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Behavioral insights in route choice models with real-time information

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Outline

Introduction
Insights from Behavioral Theories
Research Goals
Methodology
Experiment Design
VBA program
Results
Improved Discrete Choice Models
Discussion & Conclusions

Introduction

- A driver is faced with real-time information about the ranges of travel time for two routes:
  - a **faster** route (mean = 25)
  - a **slower** route (mean = 30).
- 'Traffic Control' predicts travel time ranges of ±5 or ±15 minutes respectively for each route. Imagine three possible travel scenarios by combining travel time means and ranges.
- *How do we predict the driver's choice in each case ?*

Three possible travel time scenarios			
Scenario	Description	Range (min.)	
		Faster Route	Slower Route
Safer-Fast	Low variability on F	25 ± 5	30 ± 15
Risky-Fast	High variability on F	25 ± 15	30 ± 5
Low-Risk	Equal variability	25 ± 5	30 ± 5

Insights from behavioral research

- Assumptions of rational choice are the core of modeling travel behavior. Discrete choice models provide parsimony but not an explicit abstraction of the impact of information on behavior under uncertainty.
- Research shows that human behavior deviates from the predictions of rational decision making i.e. we are more sensitive to relative outcomes than to expected utilities.
- However, different generalizations imply deviations in different directions. This is problematic!

3 contradicting predictions in our example:

Theory	Authors	Predicted behavior	Empirical evidence
Hot Stove	Denrell & March, 2001	Drivers exhibit risk aversion	Abdel Aty et al., 1997
Prospect Theory	Kahneman & Tversky,1979; 1992	Drivers exhibit risk seeking (travel time framed as loss).	Katsikopoulos et al., 2002
Payoff Variability	Myers et al., 1960; Erev & Barron, 2005	Increase in variability moves behavior towards random choice.	Avineri & Prashker, 2003

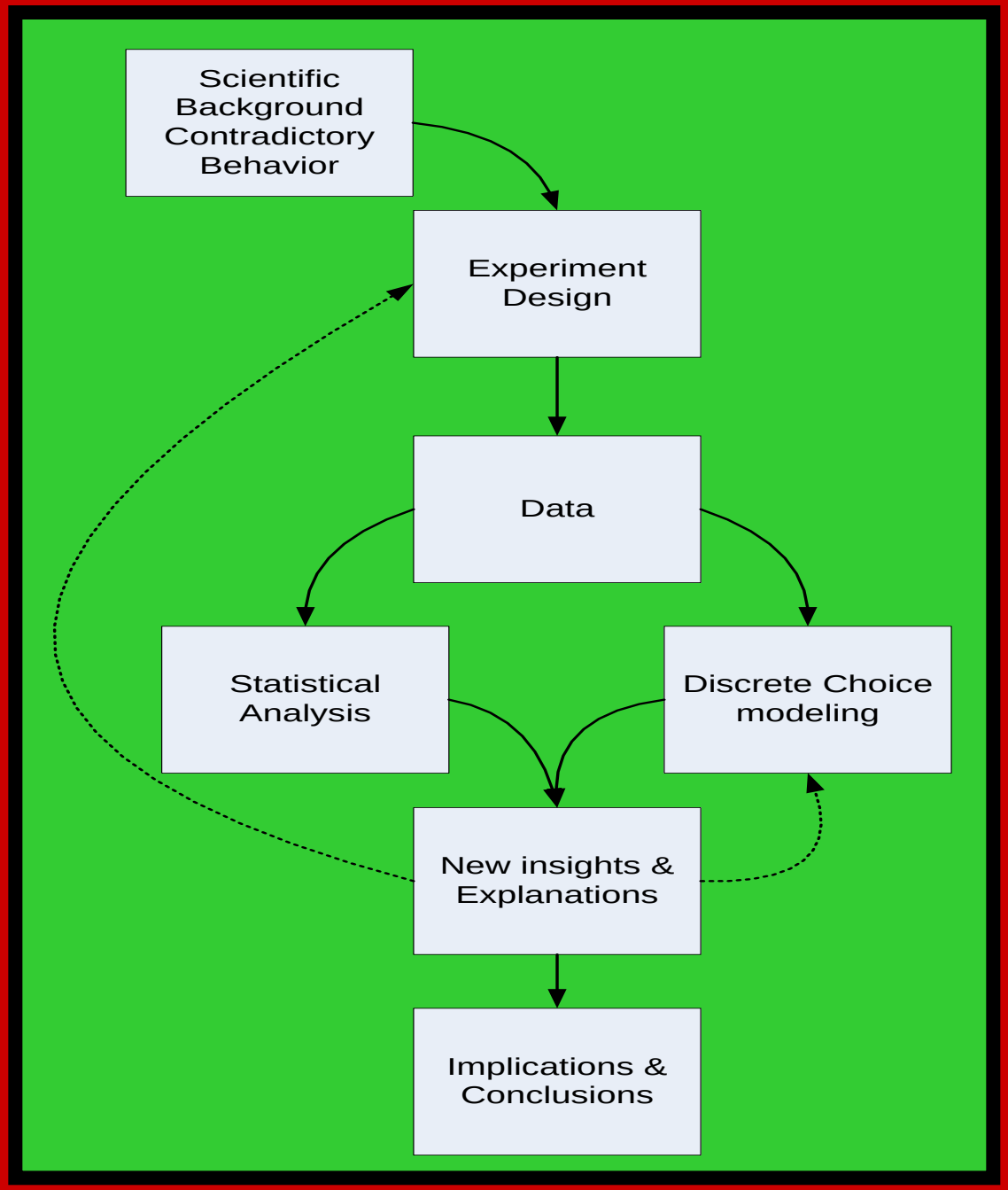
Predicted proportions of fast choices (P_F)

