Intertemporal Choice - Tradeoff between Money and Time

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Background

• Intertemporal choices refer to decisions involving consequences and relative preferences - tradeoff between cost and benefits - that occur at different time points (Frederick et al., 2002). For example, a choice with two alternative options: $10 today versus $20 in a week, and this is a standard *money-earlier-or-later* (MEL) task paradigm.

• Several models have been proposed to address individuals' decision between money and time. These models can be generally categorized into two groups: delay discounting models and heuristic models. This research examines three classical delay discounting models: exponential model, hyperbolic model, quasi-hyperbolic mode, and three heuristic models: ITCH model (Ericson, et al., 2015), Trade-off model (Read et al., 2010), and DRIFT model (Scholten et al., 2013). This research also develops some new models.

Data & Methods

• The data is from the experiment conducted by Ericson et al., (2015), which recruited 940 participants from the MTurk. Each participant was randomly assigned to one of five conditions and answer some MEL tasks:

Condition 1: Absolute Money Value, Delay Framing
Condition 2: Relative Money Value, Delay Framing
Condition 3: Standard MEL Format
Condition 4: Absolute Money, Speedup Framing
Condition 5: Relative Money, Speedup Framing

• The main method is to perform cross-validation analyses to compare six classic models. The measure of model fit is the Mean Absolute Deviation (MAD) between a model's prediction and the actual choice, both of which are probabilities of choosing the larger, later option. To estimate the parameters of the models, maximum likelihood estimation is performed. The research goal is to develop new models based on the results from the above analyses.

Classical Models

The intertemporal choice models have various versions. The version here are adapted from Ericson et al., (2015). In each of these models, the notation, *L(z)*, represents the inverse logistic function of z: $L(z) = (1+e^{-z})^{-1}$

P(LL) represents the probability that individuals prefer the larger, later option over the smaller, sooner option.

Delay Discounting Models

Exponential model. $P(LL) = L(a\,(x_2\delta^{t2} - x_1\delta^{t1}))$

Hyperbolic model.

$P(LL) = L(a\,(x_2(1+\alpha t_2)^{-1} - x_1(1+\alpha t_1)^{-1}))$

Quasi-hyperbolic model.

