Gabaix & Laibson (2006), Brown, Hossain & Morgan (2010), Piccione & Spiegler (2012)
  - Biased consumers: Ellison & Ellison (2009), Brown et al. (2010)
- **Discrete Choice Models**
  - Random Utility Models: Luce (1959), Block & Marshak (1960)
  - Literally every IO paper containing demand estimation
- **Context Effect**
  - Theory: Tversky & Simonson (1993), Bordalo, Gennaioli & Shleifer (2013), Koszegi & Szeidl (2013), Bushong et al. (2017), Natenzon (2018), Landry & Webb (2019)
  - Marketing: Kivetz et al. (2004), Rooderkerk et al (2010)
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Preview of Results

- Consider a family of stochastic choice models
(generalization of classic RUM with constant error)

- Laboratory experiment design to explore a set of hypothesis
about stochastic choice with imperfect information recall

1. Choice is stochastic and monotonic in total price difference

2. Similarity across price vectors increases accuracy

3. Context effect consistent with *salience* a' la BGS

- Characterize a systematic choice pattern determined
by the prior value distribution and a varying perceptual error

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Discrete Choice Models

Setup - Binary Choice between Price Vectors

- Evaluate two bundles of products with different prices

$$i \in \{L, R\} \qquad X^i \equiv \{x_t^i\}_{t=1}^T \qquad x_t^i \sim F(\cdot)\ \forall i, t$$

- The *true* value is linear in the dimensions' values (total)

$$v(X^i) = \sum_{t=1}^{T} x_t^i$$

- The *perceived* value may be different from the true one (measurement error, perceptual noise, imperfect memory, etc.)
- Comparison by dimension: sequence of pairs $\{(x_t^L, x_t^R)\}_t$

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Benchmark: RUM with Constant Error

The DM observes value x_t^i and memorizes it as $\hat{x}_t^i$, with an additive normal noise.

$$\hat{x}_t^i | x_t^i \sim N(x_t^i, s^2) \qquad \hat{X}^i = \sum_{t=1}^{T} \hat{x}_t^i = v(X^i) + N(0, 6 \cdot s^2)$$

The DM chooses the option with the highest *perceived* total value.

$$Pr(\text{Choose } L | X^L, X^R, s^2) = Pr(\hat{X}^L > \hat{X}^R) = \Phi\left(\frac{\sum_{t=1}^{6}(x_t^L - x_t^R)}{s \cdot \sqrt{2 \cdot 6}}\right)$$

Choice probability depend only on the total value difference $v(X^L) - v(X^R)$ and the error's variance s^2 (multiplied by T).

RUM with Biased Perception of Values

- We can relax the assumption of unbiased perception of values
- Evaluation of alternatives can occur separately or jointly:
- $\hat{x}_t^i | x_t^i \sim N(m(x_t^i), s^2)$
- $(\hat{x}_t^L - \hat{x}_t^R) | (x_t^L - x_t^R) \sim N(m(x_t^L - x_t^R)), s^2)$
- Encoding of difference $\Delta x_t = x_t^L - x_t^R$ after a direct comparison
- A concave transformation $m(\cdot)$ captures diminishing sensitivity

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RUM with Heterogeneous Error Variance

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- A convex function $s(\cdot)$ captures larger errors when magnitudes or differences are large (e.g. multiplicative error)
- Random Perception of Differences [RPD]
  $(\hat{x}_t^L - \hat{x}_t^R)|(x_t^L - x_t^R) \sim N(m(x_t^L - x_t^R), s(x_t^L - x_t^R)^2)$

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Stochastic Choice Models

	$s(x) = s$	$s(x)$	$s(\Delta x)$
$m(x) = x$	RUM		
$m(x)$			
$m(\Delta x)$			

Stochastic Choice Models

	$s(x) = s$	$s(x)$	$s(\Delta x)$
$m(x) = x$	Unbiased Value Perception		
$m(x)$			
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Stochastic Choice Models