Theory / Condition	**Hot Stove**	**Prospect Theory**	**Payoff Variability**
No Information	$P_F(RF) < P_F(SF)$	$P_F(RF) > P_F(SF)$	$P_F(LR) > P_F(SF)$ $P_F(LR) > P_F(RF)$
With Information	$P_F(SF) \downarrow$	$\uparrow P_F(RF)$	$\uparrow P_F(RF)$ $\uparrow P_F(SF)$

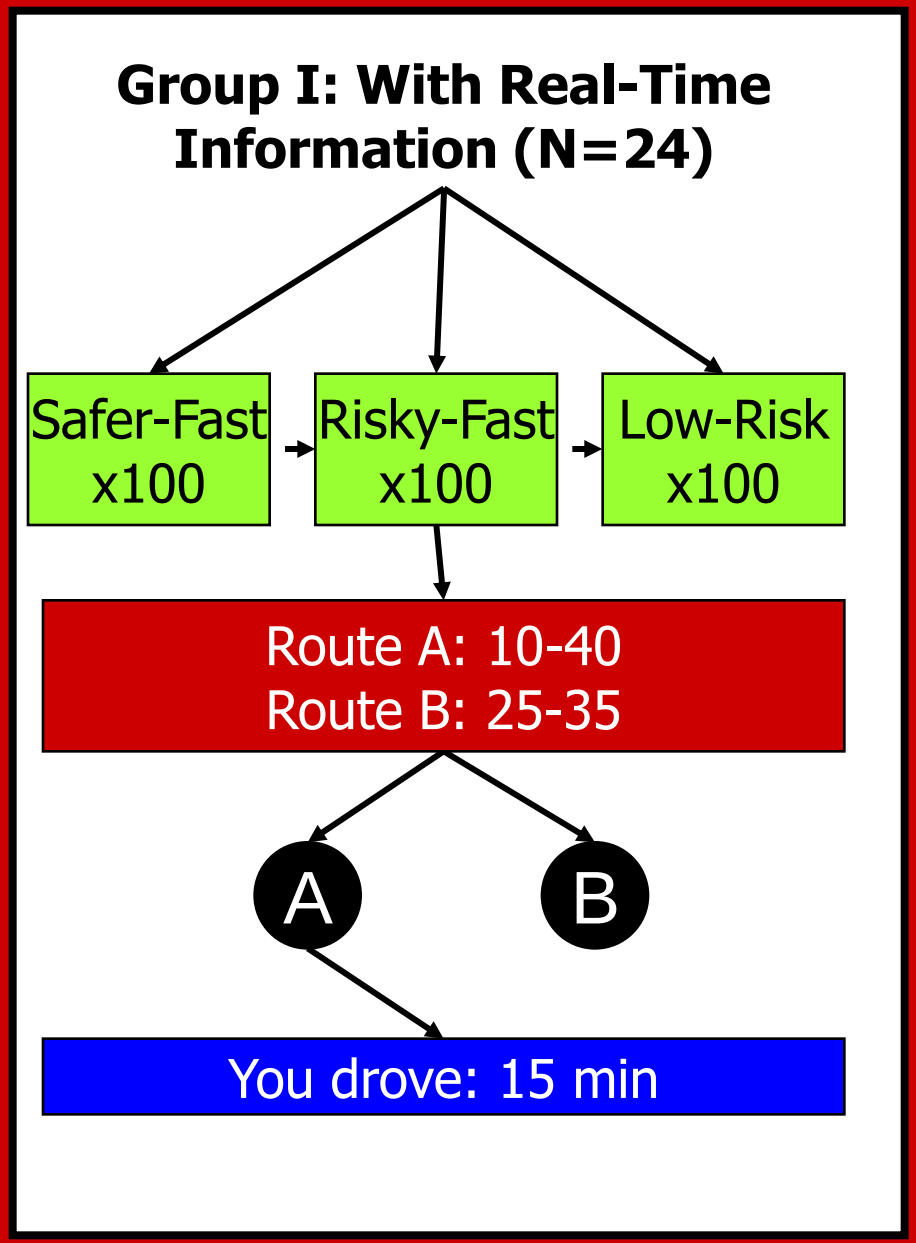
Research goals

