Testing Efficient Stated Choice Designs

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Introduction

- Adaptive personalized design:
  Attribute values based on RP data

- Problem: Find “optimal” design accounting for
  - efficient standard errors
  - robustness of parameter estimates
  - balanced trade-off distributions

- Five different designs are tested for their reliability in parameter estimates, precision and VOTs based on simulated choice data

Mode Choice Experiment

- 2 labelled choice alternatives MIV and PT:
  - Travel time
  - Travel cost
  - Delay probability
  - Walking time
  - Number of changes (PT alternative only)

- All main, all quadratic and 6 selected 2-way interaction effects → 24 degrees of freedom (without constant)

- Design matrices *Z* with 32 choice sets → 4 blocks à 8 choice sets

Mode Choice Experiment

Entscheidung 1	MIV	ÖV
Zeit Hauptverkehrsmittel	**72** min.	**63** min.
Wegspezifische Kosten	**16** CHF	**22** CHF
Fussweg- und Wartezeit	**5** min.	**20** min.
Verspätung	**5** %	**5** %
Umsteigen		**1** mal

☐ ← **Ihre Wahl** → ☐

Design Requirements: Efficient Standard Errors

– General linear model (GLM):

$$M_1 = \left(\frac{Z'Z}{n}\right) \propto \Omega_1^{-1}$$

$$max.\left[D - \text{Efficiency} = \det\left(M_1\right)^{\frac{1}{k}}\right]$$

Design Requirements: Efficient Standard Errors

– Multinomial logit (MNL):

$$\Omega_1 = I_1^{-1} = -E_1\left[\frac{\partial^2 logLL}{\partial\beta\partial\beta'}\right]$$

$$min.\left[D_Z - \text{Error} = \det\left(\Omega_1(Z,\beta_0)\right)^{\frac{1}{k}}\right]$$

$$min.\left[D_B - \text{Error} = \int_{\tilde{\beta}} \det\left(\Omega_1(Z,\tilde{\beta})\right)^{\frac{1}{k}} \phi(\tilde{\beta} \mid \theta) d\tilde{\beta}\right]$$

Design Requirements: Balance / Preference Conditions

- Balanced design levels:

Each attribute effect code (-1, 0 & 1) should occur more or less equally often within each attribute and block

- Balanced design trade-offs:

I.e. choice sets with MIV cheaper and slower; choice sets with PT cheaper and slower (relative to reference values)

- Preference Conditions:

No dominance / weak dominance / indifference between alternatives

Creating Five Different Designs

Design 1:

GLM, no strongly dominant alternatives, weakly dominant alternatives are minimized and balanced out, balanced design levels, balanced tradeoffs

Design 2:

GLM, no weakly dominant alternatives, balanced design levels, balanced tradeoffs

Design 3:

GLM, no weakly dominant alternatives, no strongly dominant travel time rel. to travel cost alternatives (or vice versa), balanced design levels, balanced tradeoffs

Creating Five Different Designs

Design 4:

MNL with zero priors, no weakly dominant alternatives, no strongly dominant travel time rel. to travel cost alternatives (or vice versa)

Design 5:

MNL with Bayesian priors (same a-priori parameter values and standard deviations as taken for simulation of choices), no weakly dominant alternatives, design levels scaled with average values of RP data (Fröhlich et al., 2012)

Key Indicators of the Designs

Design:	# 1	# 2	# 3	# 4	# 5
# parameters (k):	24	24	24	24	15
# choice sets (n):	32	32	32	32	32
# blocks (b):	4	4	4	4	4
GLM D-Efficiency: $\det(M)^{1/k}$	0.41	0.40	0.39	0.28	0.28
GLM rel. approx. theory D: $\frac{D_{opt}}{D_{approx\_theory}}$	94 %	93 %	92 %	-	-
# support points:	1768	814	816	-	-
List of all candidates:	19197	12153	9723	-	-
Diagonality: $\left(\frac{\det(M)}{\Pi diag(M)}\right)^{1/k}$	0.64	0.63	0.63	0.46	0.45
Scaled block product: $\left(\Pi \det(M^i)^{1/k}\right)^{1/b}$	0.86	0.86	0.83	-	-
MNL D-Error (priors β_0):	0.32	0.32	0.33	0.51	0.53
MNL D-Error (priors $\tilde{\beta}_k$):	0.0023	0.0023	0.0023	0.0025	0.0028