$P(LL) = L(a\,(x_2\beta^{I(t2>0)}\delta^{t2} - x_1\beta^{I(t1>0)}\delta^{t1}))$

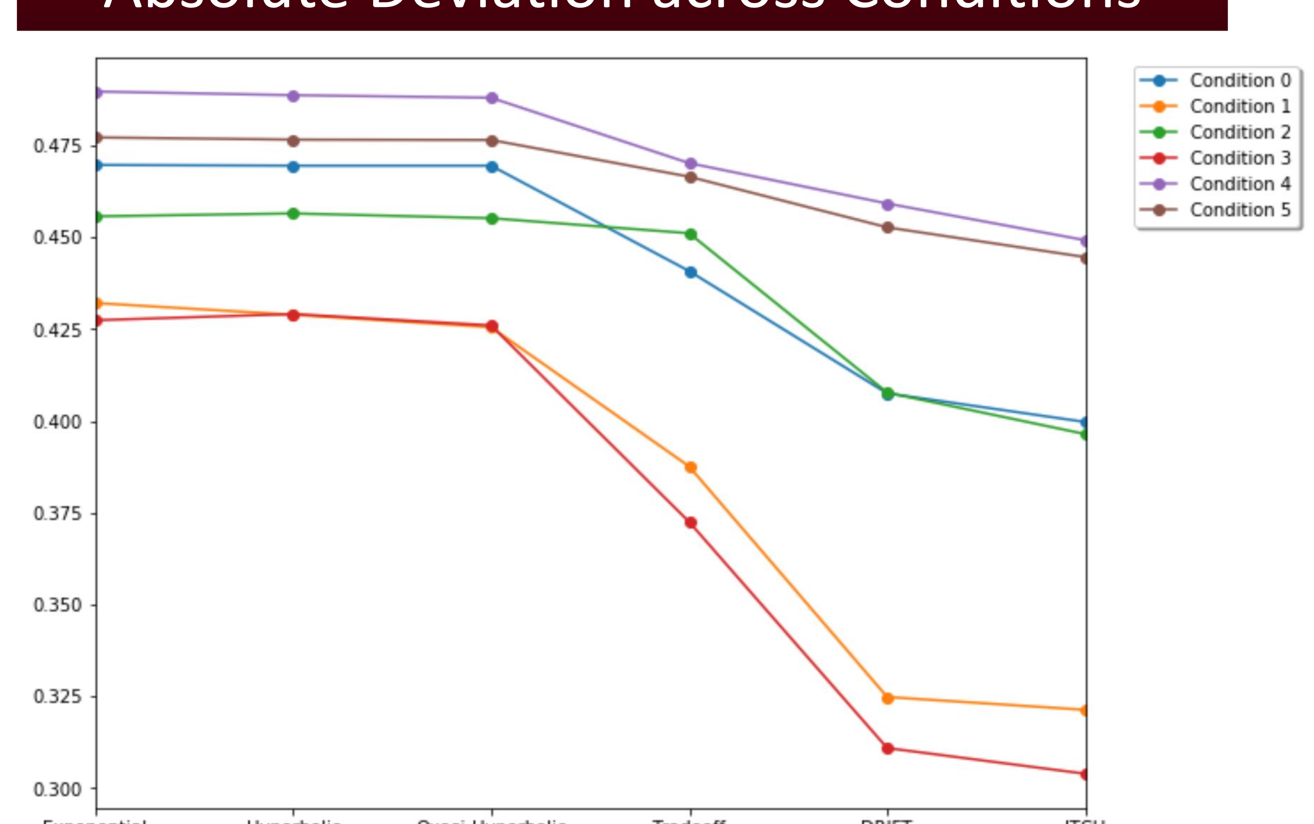
Heuristic Models

ITCH model. $P(LL) = L(\beta_I + \beta_{xA}(x_2-x_1) + \beta_{xR}\frac{x_2-x_1}{x^*} + \beta_{tA}(t_2-t_1) + \beta_{tR}\frac{t_2-t_1}{t^*})$

Trade-off model. $P(LL) = L(a\,((\frac{\log(1+\gamma_x x_2)}{\gamma_x} - \frac{\log(1+\gamma_x x_1)}{\gamma_x} - k(\log(1+\gamma_x t_2) - \frac{\log(1+\gamma_x t_1)}{\gamma_x})))$

DRIFT model. $P(LL) = L(\beta_0 + \beta_1(x_2-x_1) + \beta_2\frac{x_2-x_1}{x^*} + \beta_3 {\frac{x_2}{x_1}}^{\frac{1}{t2-t1}} + \beta_4(t_2-t_1))$

Comparing Classical Models by Mean Absolute Deviation across Conditions



Examining the Terms in the ITCH Model

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

New Model 1: $P(LL) = L(\beta_I + \beta_2(x_2-x_1) + \beta_3(t_2-t_1) + \beta_4(d_2-d_1))$

New Model 2: $P(LL) = L(\beta_I + \beta_2(x_2-x_1) + \beta_3\frac{x_2-x_1}{x^*} + \beta_4(t_2-t_1) + \beta_5(d_2-d_1))$

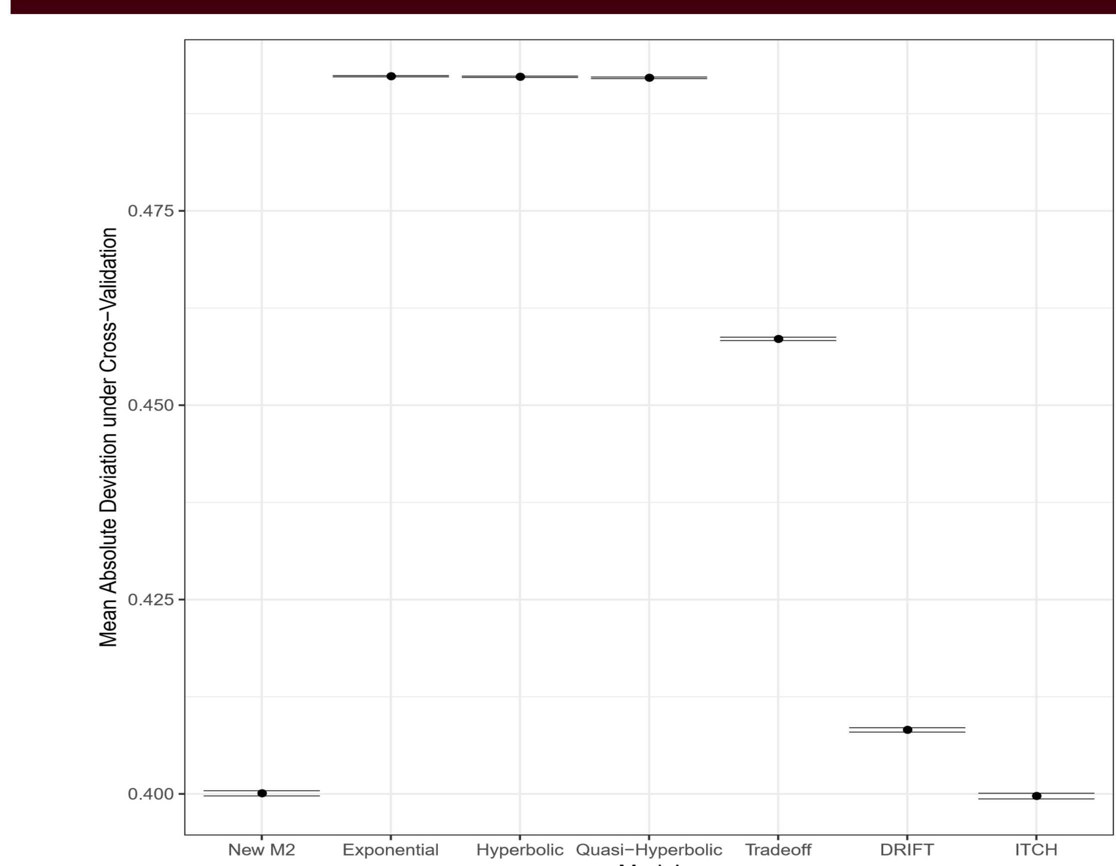
New Model 3:
$P(LL) = L(\beta_I\,(x_2\delta^{t2} - x_1\delta^{t1}) + \beta_2(x_2-x_1) + \beta_3\frac{x_2-x_1}{x^*} + \beta_4(t_2-t_1) + \beta_5(d_2-d_1))$