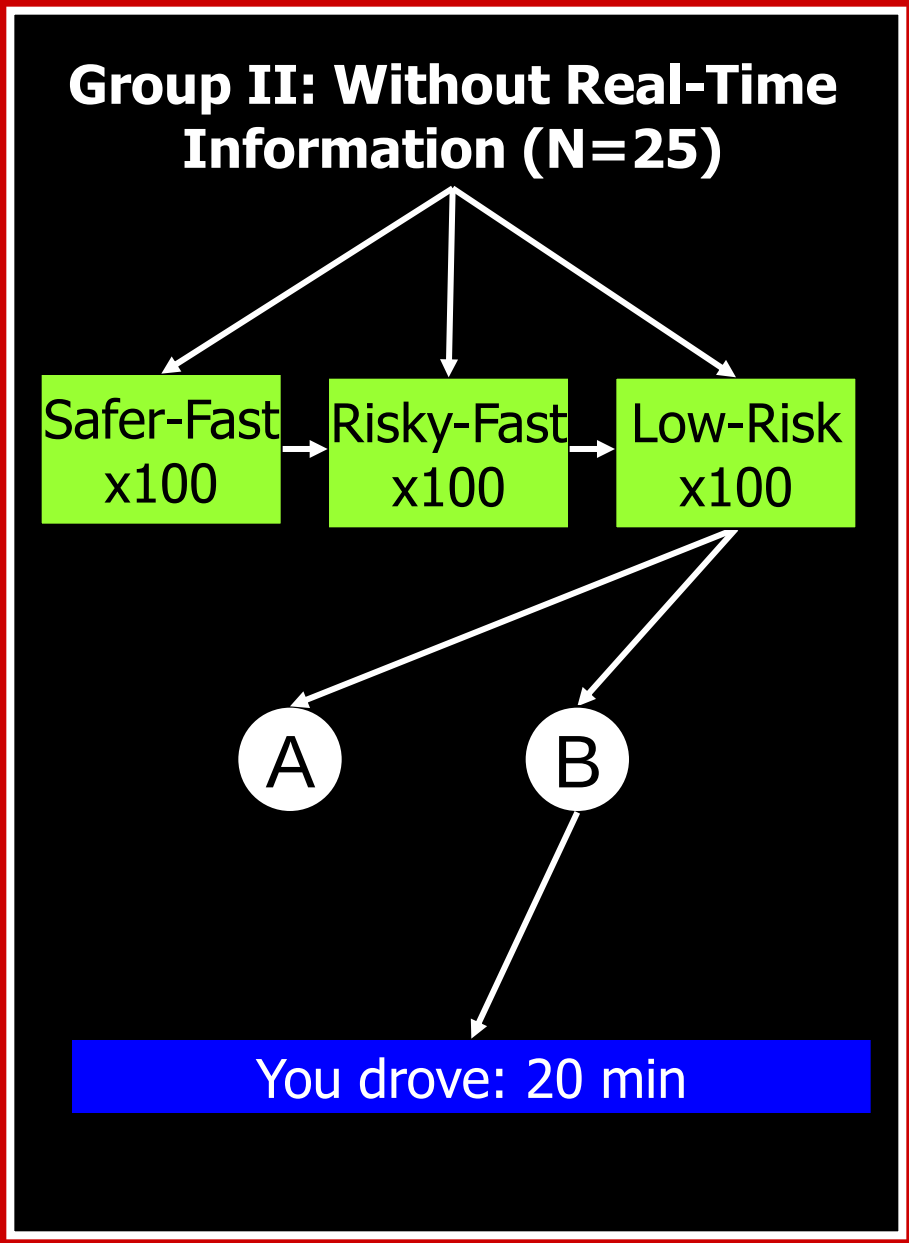
- Improve understanding of applying insights from behavioral research in route choice modeling
- Study the combined effects of information and experience on route-choice behavior.
- Estimate an improved 'positive' discrete choice model that incorporates behavioral insights.