RP Data

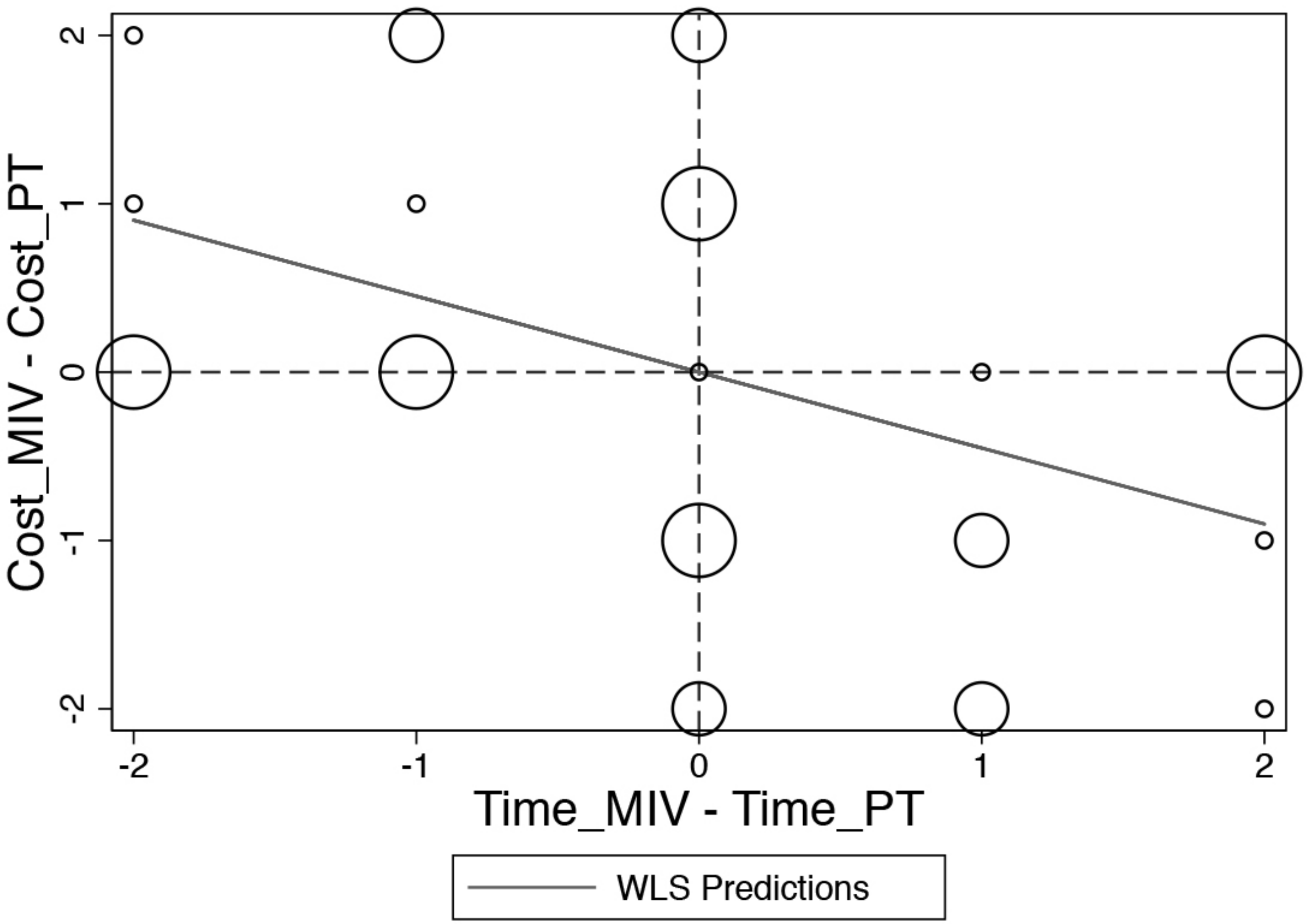
Calculation of actual attribute values based on designs and reference trips:

Attribute	Effect code:	–1	0	1
Travel time (MIV and PT) [%]		70	90	110
Travel cost (MIV and PT) [%]		80	110	130
Delay prob. (MIV and PT) [%]		5	10	20
Walking / waiting time (MIV and PT) [min.]		5	10	20
Number of changes (PT) [#]		–1	0	1

