MRC Epidemiology Unit

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Welcome

Incorporating day-to-day stability into agent-based models

3rd Symposium on Activity-Based Modeling, 12 December 2024

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Agenda

1 Stability in Travel Behavior

Relevance for public health applications,
state of practice in ABMs

2 Fixed Error Terms

Stabilising the unobserved part of utility for decision makers

3 Mode Set

Restricting modes available to each decision maker

4 Discussion

Advanced approaches and potential applications

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Day-to-day stability in Travel Behavior

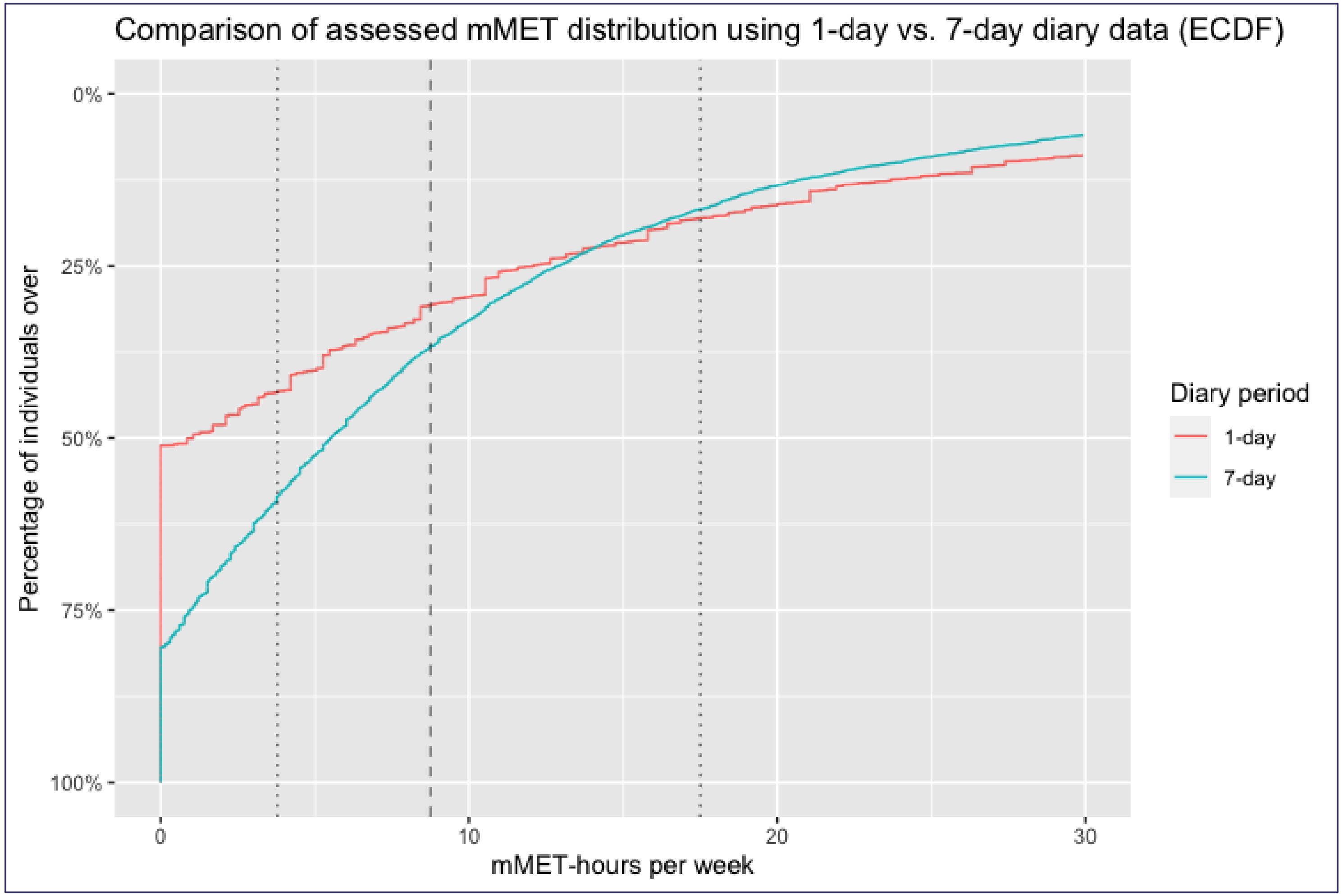
- Many transport analyses, including health, aim to understand ***habitual behaviour***
  - *How much **physical activity** does a person perform through walking and cycling?*
  - *How much **air pollution** is somebody exposed to as they travel?*
  - *How at risk is somebody to **traffic injuries**?*

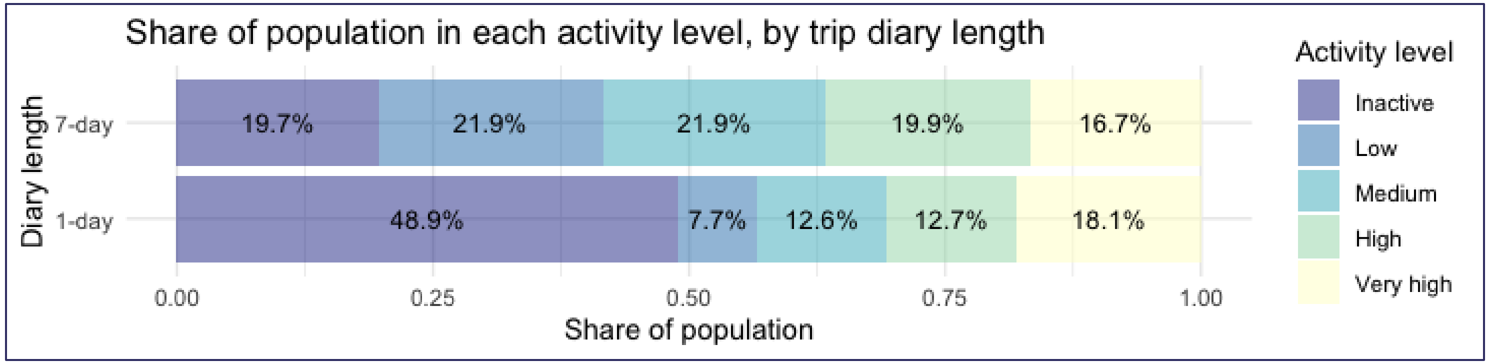
- Epidemiological studies, which relate behaviour to health, consider ***one week*** at minimum

- However, most transport surveys and models consider ***one day***
  - Exceptions: Mobilitätspanel, Mobidrive, mobiTopp