Methodology

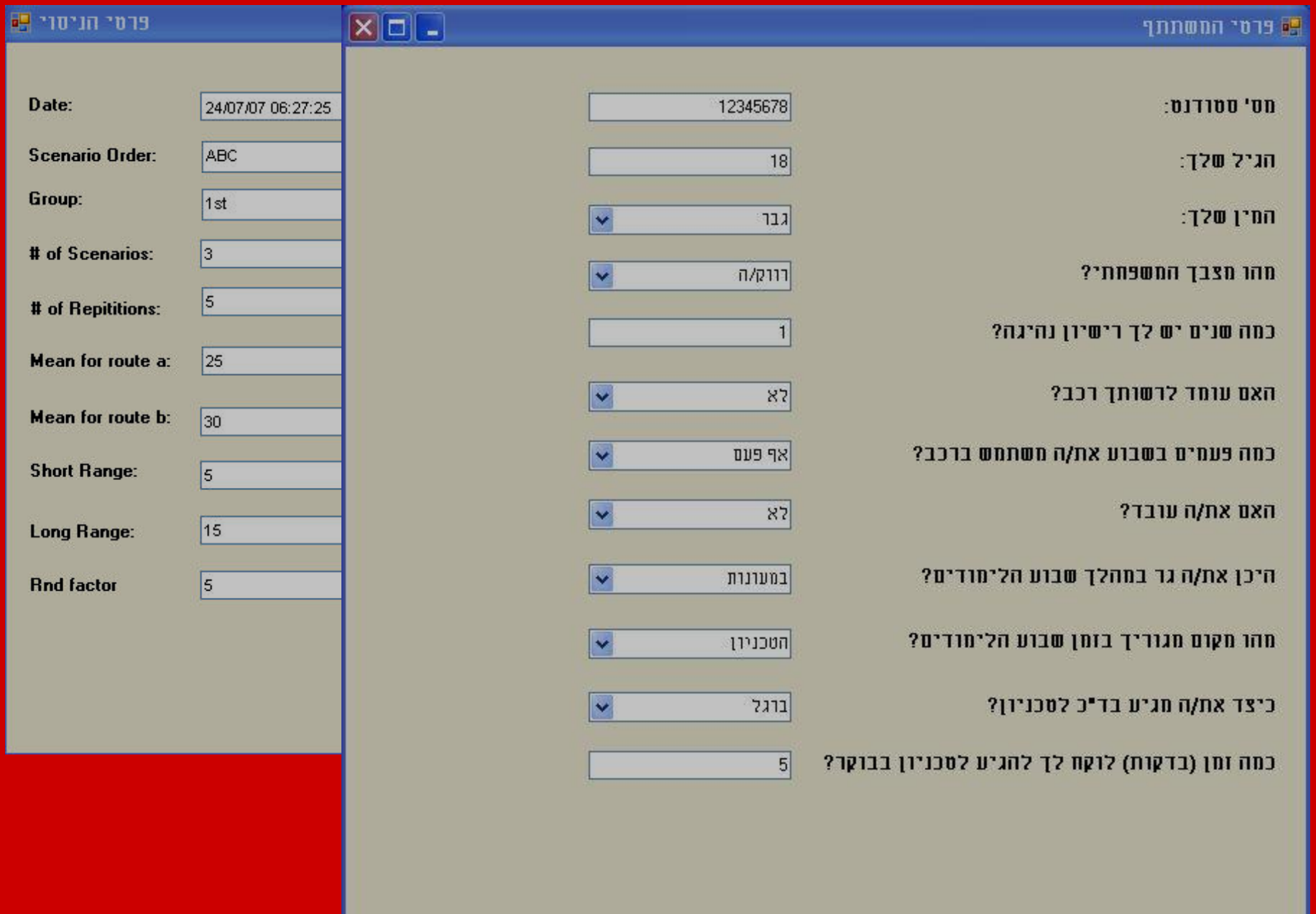


Experiment Design



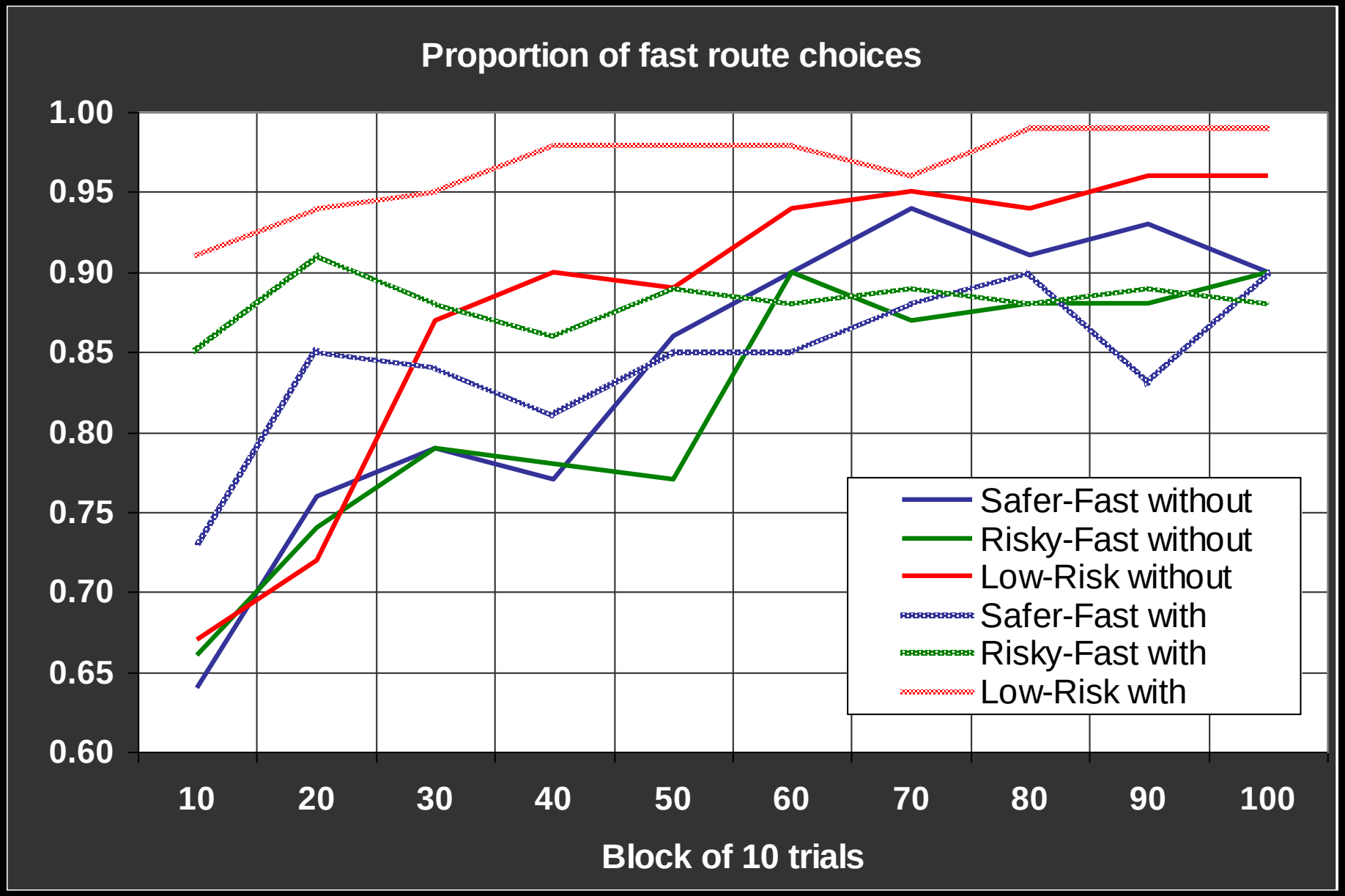


Snaps from the VBA Program



Snaps from the VBA Program

Results


Proportion of fast route choices
1.00
0.95
0.90
0.85
0.80
0.75
0.70
0.65
0.60
10
20
30
40
50
60
70
80
90
100
Block of 10 trials
Safer-Fast without
Risky-Fast without
Low-Risk without
Safer-Fast with
Risky-Fast with
Low-Risk with

Scenario	Conditions (groups)		Sig. Between
	With information	Without information	
Full data set			
Safer-Fast	84.4	83.8	-
Risky-Fast	88.1	81.7	-
Low-Risk	96.6	88.0	<0.05
Sig. within	<0.05	-	
First 10 trials			
Safer-Fast	72.9	63.6	-
Risky-Fast	85.0	66.0	<0.05
Low-Risk	91.2	67.2	<0.05
Sig. within	<0.05	-	
Last 50 trials			
Safer-Fast	87.3	91.4	-
Risky-Fast	88.5	88.6	-
Low-Risk	98.6	95.4	-
Sig. within	<0.05	<0.05	