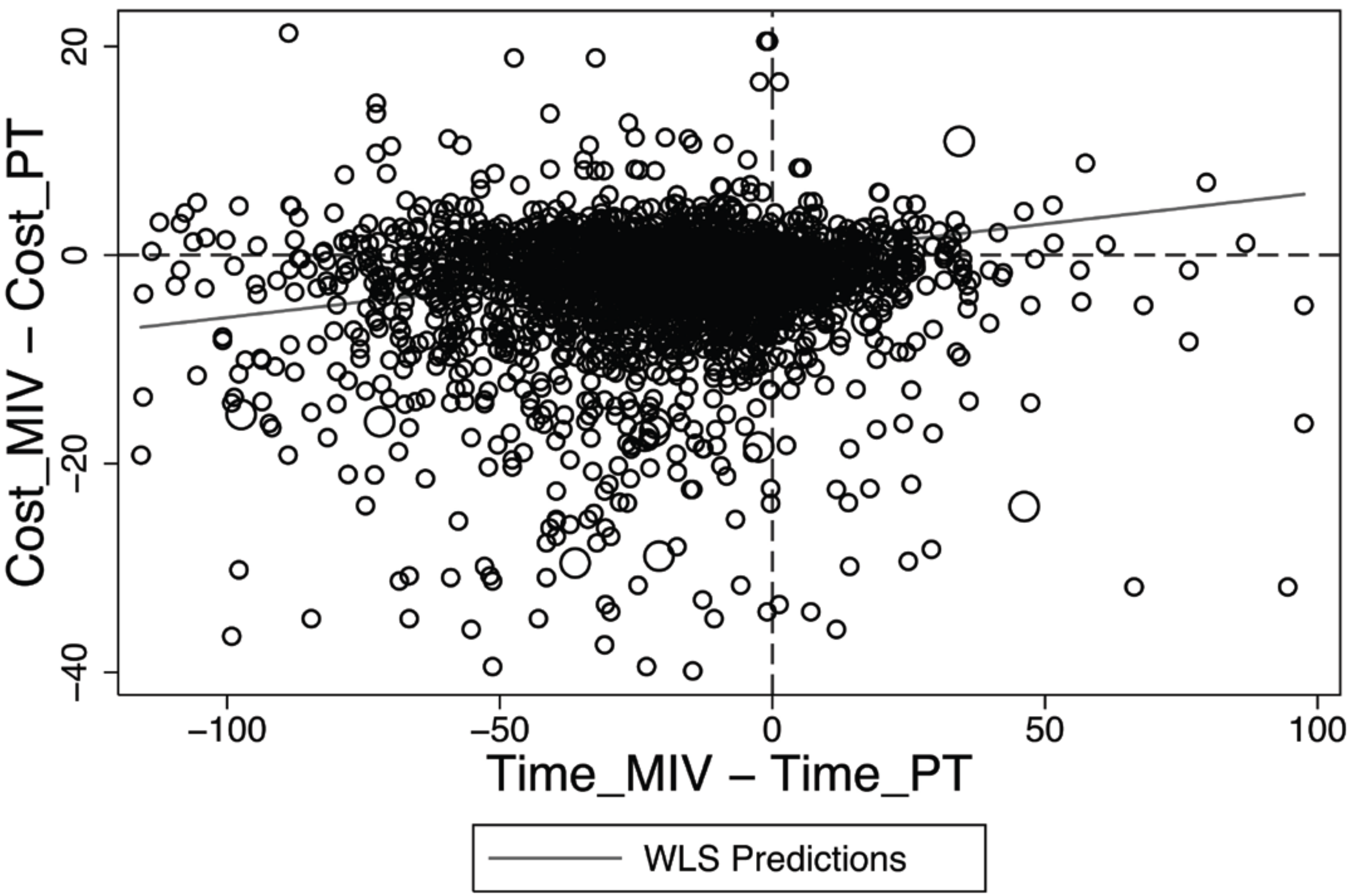
Problem:

RP data are right-skewed and MIV alternative is mostly superior than PT alternative