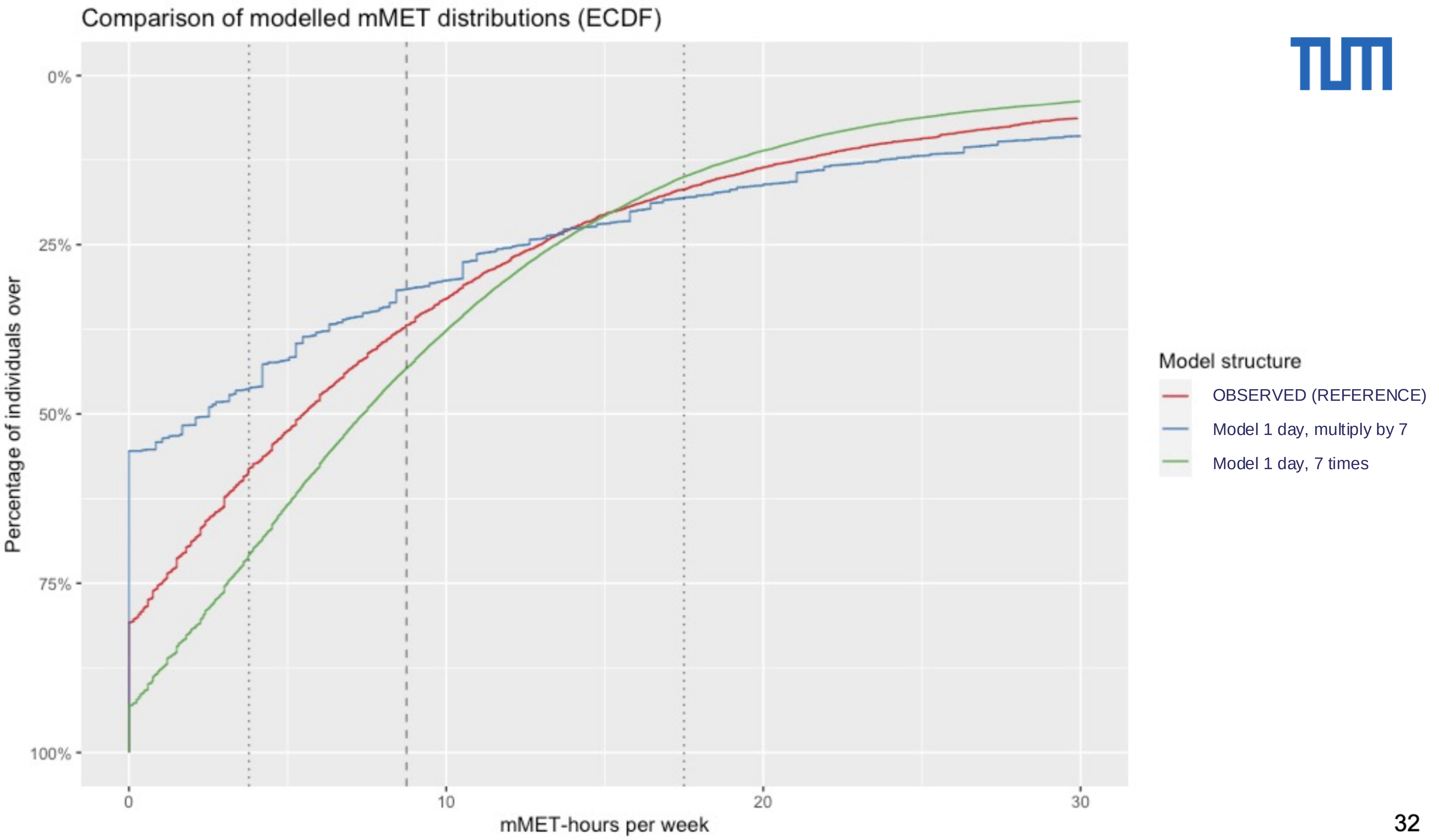
Physical Activity Demonstration

- Population's walking and cycling can be used to assess physical activity
- Units: mMET-hours
  - Walking ≈ 3.6 mMET
  - Cycling ≈ 5.4 mMET
- Distribution looks different when you use a 1-day vs. 7-day diary