Discussion (1)

- Behavior **without** real time information reflects the Payoff Variability Effect. Overall, increase in the variability moves behavior towards random choice.

- The initial effect of **information** is positive and consistent with Prospect Theory. However, with more experience risk seeking behavior disappears leaving payoff variability as the main effect.

- Information has three main effects:
  1. reducing initial exploration,
  2. increasing initial risk seeking
  3. increasing between-subject differences in attitudes towards risk.

An improved discrete choice model

- The utility of alternative *j* for person *n* in period *t* is: $U_{njt} = \beta_n x_{njt} + \varepsilon_{njt}$.
- A **Mixed Logit** specification with **panel data** was applied whereby each participant provided 300 responses.
- MXL is generalized for repeated choices with the coefficients - β varying over individuals but remaining constant over each ones' responses.

$$P_{ni}(\beta) = \int \prod_{t=1}^{T} \left[\frac{e^{\beta' n x_{nit}}}{\sum_j e^{\beta' n x_{njt}}} \right] f(\beta) d\beta$$

- MXL were estimated with the BIOGEME software and applying the CFSQP algorithm and with 1000 Halton draws in the simulated log likelihood.

- 3 alternative model specifications were estimated:
  1. Absolute travel times (best)
  2. Gains/Losses in travel times
  3. Absolute travel times + travel time variance.

- Explanatory variables (i.e. $\beta' x_i$) included:
  1. Route characteristics;
  2. Scenario characteristics (travel time ranges);
  3. Travel time feedbacks;
  4. Learning (long & short term) and level of experience;
  5. Individual's characteristics were discarded.