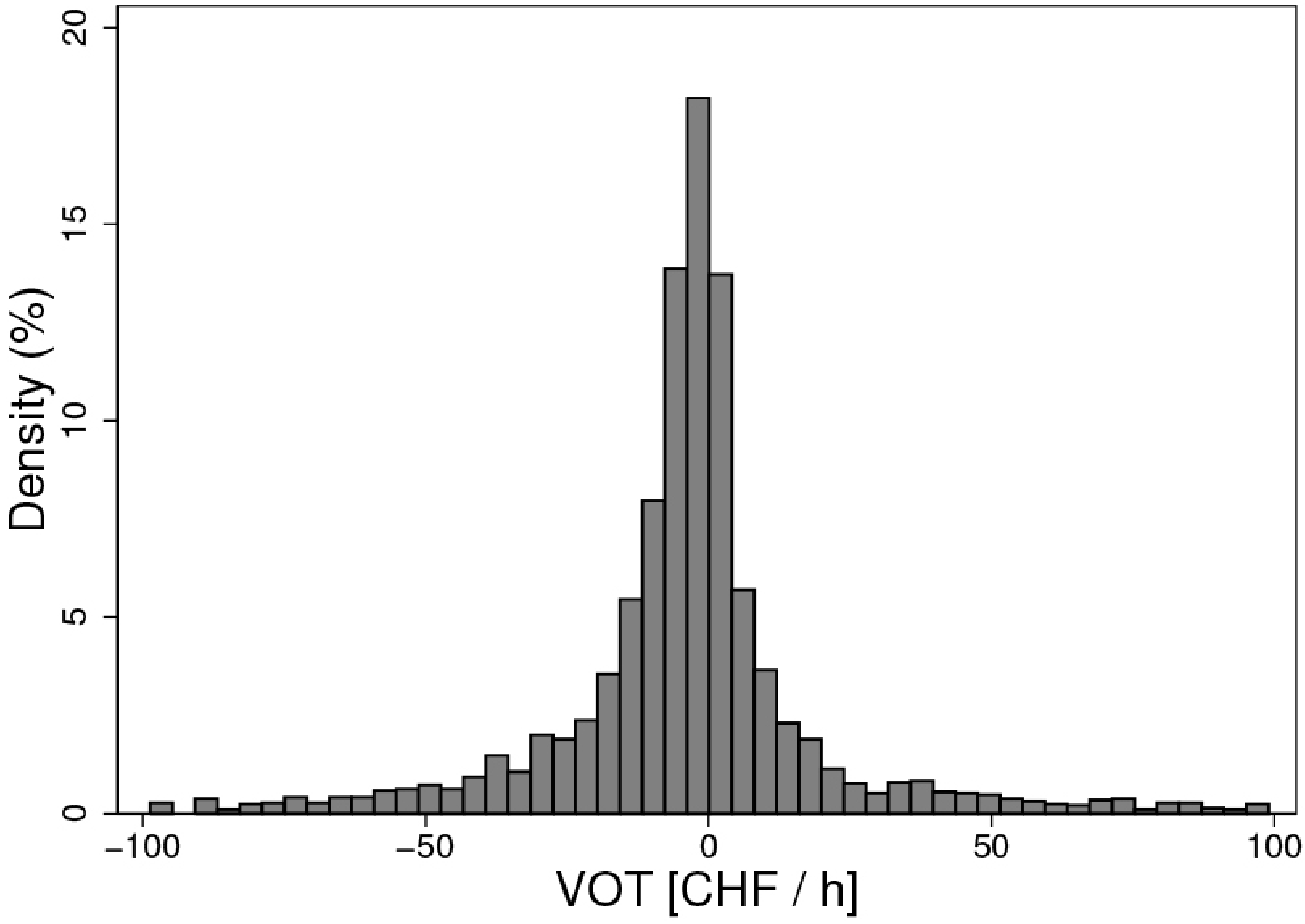
Design #3: VOT Design Trade-Off Distributions



Design #3: RP Based Trade-Off Distributions



Design #3: RP Based Trade-Off Distributions



A-Priori Parameters

Coefficient	Mean	SD	Type
ASC_{MIV}	0.172	0.5	Alternative-specific
$\beta_{time_{MIV}}$	-0.022	0.005	Alternative-specific
$\beta_{time_{PT}}$	-0.021	0.005	Alternative-specific
β_{cost}	-0.088	0.01	Generic
$\beta_{delay_{MIV}}$	-0.058	0.01	Alternative-specific
$\beta_{delay_{PT}}$	-0.027	0.005	Alternative-specific
β_{walk}	-0.047	0.01	Generic
$\beta_{changes_{PT}}$	-0.4	0.1	Alternative-specific
VOT_{MIV}	15.0 CHF / h		
VOT_{PT}	14.2 CHF / h		
Number of simulated coefficient vectors β_{ik}		400	

Simulation

$$U_{ijs} = V_{ijs} + \epsilon_{ijs}$$

$$\epsilon_{ijs} \sim GEV(0,1,0)$$

$$V_{ijs} = \sum_{k=1}^{K} \beta_{ik} X_{ijsk}$$

$$if \;\; U_{is1} > U_{is2} : choice_{is} = \begin{cases} \text{MIV} \\ else \; \text{PT} \end{cases}$$

Estimation

- Get insights into distributions of coefficients, standard errors and VOTs and compare them with a-priori parameter values