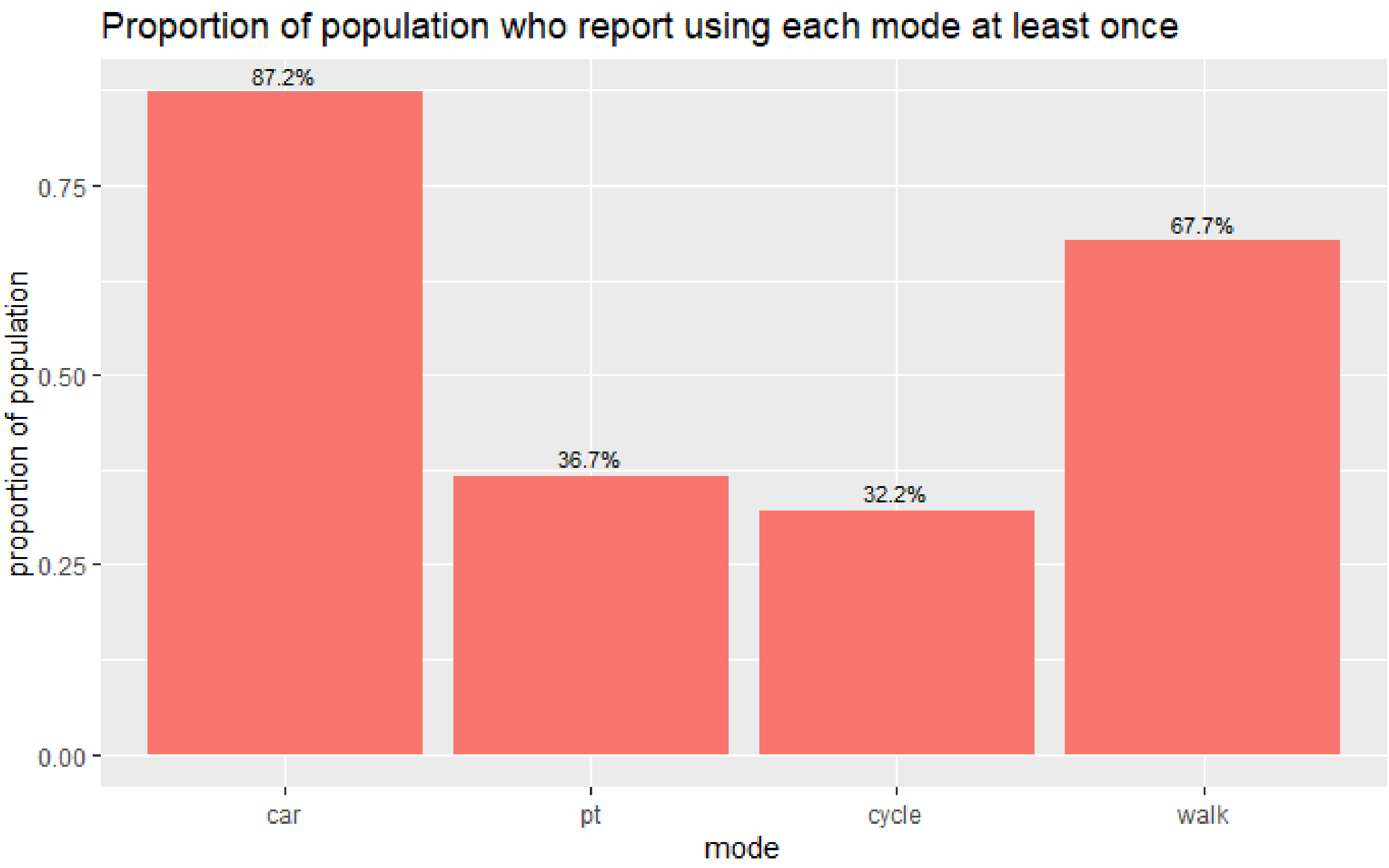




Modelling 7-day physical activity with a 1-day model



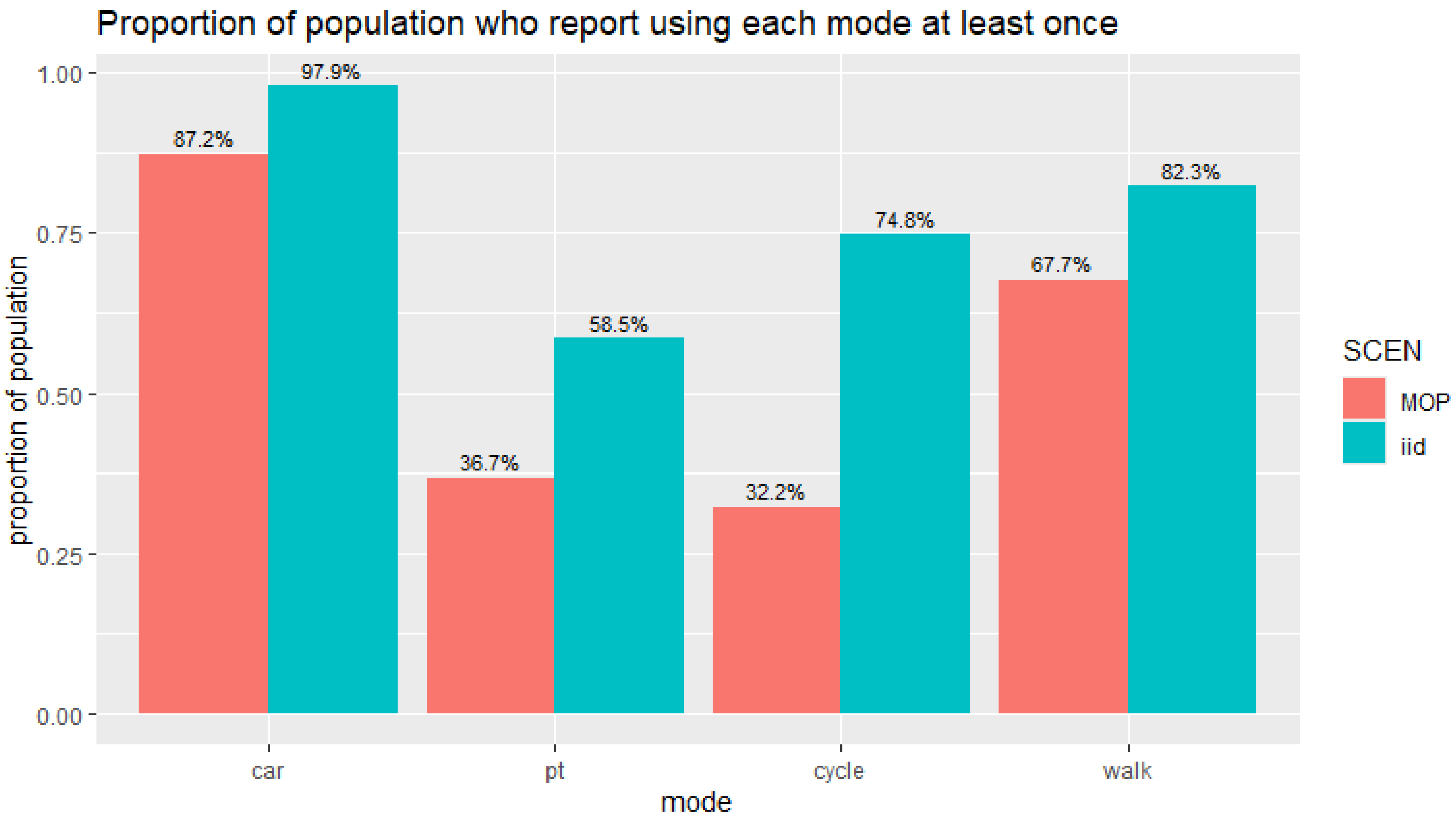
Findings from 7-day *Mobilitätspanel*



Other findings:

- 21% of respondents report trips by car only (no other modes)
- 75% of respondents report at least one active trip (cycle or walk)

Mobilitätspanel vs. 7-days Modelled (Multinomial Logit)



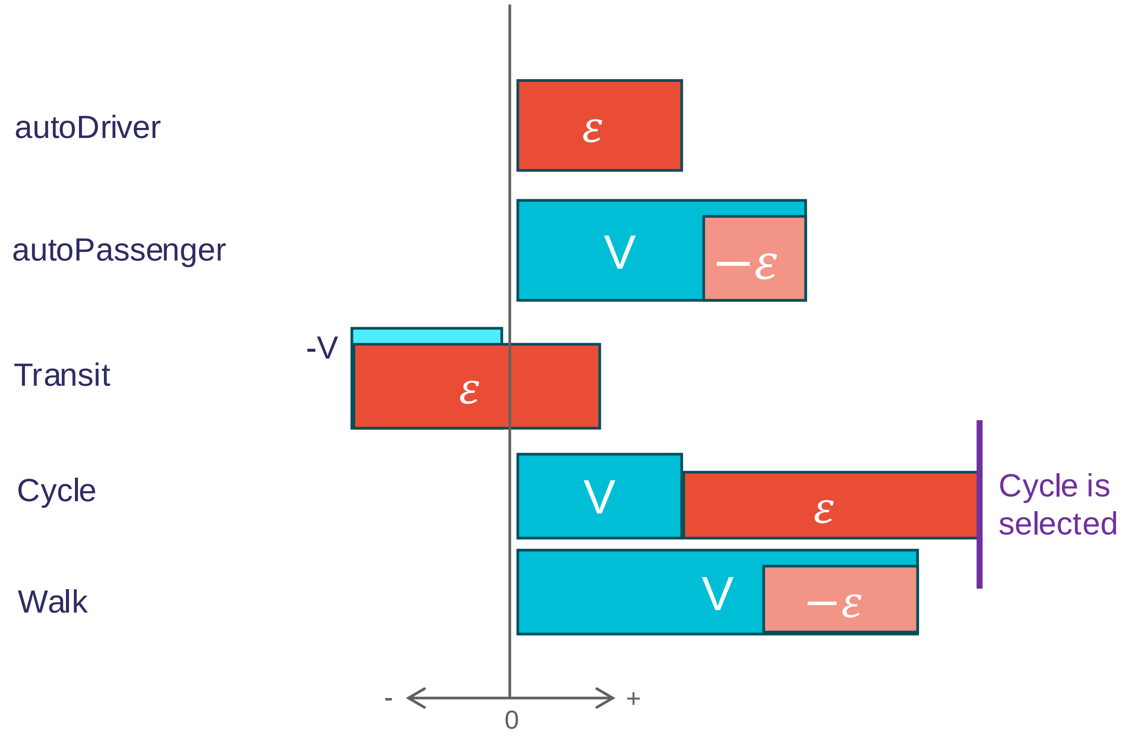
i.i.d. Assumption in Discrete Choice Models