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$m(x)$	(Stochastic) Prospect Theory		
$m(\Delta x)$	Direct Comparison		

Stochastic Choice Models

	$s(x) = s$	$s(x)$	$s(\Delta x)$
$m(x) = x$	RUM		
$m(x)$		PT	
$m(\Delta x)$			RPD

Salience

- Bordalo, Gennaioli, and Shleifer (2013, 2017) [BGS]
- An attribute is salient if it unusual, in the sense of being furthest from the reference

- BGS (2013) Salience and consumer choice: context = choice set
- BGS (2017) Memory, attention, and choice: context = memory

- Memory as a database of past experience (Kahana 2012)

Models' Predictions

Pr(Choose x) may vary based on	RUM	PT	RPD	BGS
True diff: $v(X^L) - v(X^R)$	X	X	X	X
Concavity: $\Sigma_t 1(x_t^L > x_t^R)$		X	X	X
Similarity: $\Sigma_t \lvert x_t^L - x_t^R \rvert$			X	
Prior distr: $x_t^i \sim F(\cdot)$				X

Experimental Design

Experimental Design - Task

- **Binary choice**: 2 Compound Lotteries, L(eft) vs R(ight)
- Each CL has 6 Simple Lotteries, equally likely to be selected
- Each SL is a 10-90% probability of winning one point

- **Lab experiment** at CELSS (Columbia University), N=51
- 300 trials per participant ($\sim$ 40 min), part of a 80 min session
- Training and feedback (to ensure familiarity with the environment)
- Payment: (# points - 300) $\cdot$ 20 ¢   Avg. payment $24.60

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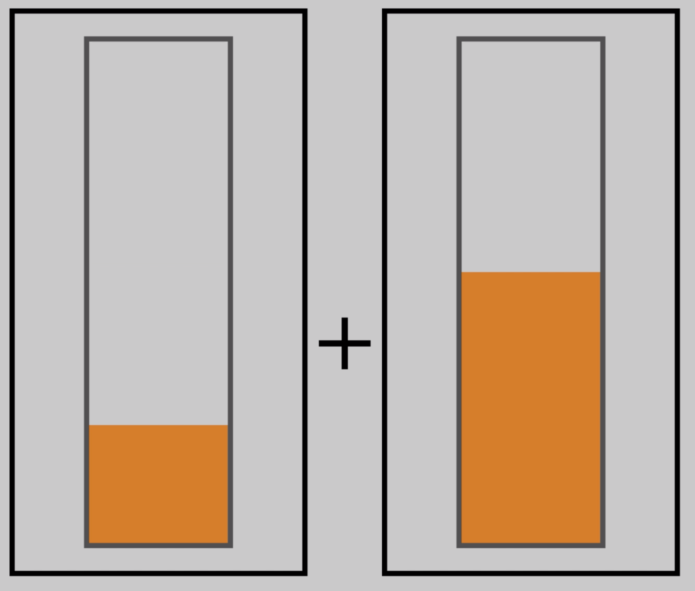
Experimental Design - Interface