- Normally distributed disturbance coefficients (σi) were defined for some variables.
- Between groups segmentation –group scales (μ) are estimated for each group with/without information.
- Model identification was considered

Example of the 1st model's specification:

$$U_{fast} = \beta_{MEAN} \times meanF + \beta_{timeF}[\sigma_{timeF}] \times timeF + \beta_{RANGLL}[\sigma_{RANGLL}] \times rangLL + \beta_{RANGHL}[\sigma_{RANGHL}] \times rangHL + \beta_{low} \times Low + \beta_{high} \times High + \beta_{stick}[\sigma_{stick}] \times Stick + \beta_{CWA}[\sigma_{CWA}] \times Cwa$$

$$U_{slow} = \beta_{MEAN} \times meanS + \beta_{timeS}[\sigma_{timeS}] \times timeS$$

Model estimation (1)

Coef.	Definition	Unrestricted model				
		With Information group		Without Information group		t-stat between groups
		Value	t-stat	Value	t-stat	
β_{STICK}	Lagged choice (stickiness)	8.15	7.14	16.46	6.54	-6.12
β_{CWA}	Weighted average of past choices	4.68	5.10	-1.60	*-1.65*	6.46
β_{HIGH}	High experience (last 50 trials)	0.24	*1.22*	1.64	4.49	-2.65
β_{LOW}	Low experience (first 10 trials)	-1.24	-3.41	-2.30	-4.42	*1.59*
β_{TIMEF}	Travel time if last choice was fast	-0.13	-4.48	-0.24	-4.86	*0.57*
β_{TIMES}	Travel time if last choice was slow	-0.09	-5.88	-0.21	-10.48	*0.92*
β_{MEAN}	Mean of route (fixed)	1.00		1.00		-
$\beta_{RISK-FAST}$	Risky-Fast scenario	1.75	3.60	0.13	*0.51*	2.69
$\beta_{LOW-RISK}$	Low Risk scenario	4.73	4.30	0.76	2.33	4.72

Model estimation (2)

Coef.	Definition	Unrestricted model				
		With information group		Without Information group		t-stat between groups
		Value	t-stat	Value	t-stat	
σ_{STICK}	Stickiness disturbance	2.14	4.51	3.83	4.88	-2.13
σ_{CWA}	Weighted average of past choices disturbance	-2.40	-3.97	1.67	4.58	-5.86
σ_{TIMEF}	Travel time disturbance if last choice was fast	-0.004	*-0.34*	0.06	4.72	*-0.60*
σ_{TIMES}	Travel time disturbance if last choice was slow	0.06	3.88	0.08	4.56	*-0.15*
$\sigma_{RISK-FAST}$	Scenario Risky-Fast disturbance	2.79	4.05	0.88	3.71	2.83
$\sigma_{LOW-RISK}$	Scenario Low Risk disturbance	3.36	4.23	-2.32	-4.43	7.01
μ	Group's Scale	0.60	-4.01	0.48	-5.99	2.73

Model estimation (3)

Parameter	Restricted model (no group difference)	Unrestricted model
Number of draws:	1000	1000
Number of estimated parameters:	16	30
Number of observations:	14,553	14,553
Number of individuals:	49	49
Null log-likelihood:	-10087.4	-10,087.4
Final log-likelihood:	-3,566.21	-3,512.9
Likelihood ratio test:	13,042.30	13,148.9
Rho-square:	0.65	0.65
Adjusted rho-square:	0.64	0.65
Significance χ^2		106.56 , $p<0.05$

Discussion (2)

- **Non-informed participants**:
  1. Rely on recent events (i.e. stickiness).
  2. Have slower adaptation rates.
  3. Sensitive to travel times (i.e. feedbacks).
  4. Lower sensitivity to travel time variability (i.e. scenarios) in line with the payoff variability effect.
- **Informed participants**:
  1. Have a longer learning perspective.
  2. Have faster adaptation rates.
  3. Have greater sensitivity to travel time variability (i.e. scenarios).
  4. Show evidence for risk seeking behavior.

Concluding remarks

1. The experimental-econometrical methodology contributes to better understanding of behavioral insights.
2. Providing real-time information has benefit when drivers lack long term experience. This is relevant for better traffic management.
3. Information has a key role in expediting the learning process of drivers and sustaining awareness to travel-time. However, it also promotes risk seeking behavior and greater sensitivity to variability.
4. more research is necessary to better understand the behavioral impacts of informed users on the general equilibrium of transport networks especially the effect of driver interaction and joint decision making effects.

Merci
de vos attention.