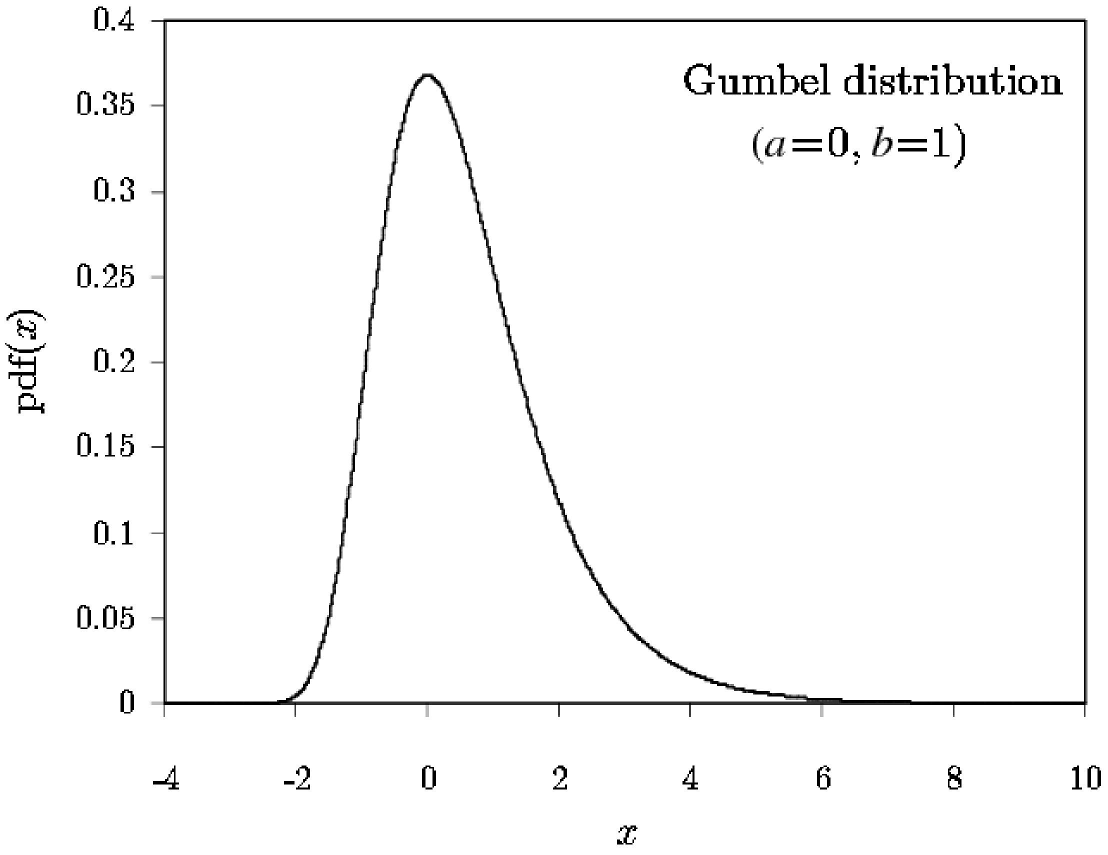
Utility contains an **observed** and **unobserved** component

$$U = V + \varepsilon$$

We commonly assume the error terms to be **independent and identically distributed (i.i.d.)**

Example decision (Multinomial logit model)



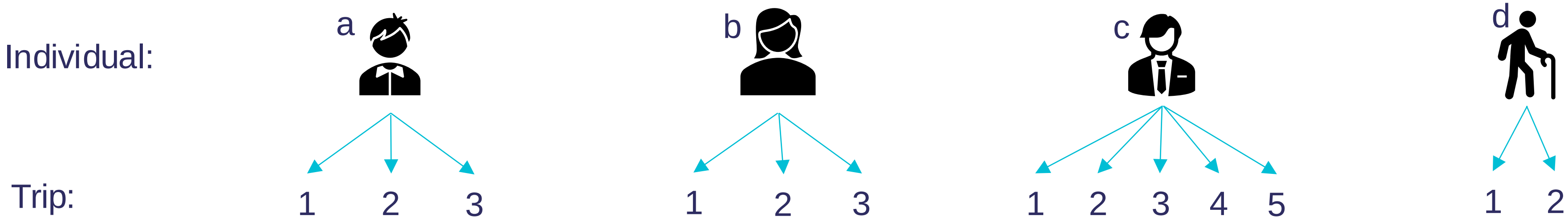


In many cases, unobserved utility is correlated

Between alternatives (e.g., red bus / blue bus problem)

(Image from Rolf Moeckel's Lecture Notes)

Between choices (e.g., of the same person)



Standard Mode Choice Implementation in ABMs

$$U_i = V_i + \varepsilon_i$$

Utility is commonly converted to a probability….

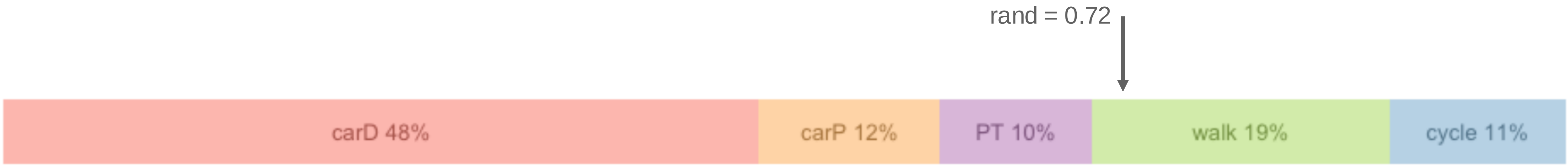
Multinomial logit

$$p_i = \frac{e^{V_i}}{\sum_{j \in M} e^{V_j}}$$

Nested logit

$$p_i = \frac{e^{V_i/\lambda_k} \left(\sum_{j \in B_k} e^{V_i/\lambda_k} \right)^{\lambda_k - 1}}{\sum_{l=1}^{k} \left(\sum_{j \in B_l} e^{V_j/\lambda_k} \right)^{\lambda_l}}$$