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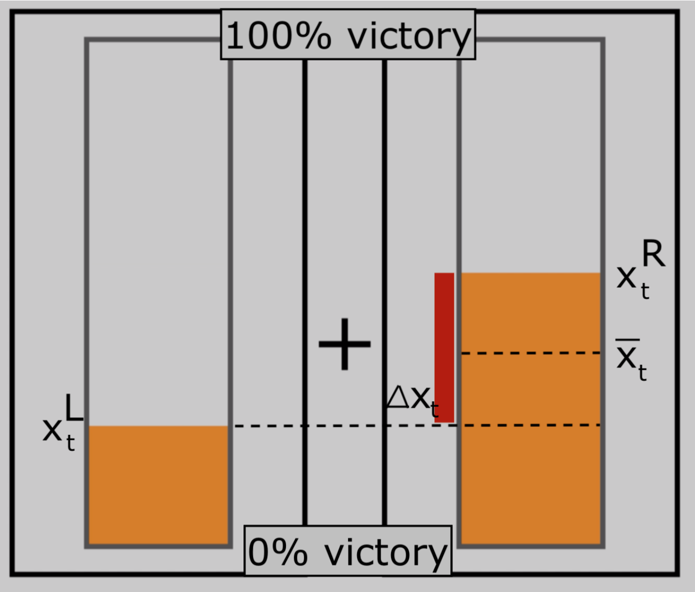
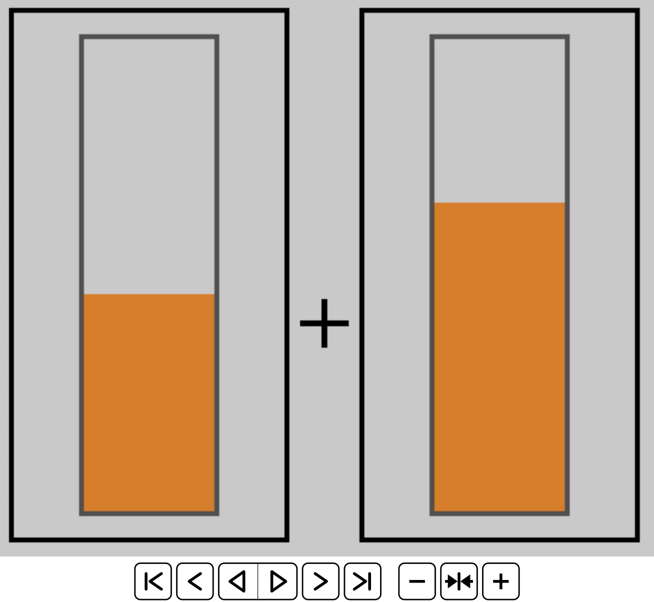
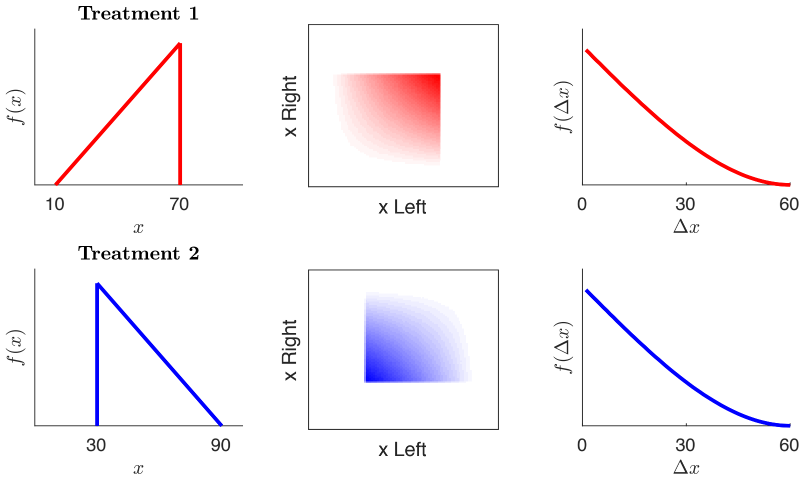


Experimental Design - Interface GIF



Experimental Design - Treatments

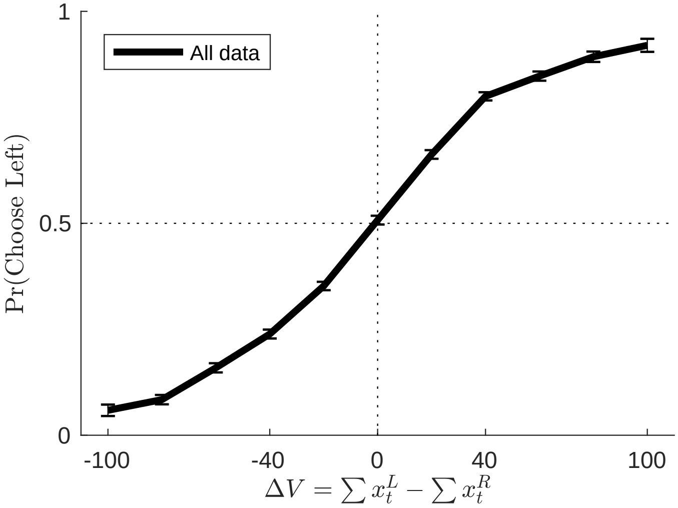
- Upward and Downward triangular distributions