New Model 4: $P(LL) = L(\beta_I\,({x_2}^{\alpha}\delta^{t2} - {x_1}^{\alpha}\delta^{t1}) + \beta_2(d_2-d_1))$

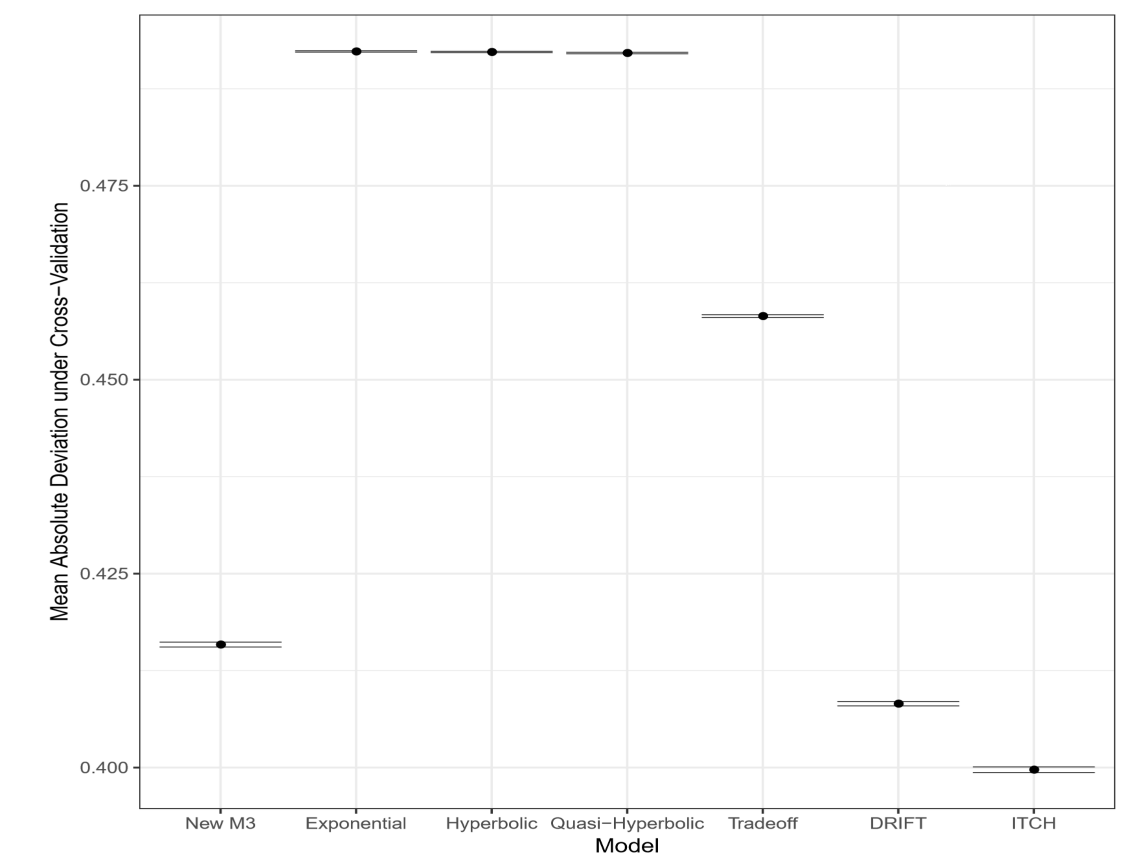
New Model 5: $P(LL) = L(\beta_I\,[(\beta_2 x_2 + \beta_3\frac{x_2}{x_1})\,\delta^{t2-t1}) - x_1] + \beta_4(d_2-d_1))$

New Model 6:
$P(LL) = L(\beta_1(v_2-v_1) + \beta_2\frac{v_2-v_1}{v^*})$ where $v_1 = x_1\delta^{t1}$, $v_2 = x_2\delta^{t2}$, and $v^* = \frac{v_2+v_1}{2}$.