…. and then the choice is sampled from a Uniform (0,1) Distribution



Equivalent Implementation by Sampling ε_i

$$U_i = V_i + \varepsilon_i$$

ε_i for each alternative is sampled from a distribution…

Multinomial logit

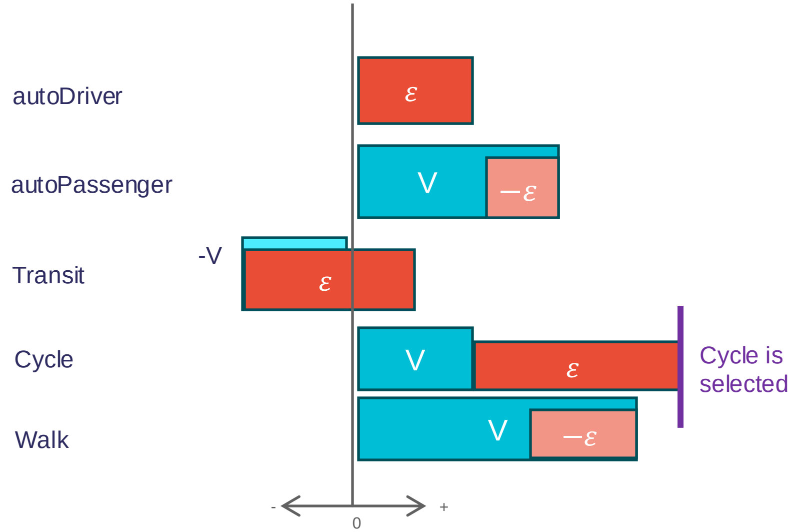
Sample i.i.d. from Gumbel (0,1)

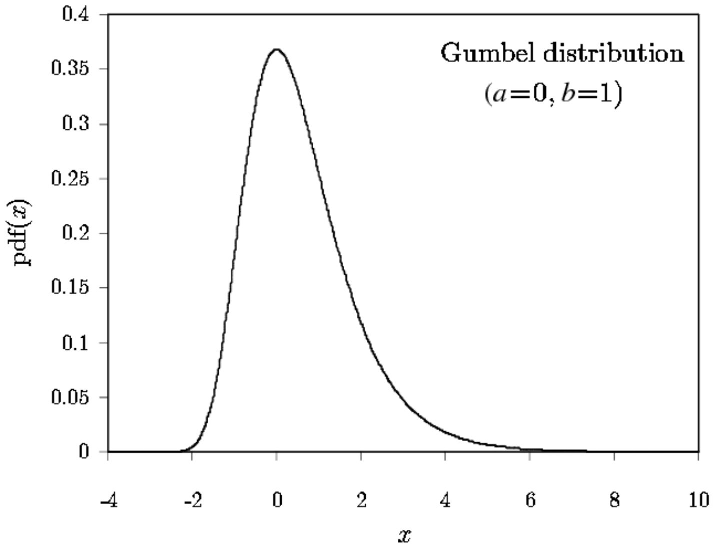
Nested logit

Outside nests: Sample i.i.d. from Gumbel (0,1)

Within nests: Sample from joint CDF $F = \exp\left(-\left(\sum e^{-\frac{\varepsilon}{\lambda}}\right)^{\lambda}\right)$

…. and then choose the highest





Potential solutions to improve stability

Multinomial / nested logit

$$U = V + \varepsilon$$

V systematic
ε sampled per ***trip***

Fixed error terms

$$U = V + \varepsilon$$

V systematic
ε sampled per ***person***

Preliminary Mode Set Choice

Mode Set

RESTRICTED CHOICE SET

$$U = V + \varepsilon$$

V systematic
ε sampled per ***trip***

Random Parameters

$$U = V + W + \varepsilon$$

V systematic
W sampled per ***person***
ε sampled per ***trip***

[Standard practice] **Simple** **Complicated**

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Advanced approaches and potential applications

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1) Fixed Error Terms

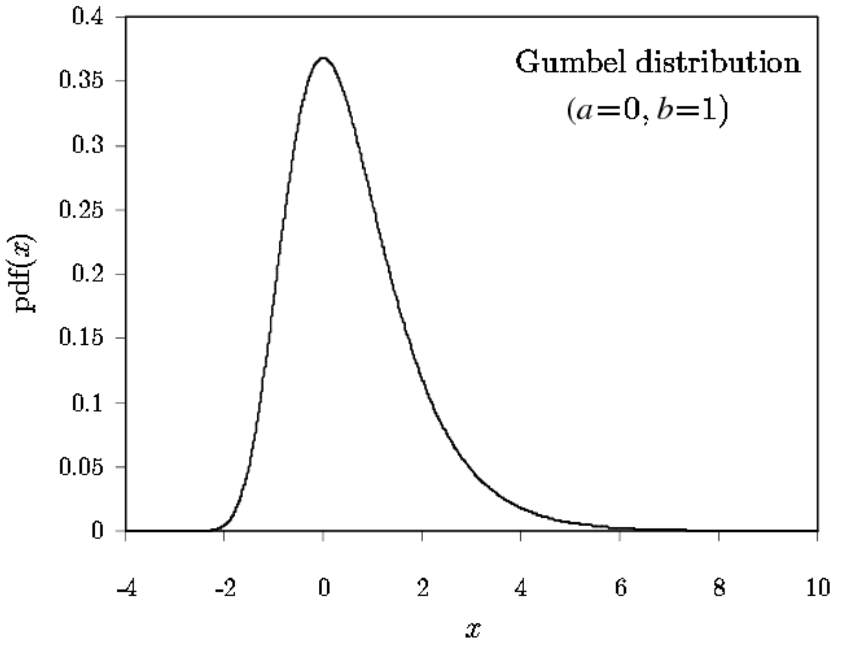
$$U = V + \varepsilon$$

Instead of sampling ε once per ***decision***, we sample ε once per ***person***

Assumption: 100% of unobserved utility is due to personal characteristics

		Without Fixed Error Terms				
Person	**Trip**	ε_{drive}	ε_{pax}	ε_{pt}	ε_{bike}	ε_{walk}
1	**1**	1.85	2.01	0.22	1.42	1.38
1	**2**	-0.73	-1.02	0.6	-0.07	0.73
2	**1**	-0.26	-0.09	-0.61	-0.02	0.27
2	**2**	0.06	0.76	1.04	-1.13	-0.22
2	**3**	0.71	0.79	-0.83	-0.36	-1.4

$$\underbrace{\varepsilon_{drive} \quad \varepsilon_{pax}}_{\lambda_{car} = 0.25}$$