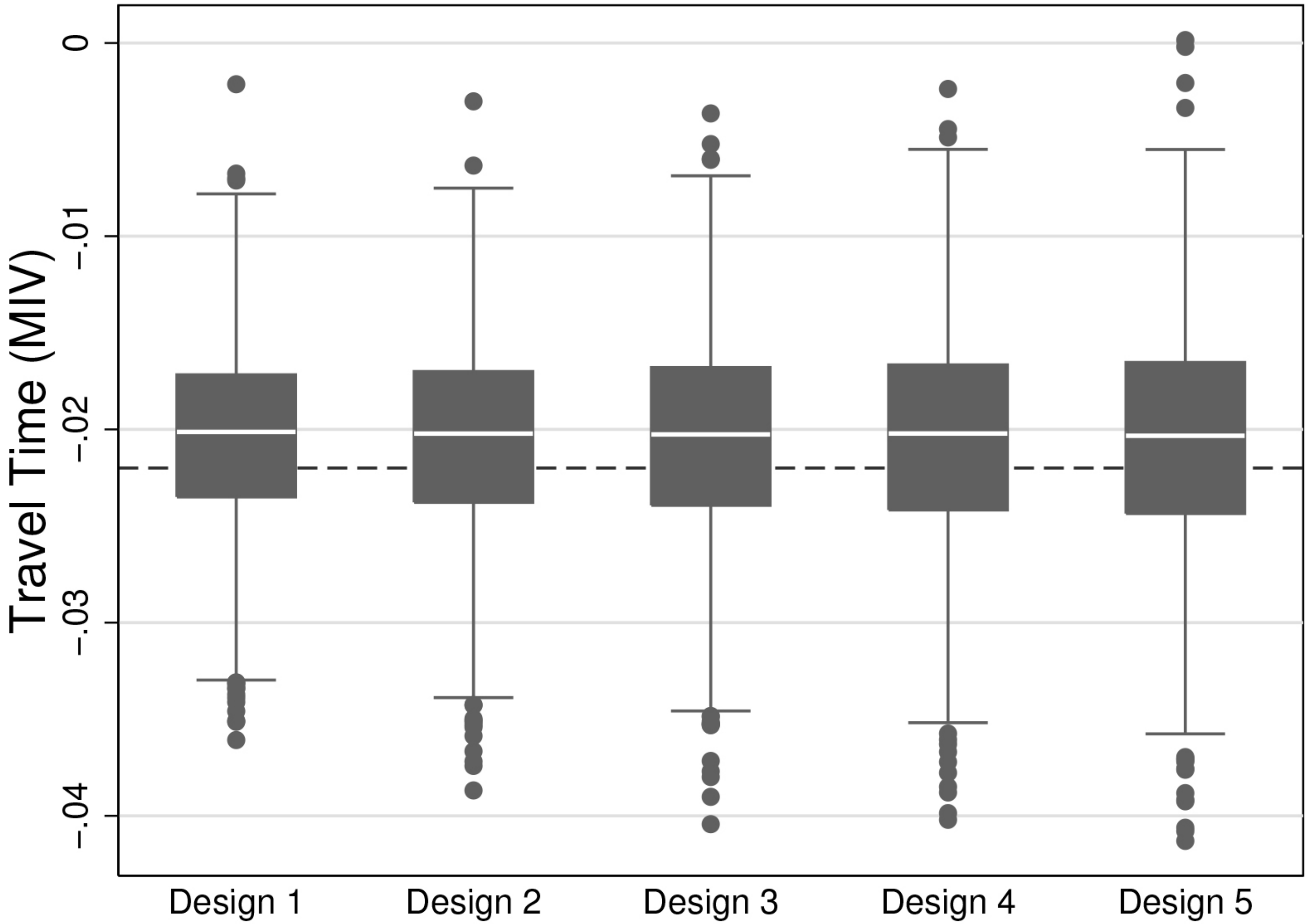
- Standard MNL estimation of each design 2000 times (N = 400, Obs. = 3200), each time with different (random draws of) RP data, coefficient vectors and error terms, but for a given run held constant between designs

Results

	D #1 E(β_k)	E(SE_k)	D #2 E(β_k)	E(SE_k)	D #3 E(β_k)	E(SE_k)	D #4 E(β_k)	E(SE_k)	D #5 E(β_k)	E(SE_k)
ASC_{MIV}	**0.174**	0.124	0.175	0.127	0.176	*0.121**	0.175	0.133	0.166	0.168
$\beta_{time_{MIV}}$	-0.020	0.002	-0.020	0.002	**-0.021**	0.002	-0.020	0.002	-0.020	*0.002**
$\beta_{time_{PT}}$	-0.019	0.002	-0.019	0.002	**-0.019**	0.002	-0.019	0.002	-0.019	*0.002**
β_{cost}	-0.081	0.010	-0.082	0.009	-0.082	0.009	**-0.082**	0.009	-0.081	*0.009**
$\beta_{delay_{MIV}}$	-0.054	*0.006**	-0.054	0.006	**-0.054**	0.006	-0.054	0.007	-0.054	0.008
$\beta_{delay_{PT}}$	**-0.025**	0.006	-0.025	0.006	-0.025	*0.006**	-0.025	0.006	-0.025	0.008
β_{walk}	-0.044	*0.004**	-0.044	0.005	**-0.044**	0.004	-0.044	0.005	-0.044	0.005
$\beta_{changes_{PT}}$	-0.371	0.049	-0.373	0.050	-0.373	0.050	**-0.375**	0.051	-0.374	*0.048**
VOT_{MIV}	16.1		16.1		16.4		**16.1**		16.3	
VOT_{PT}	**14.9**		14.9		15.2		15.0		15.3	

