Integrating Delay Discounting and Heuristics to Better Explain Intertemporal Choice

Xi Chen

Thesis Advisor: Dr. Oleg Urminsky

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Introduction

Decisions involving consequences at different time points are referred to as *Intertemporal Choice* (Frederick, Loewenstein, & O'Donoghue, 2002).

Heuristic models can outperform traditional delay discounting models. (Ericson, White, Laibson, & Cohen, 2015).

Research Questions:

- Comparing heuristic models and delay discounting models which are better explaining intertemporal choices, and why?
- By integrating discounting and heuristics, can we find new insights in modeling intertemporal choice?

Literature

Delay Discounting Models

- Exponential model: $L(a(x_2\delta^{t_2}-x_1\delta^{t_1}))$
- ► Hyperbolic model: $L(a(x_2(1+\alpha t_2)^{-1}-x_1(1+\alpha t_1)^{-1}))$
- Quasi-Hyperbolic model $/\beta \delta$ discounting model: $L(a(x_2\beta^{I(t_2>0)}\delta^{t_2} x_1\beta^{I(t_1>0)}\delta^{t_1}))$

Heuristic Models

- ► Tradeoff model: $L(a((log(1+\gamma_x x_2)/\gamma_x log(1+\gamma_x x_1))/\gamma_x k(log(1+\gamma_t t_2)/\gamma_t log(1+\gamma_t t_1)/\gamma_t)))$
- ▶ DRIFT model: $L(\beta_0 + \beta_1(x_2 x_1) + \beta_2 \frac{x_2 x_1}{x_1} + \beta_3((\frac{x_2}{x_1})^{\frac{1}{t_2 t_1}} 1) + \beta_4(t_2 t_1))$
- ► ITCH model: $L(\beta_I + \beta_{xA}(x_2 x_1) + \beta_{xR} \frac{x_2 x_1}{x^*} + \beta_{tA}(t_2 t_1) + \beta_{tR} \frac{t_2 t_1}{t^*})$

Experiments & Data

Dataset I

- Ericson, White, Laibson & Cohen (2015)
- ▶ 940 participants; each participant answered 25 MEL questions
- 5 conditions: delay vs. speedup framing
- ► Money range: \$0.01 to \$100,000.00
- ► Time range: 0 weeks to 6 weeks

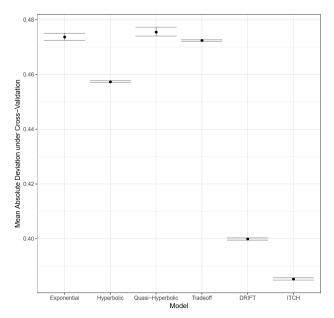
Dataset II

- ▶ 377 participants; each participant answered 44 MEL questions
- 4 repeated questions
- Money range: \$0.01 to \$100,000.00 (more amounts)
- ▶ Time range: 0, 1, 2 ... 365 days ... 30 years (wider range)

Method

- ▶ Binary outcome Logistic regression: $L(x) = (1 + e^{-x})^{-1}$
- Generalized Linear Models
- Maximum Likelihood Estimation
- Cross-validation techniques
- ▶ Error metrics: Mean Absolute Deviation, AIC, BIC

Results (Dataset II)



Results (Dataset I)

ITCH model:

$$L(\beta_{I} + \beta_{xA}(x_{2} - x_{1}) + \beta_{xR}\frac{x_{2} - x_{1}}{x^{*}} + \beta_{tA}(t_{2} - t_{1}) + \beta_{tR}\frac{t_{2} - t_{1}}{t^{*}})$$

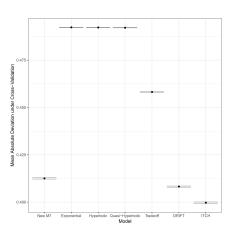
Model Manipulation: Removing	Model Fit (Mean Absolute Deviations/MAD)					
	Pooled Data	Condition 1	Condition 2	Condition 3	Condition 4	Condition 5
Baseline / ITCH	0.3997	0.3213	0.3899	0.3158	0.4527	0.4410
Relative Time Term	0.4034	0.3225	0.3924	0.3172	0.4619	0.4460
Absolute Time Term	0.4034	0.3240	0.3948	0.3197	0.4562	0.4440
Relative Money Term	0.4524	0.3963	0.4578	0.3938	0.4761	0.4779
Absolute Money Term	0.4063	0.3320	0.3933	0.3277	0.4572	0.4464
Relative Terms	0.4554	0.3976	0.4592	0.3950	0.4839	0.4829
Absolute Terms	0.4099	0.3350	0.3974	0.3327	0.4603	0.4493
Constant Term	0.4318	0.4097	0.4199	0.4029	0.4585	0.4466

New Models (Dataset I)

New Model 6: $\beta_1(v_2-v_1)+\beta_2\frac{v_2-v_1}{v^*}, v_1=x_1\delta^{t_1}, v_2=x_2\delta^{t_2}$

New Model 7: $\beta_1(v_2 - v_1) + \beta_2 \frac{v_2 - v_1}{v^*} + \beta_3(d_2 - d_1)$

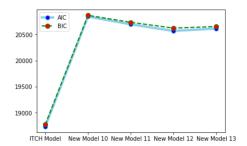
New Model 8: $\beta \frac{v_2 - v_1}{v^*}$



New Models (Dataset II)

New Model 10: $\alpha + \beta_1(x_2 - x_1) + \beta_2(t_2 - t_1)$ New Model 11: $\alpha + \beta_1(x_2 - x_1) + \beta_2(t_2 - t_1) + \beta_3 x_1 + \beta_4 t_1$ New Model 12: $\alpha + \beta_1(x_2 - x_1) + \beta_2(t_2 - t_1) + \beta_3 x_1 + \beta_4 t_1 + \beta_5(x_2 - x_1) x_1 + \beta_6(t_2 - t_1) t_1$ New Model 13:

$$\alpha + \beta_1(x_2 - x_1) + \beta_2(t_2 - t_1) + \beta_3(x_2 - x_1)x_1 + \beta_4(t_2 - t_1)t_1$$



Discussion

- Heuristics models capture some important characteristics of intertemporal choice that the standard economic models haven't.
- ▶ People's decisions do seem to incorporate relative judgments.
- Integrating discounting and heuristics may be a promising way to develop better intertemporal choice models.

Future Direction:

- Parameter recovery stimulating data from models
- ► Heterogeneity individual level modeling