1) Fixed Error Terms

$$U = V + \varepsilon$$

Instead of sampling ε once per ***decision***, we sample ε once per ***person***

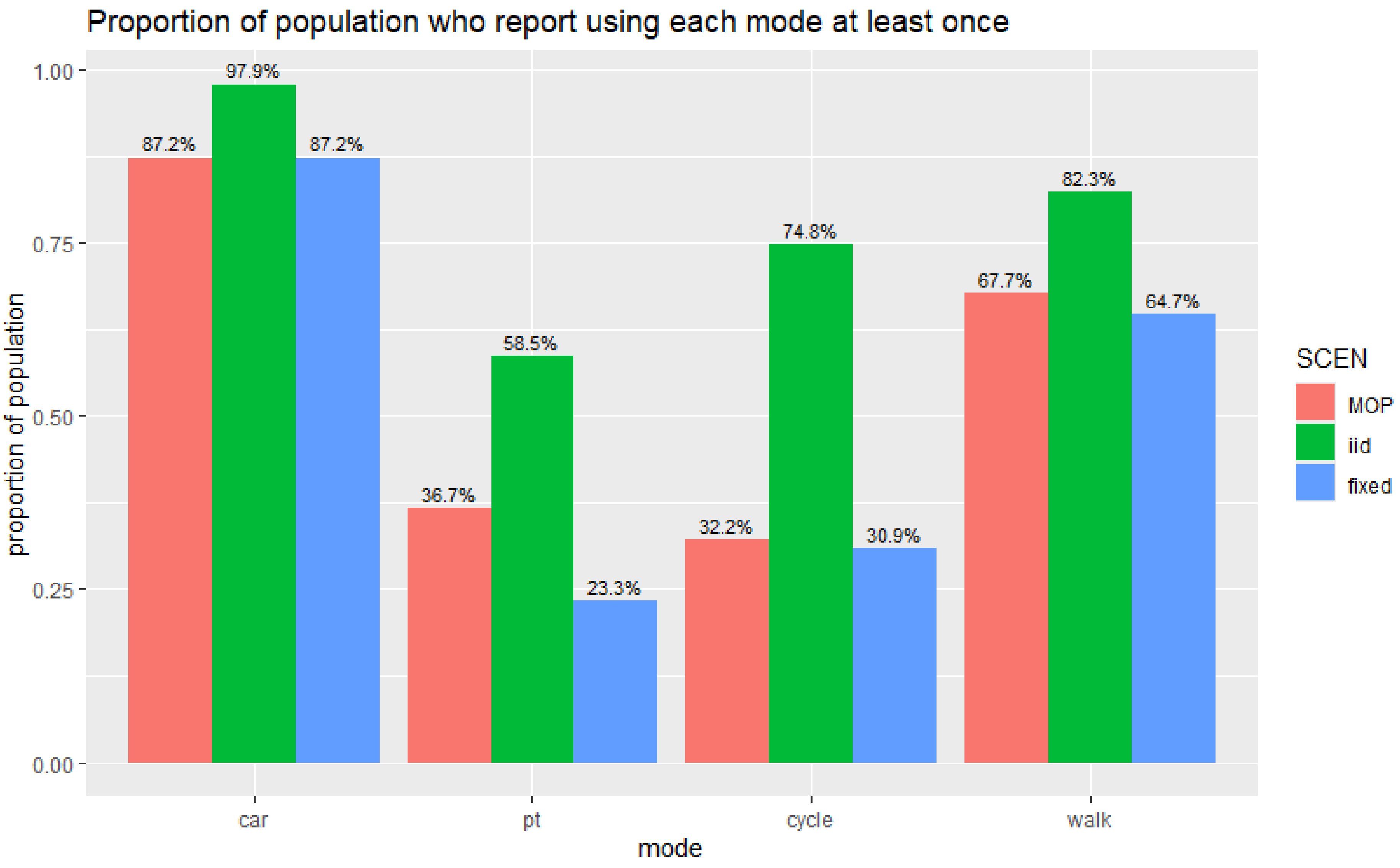
Assumption: 100% of unobserved utility is due to personal characteristics

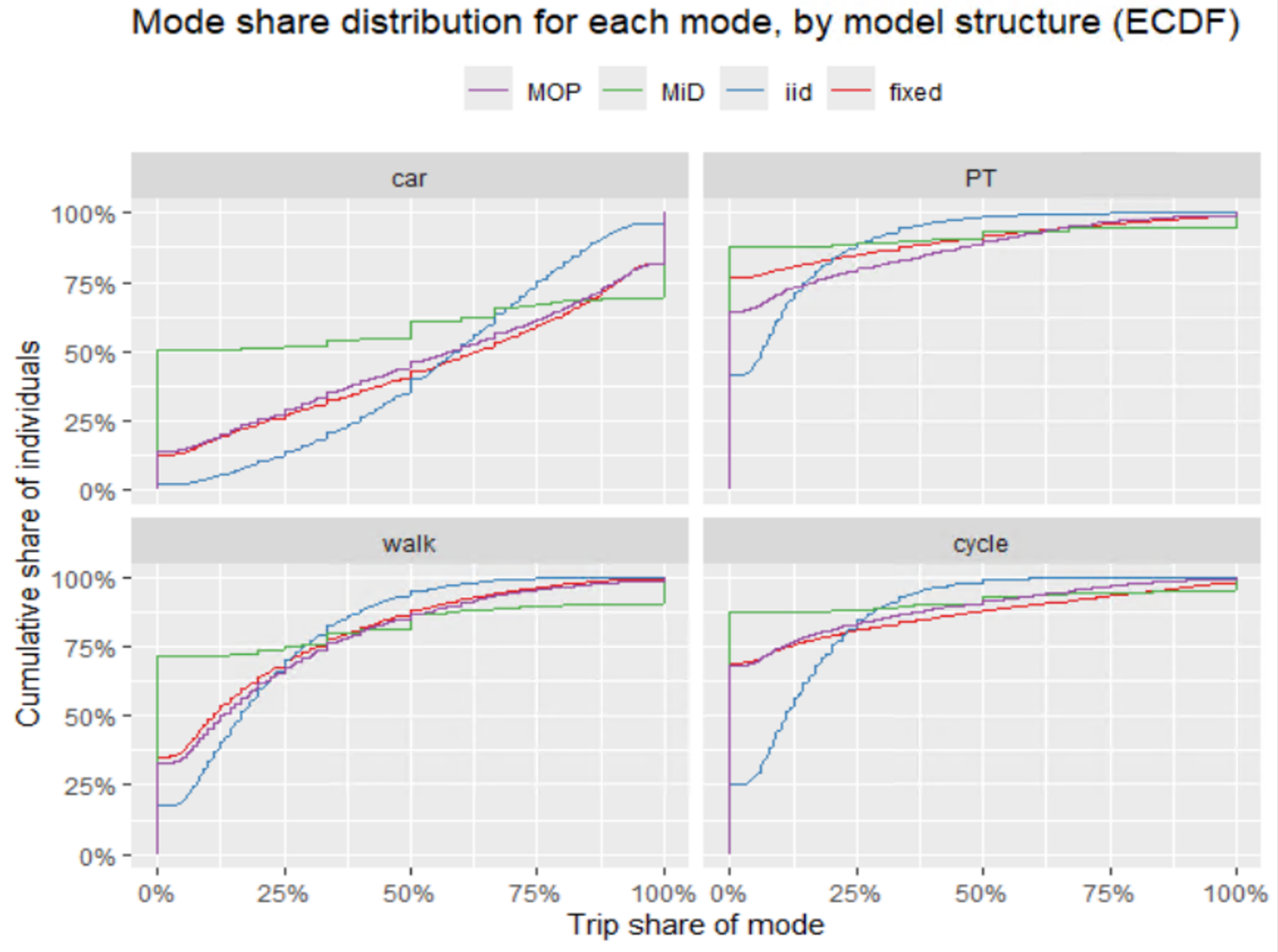
		Without Fixed Error Terms					With Fixed Error Terms				
Person	**Trip**	ε_{drive}	ε_{pax}	ε_{pt}	ε_{bike}	ε_{walk}	ε_{drive}	ε_{pax}	ε_{pt}	ε_{bike}	ε_{walk}
1	**1**	1.85	2.01	0.22	1.42	1.38	1.85	2.01	0.22	1.42	1.38
1	**2**	-0.73	-1.02	0.6	-0.07	0.73	1.85	2.01	0.22	1.42	1.38
2	**1**	-0.26	-0.09	-0.61	-0.02	0.27	-0.26	-0.09	-0.61	-0.02	0.27
2	**2**	0.06	0.76	1.04	-1.13	-0.22	-0.26	-0.09	-0.61	-0.02	0.27
2	**3**	0.71	0.79	-0.83	-0.36	-1.4	-0.26	-0.09	-0.61	-0.02	0.27