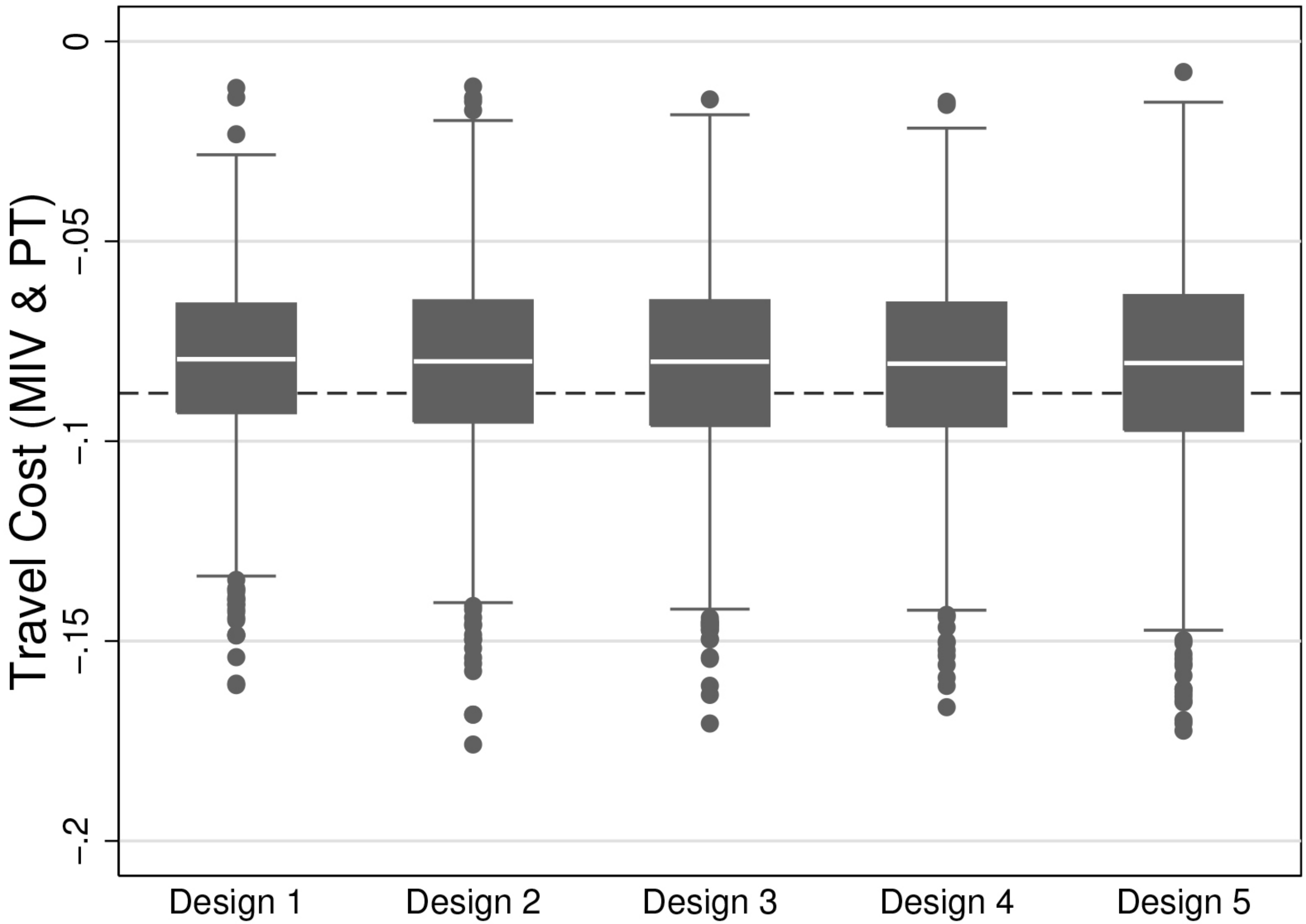
- Design 3 performs well regarding the a-priori mean coefficients
- Design 1 and 4 reproduce the a-priori VOT values most accurately [in CHF / h]
- Design 5 results in the most efficient standard errors, but
  - only for attributes based on RP data
  - standard errors of *ASC* and *Delay* are significantly larger