Value distributions used to generate data in the two treatments

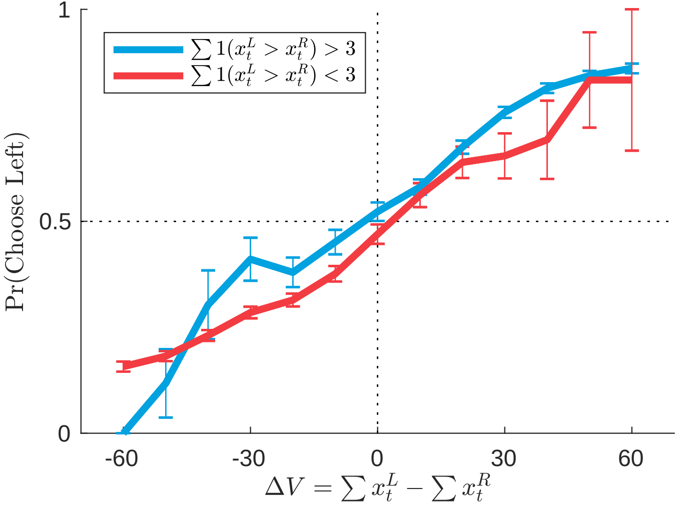
Results

Stochastic Choice



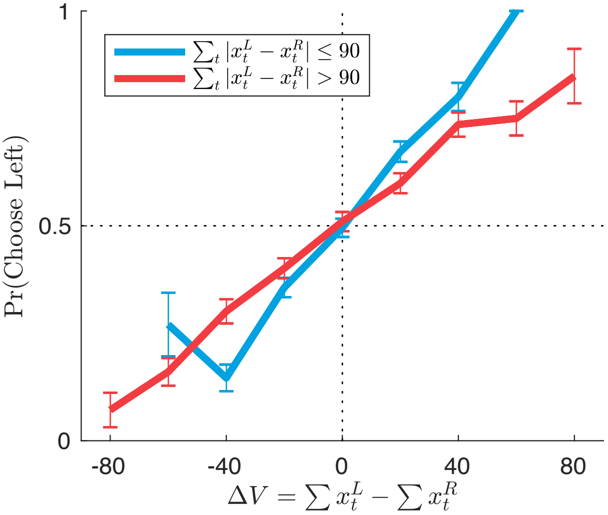
Choice probability in trials with different difficulty

Frequency of Local Comparisons



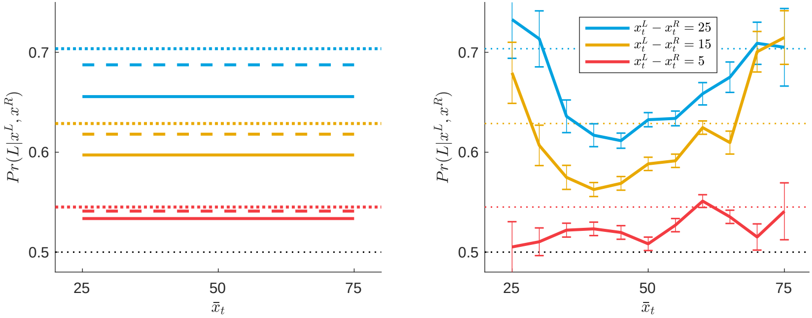
Frequent local winners (blue) chosen more often after controlling for ΔV