$\lambda_{car} = 0.25$

$\lambda_{car} = 0.25$

Implementing Fixed Error Terms in MITO




Mode share distribution for each mode, by model structure (ECDF)
MOP
MiD
iid
fixed
car
PT
walk
cycle
Cumulative share of individuals
0%
25%
50%
75%
100%
Trip share of mode

Further development: correlated error terms

		With Fixed Error Terms					With Correlated Error Terms				
Person	Trip	ε_{drive}	ε_{pax}	ε_{pt}	ε_{bike}	ε_{walk}	ε_{drive}	ε_{pax}	ε_{pt}	ε_{bike}	ε_{walk}
1	1	1.85	2.01	0.22	1.42	1.38	1.85	2.01	0.22	1.42	1.38
1	2	1.85	2.01	0.22	1.42	1.38	1.99	1.62	0.28	1.47	1.22
2	1	-0.26	-0.09	-0.61	-0.02	0.27	-0.26	-0.09	-0.61	-0.02	0.27
2	2	-0.26	-0.09	-0.61	-0.02	0.27	-0.03	-0.15	-0.69	0.01	0.29
2	3	-0.26	-0.09	-0.61	-0.02	0.27	-0.30	-0.11	-0.59	-0.09	0.23

λ_p

λ_p

$\lambda_{car} = 0.25$

$\lambda_{car} = 0.25$

1) Fixed Error Terms (Discussion)

- Simple to implement
- Works with models estimated on 1-day data
- Implementation contradicts i.i.d. assumption
- For a 7-day model, results are closer to reality (for a given input) than assuming i.i.d. error terms.

$$U = V + \varepsilon$$

V systematic
ε sampled per ***person***

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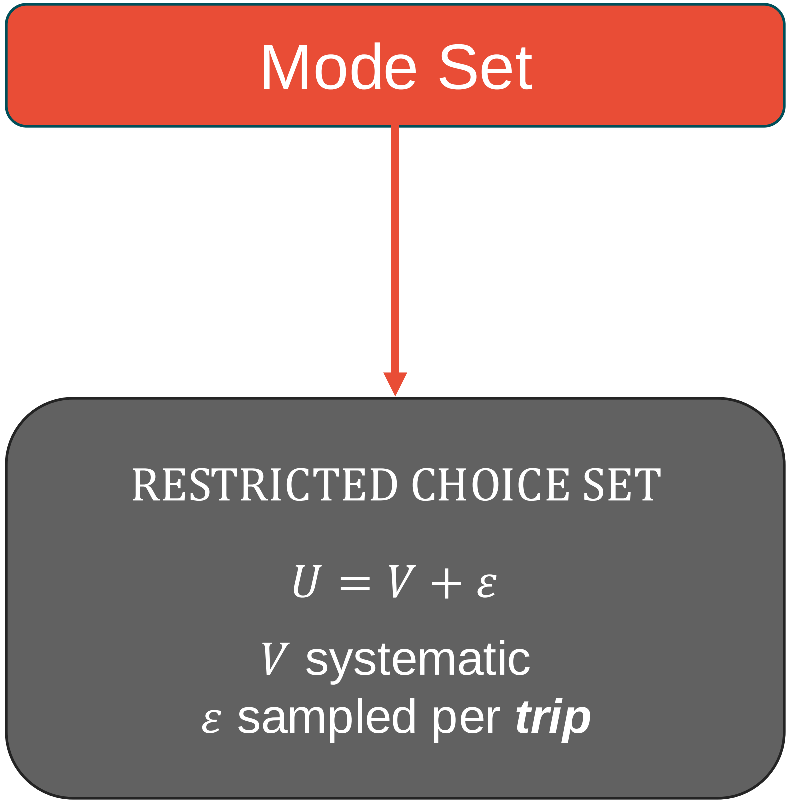
2) Mode Set Model

- Prior to mode choice, **estimate the available alternatives** for each person. This is called the “mode set”
- During mode choice, **restrict availability** of alternatives to the mode set
- Ton et al., (2019) developed an empirical approach to help



Mode Set as a Multinomial Logit Model

Modes $m \in M$

Car | PT | Cycle | Walk

Alternatives $i \subseteq M, i = 1, \ldots, 15$

- Car
- Car, PT
- Car, Cycle
- Car, PT, Walk
- Car, Walk
- PT
- Car, PT, Cycle
- Car, PT, Cycle, Walk
- Car, Cycle, Walk
- PT, Cycle
- Cycle
- PT, Cycle, Walk
- Cycle, Walk
- PT, Walk
- Walk

Utility for mode *m*: $V_m = \alpha_m + \boldsymbol{\beta}_m \boldsymbol{x}$

Where $\alpha_m = mode\ specific\ constant$

$\boldsymbol{\beta}_m = vector\ of\ coefficients\ for\ mode\ m$

$\boldsymbol{x} = vector\ of\ trip\ attributes$

Utility for alternative i, person *n*:

$$V_i = ASC_i + \sum_{m \in i} V_m$$

Ton et al., (2020)