Results



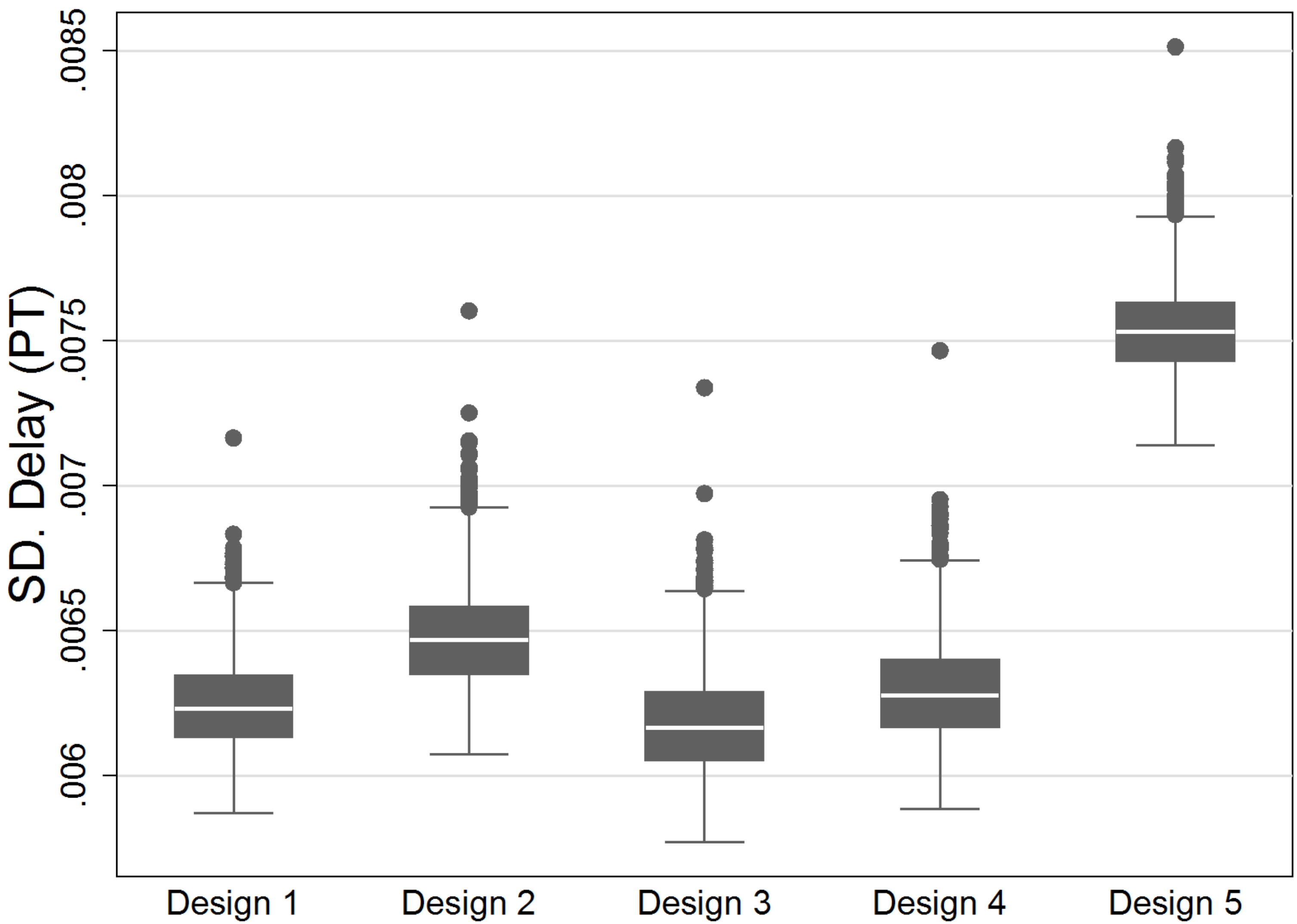
Travel Time (MIV)
0
−.01
−.02
−.03
−.04
Design 1
Design 2
Design 3
Design 4
Design 5