Similarity improves Accuracy



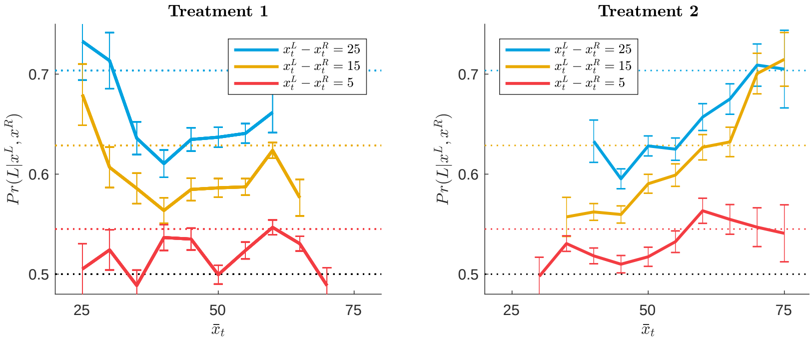
Participants are more accurate (steeper blue curve) when the options are similar, after controlling for ΔV and $\Delta W = 0$ (no frequent local winners)

Decision Weights - Predictions and Data



- **Decision weight** $Pr(L|x_t^L, x_t^R)$
- Increasing in $x_t^L - x_t^R$ [color], decreasing in $s(x_t^L, x_t^R)$ [line]
- RUM and RPD: the decision weight should only depend on Δx
- BGS: it can also depend on the environment (prior distribution)
- PT: possible effect of magnitudes (but not the prior)

Decision Weights - Treatments



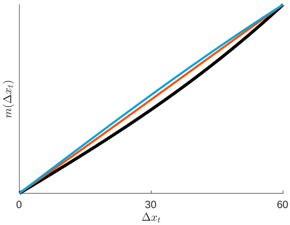
- Treatment 1: low values are rare, and display higher weights
- Treatment 2: high values are rare, and display higher weights
- Consistent with BGS' salience model

Model Fit - Summary

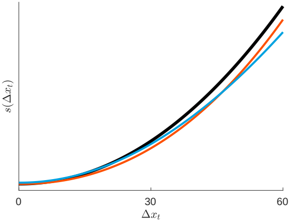
Model	Merge T1 and T2		Separate T1 and T2	
	LL	BIC	LL	BIC
Classic RUM x, s^2	-7,976	15,972	-7,965	15,969
Prospect Theory $m(x), s(x)^2$	-7.931	15,929	-7.882	15,900
RPD $m(\Delta x), s(\Delta x)^2$	-7,867	15,801	-7,846	15,826
RPD+BGS $m(\Delta x), s(\Delta x)^2, \sigma(\cdot)$	-7,719	15,525	-7,675	15,524

Summary table reporting the BIC for the main fitted models

Model Fit - RPD+Salience



Transformation $m(\Delta x)$



Varying noise $s(\Delta x)$

Fitted curves $m(\Delta x)$ and $s(\Delta x)$ for RPD+BGS.
Treatment 1 (red lines), Treatment 2 (blue lines), All data (black lines).

- $m(\Delta x)$: polynomia of degree 3, $m(0) = 0$, $m(1) = 1$
- $s(\Delta x)$: polynomia of degree 3, $s(\Delta x) \geq 0$
- δ: recency effect, decaying memory
- μ: salience effect [$\mu_1 = 0.99$, $\mu_2 = 2.18$]

Conclusions

Summary of Results

- Choice probabilities depend on the ease of comparison between vectors of values, not only on their sums
- The environment (prior distribution) plays an important role, DMs over-react to unusual values (salience)
- The choice pattern is consistent with an unbiased model of random perception of differences (RPD)

Limitations

- Our experimental design facilitates direct comparison
- Values are displayed as bars, lengths proportional to values
- We use compound lotteries (maximize success rate)
- We used binary choice problems only

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Implications and Applications