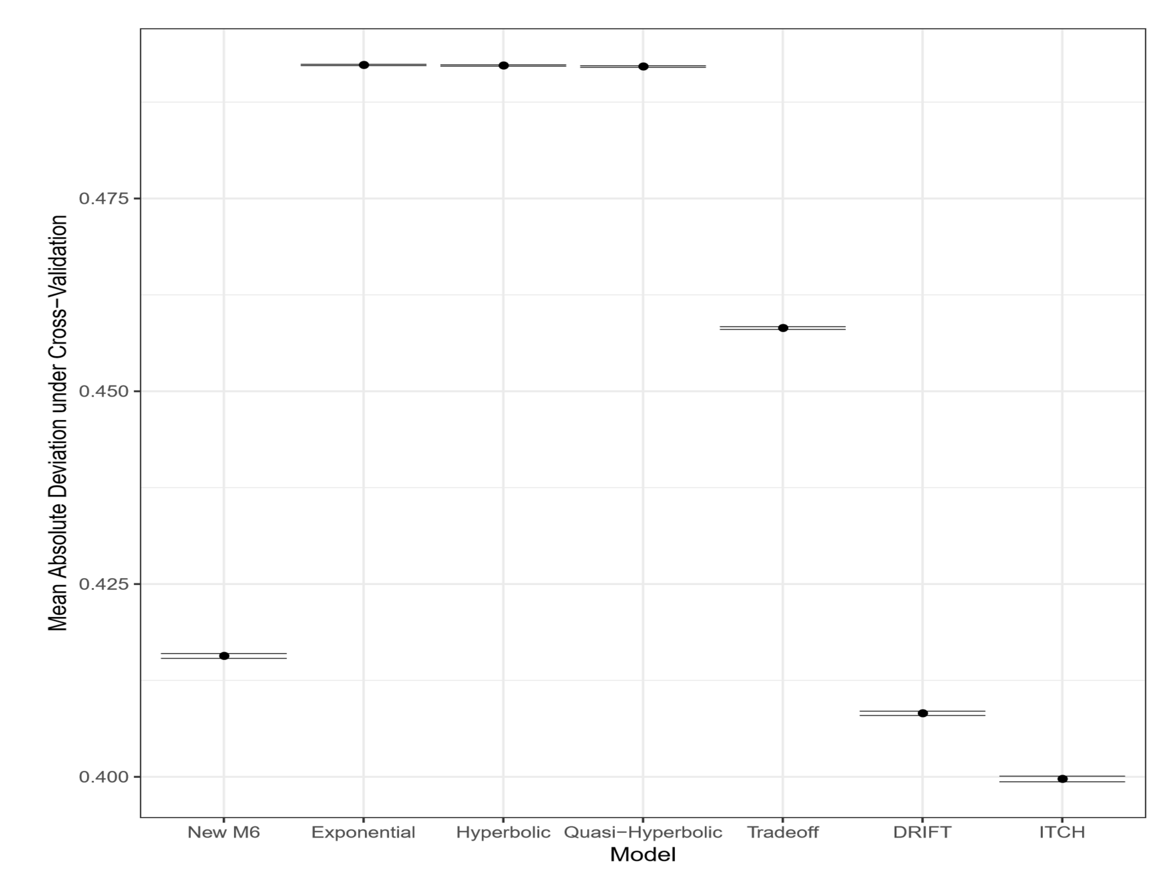
Comparing Model Fit between the New Model 2 and Classical Models



Comparing Model Fit between the New Model 3 and Classical Models



Comparing Model Fit between the New Model 5 and Classical Models



Conclusion

• Based on the examination of each term in the ITCH model by backward selection techniques, the results show that both of the two relative terms are of great importance; the relative money term is especially important; the constant term also plays a significant role in the model.

• Among the new models, Model 2 performs as well as the ITCH model; Model 3 and 6 have similar performance, which is better than all the delay discounting models and one of the heuristic models. The future direction is to develop another model which could outperform all the models.