Results

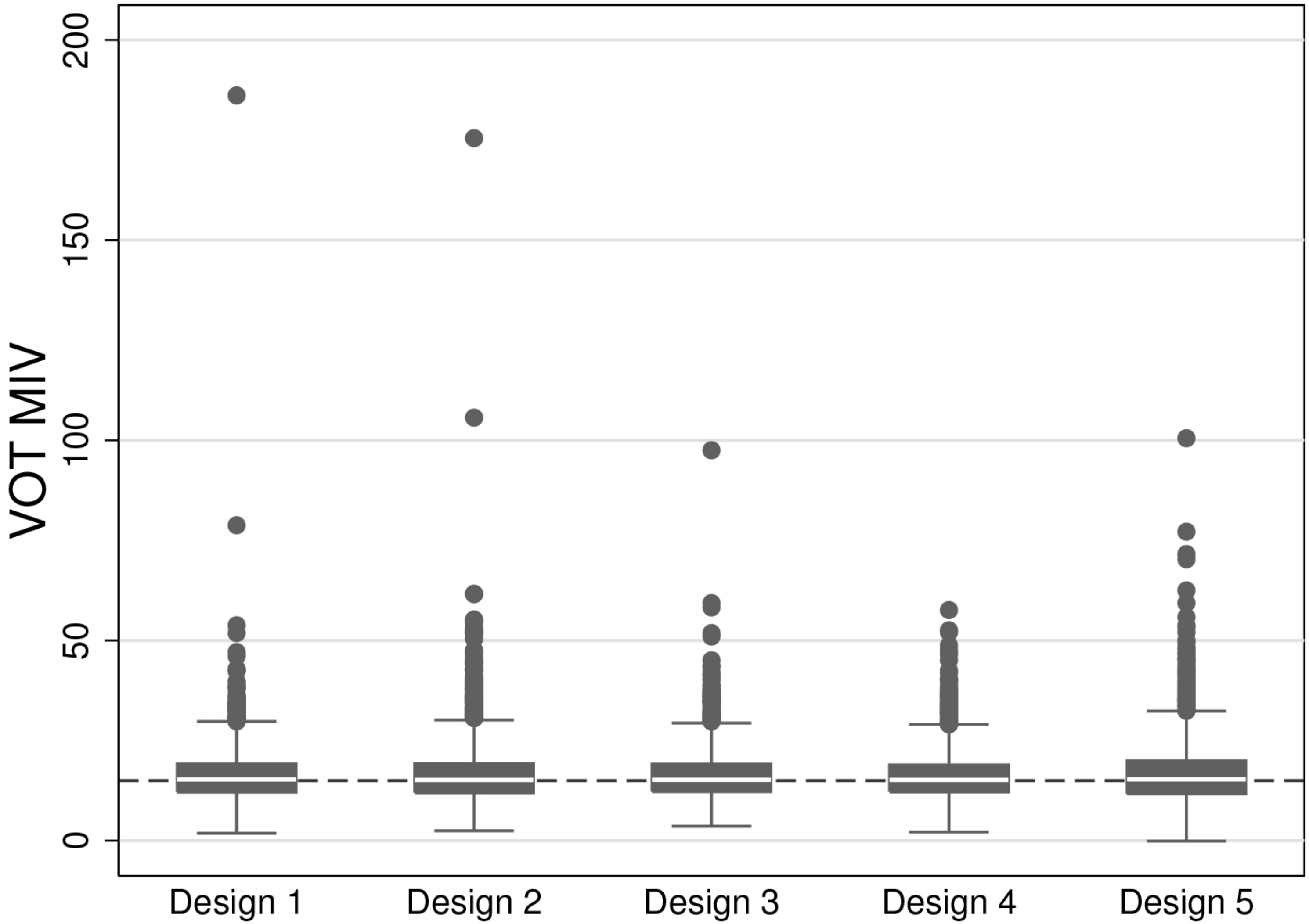


Travel Cost (MIV & PT)
0
−.05
−.1
−.15
−.2
Design 1
Design 2
Design 3
Design 4
Design 5

Results


SD. Delay (PT)
.006
.0065
.007
.0075
.008
.0085
Design 1
Design 2
Design 3
Design 4
Design 5

Results



VOT MIV
200
150
100
50
0
Design 1
Design 2
Design 3
Design 4
Design 5

Conclusions

- All designs perform well in reproducing the a-priori parameter values and VOTs

- GLM designs with additional constraints (preference conditions, tradeoff and design balance) perform slightly better than MNL designs regarding robustness and efficiency

- Using RP data to create discrete choice experiments may lead to some challenges regarding dominance of alternatives and offered tradeoff variations

- Consistent underestimation of coefficients
  - Use relative changes when estimating models
  - Apply Mixed Logit and compare coefficient ratios btw. designs