- Sophisticated sellers can induce naive consumers to make more mistakes by facilitating attribute-by-attribute comparisons
- Discrete Choice Models with parsimonious assumptions about the error structure based on direct comparison
- Nest the reported results in a standard strategic setting (duopoly and price competition)
- Empirical applications, e.g. choice between contractors
- Further applications beyond price obfuscation, for example comparison between multiattribute products
- Follow-up experiment with more display conditions

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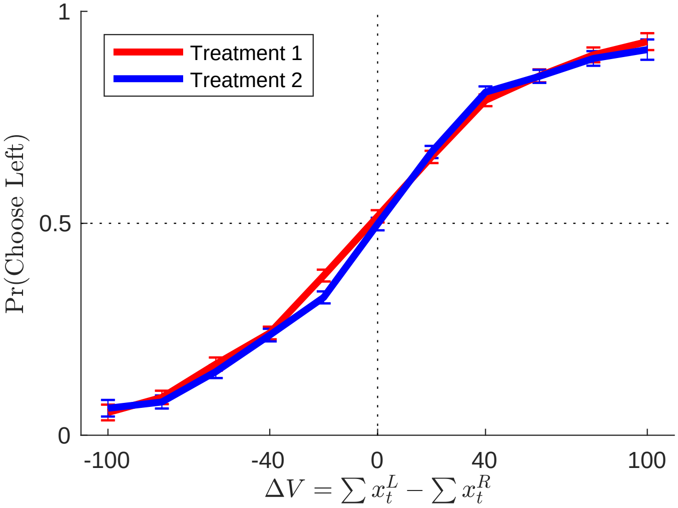
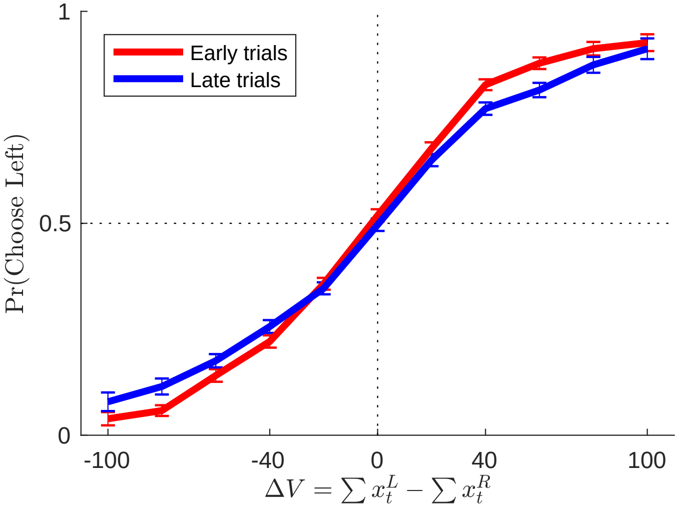
Appendix

Treatments



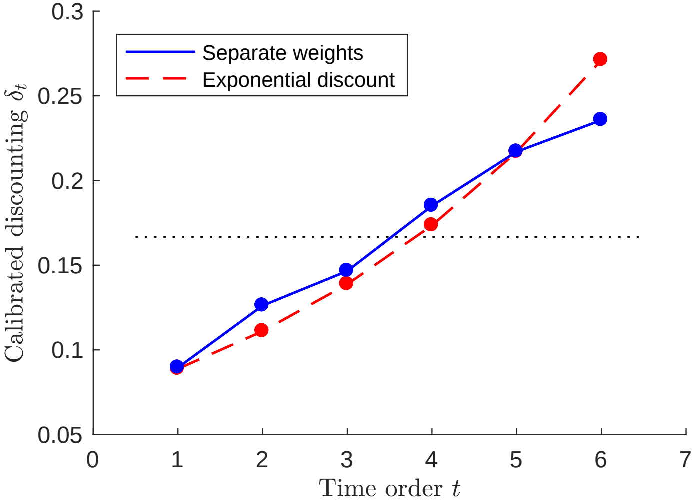
No significant accuracy difference across treatments

Learning



No learning over time. Some evidence of boredom

Recency



Exponential discounting approximates well the data