Mode Set: Empirical Results from *Mobilitätspanel*

Alternative Specific Constants

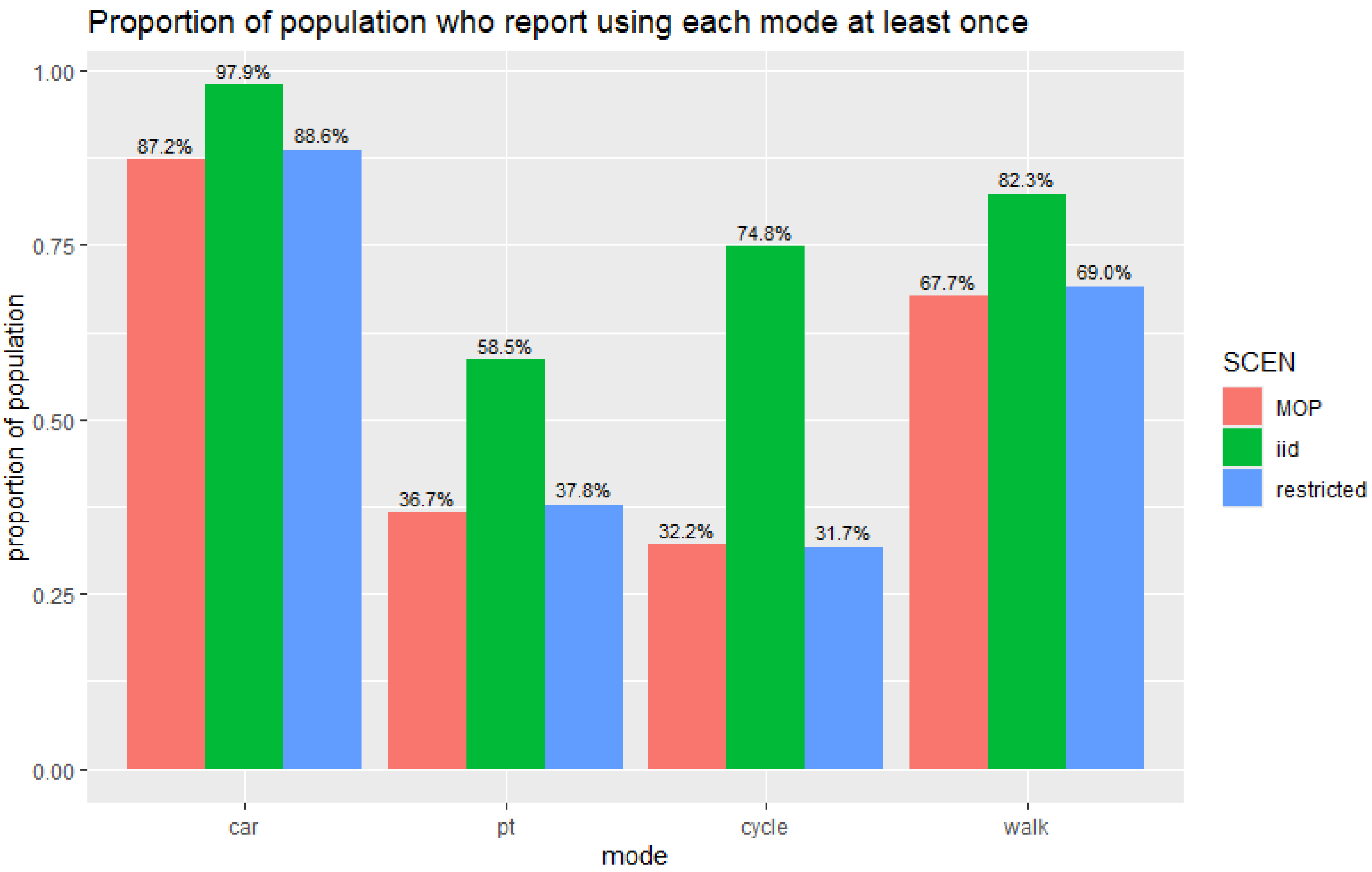
Car	Pt	Walk	Cycle	Share	ASC
√				20.53%	—
√	√			5.91%	-0.15
√		√		12.22%	0.167
√			√	3.83%	-0.721
√	√	√		2.07%	0.985
√	√		√	6.66%	-0.601
√		√	√	12.89%	-0.493
√	√	√	√	25.97%	—
	√			0.49%	—
	√	√		1.20%	1.582
	√		√	0.68%	-0.191
	√	√	√	0.44%	0.858
		√		2.15%	—
		√	√	3.89%	0.27
			√	1.06%	—

Mode Coefficients

McFadden R^2 = 0.43

	car	pt	walk	cycle
INTERCEPT	-1.95 [-1.816 `]	-2.968 [-1.486]	-0.337 [-1.192]	-3.211 [-1.669 `]
hh.econStatus_2	0.271 [7.276 ***]	0 [NA]	0 [NA]	0.068 [6.243 ***]
hh.econStatus_3	0.333 [4.285 ***]	0 [NA]	-0.033 [-11.113 ***]	0 [NA]
hh.econStatus_4	0.37 [3.949 ***]	0 [NA]	-0.145 [-8.842 ***]	0 [NA]
hh.econStatus_34	0 [NA]	0.279 [5.049 ***]	0 [NA]	0.119 [4.639 ***]
hh.urban	-0.436 [-6.474 ***]	0.95 [6.91 ***]	-0.021 [-13.429 ***]	0.168 [7.035 ***]
hh.homePT	0 [NA]	0.52 [6.783 ***]	0.212 [11.699 ***]	0.057 [6.709 ***]
hh.children_1	0 [NA]	0 [NA]	0 [NA]	0.098 [4.025 ***]
hh.children_2	0 [NA]	0 [NA]	-0.074 [-8.507 ***]	0.336 [3.257 **]
hh.children_3	0 [NA]	0 [NA]	-0.035 [-5.213 ***]	0.425 [1.73 `]
hh.children_123	0.483 [5.131 ***]	0.383 [4.279 ***]	0 [NA]	0 [NA]
hh.cars_1	2.722 [6.116 ***]	-1.377 [-2.667 **]	0 [NA]	-0.012 [-2.961 **]
hh.cars_2	0 [NA]	-1.508 [-2.328 *]	0 [NA]	-0.381 [-2.528 *]
hh.cars_3	0 [NA]	-1.497 [-2.114 *]	0 [NA]	-0.866 [-2.277 *]
hh.cars_23	3.5 [4.808 ***]	0 [NA]	0 [NA]	0 [NA]
hh.autosPerAdult	0 [NA]	-1.506 [-2.947 **]	-0.368 [-8.729 ***]	-0.336 [-2.842 **]
p.age_gr_1	-0.569 [-2.759 **]	1.057 [1.543]	0.007 [4.095 ***]	0.198 [2.062 *]
p.age_gr_2	-0.002 [-3.775 ***]	0.746 [3.098 **]	0.202 [6.869 ***]	0.336 [3.364 ***]
p.age_gr_4	0.316 [3.801 ***]	0.135 [4.337 ***]	-0.025 [-10.086 ***]	0.3 [4.434 ***]
p.age_gr_5	0.537 [3.697 ***]	0.289 [4.066 ***]	-0.192 [-8.625 ***]	0.619 [3.942 ***]
p.age_gr_6	0.667 [3.871 ***]	0.373 [3.888 ***]	0.06 [7.324 ***]	0.401 [3.799 ***]
p.female	0.165 [7.706 ***]	0.401 [6.658 ***]	0.01 [14.618 ***]	-0.273 [-6.462 ***]
p.driversLicense	0.209 [6.231 ***]	-0.066 [-2.992 **]	-0.393 [-7.162 ***]	0.15 [4.262 ***]
p.ownBicycle	-0.004 [-6.129 ***]	0.095 [6.688 ***]	-0.089 [-12.092 ***]	2.303 [6.846 ***]
p.km_min_T	-0.251 [-14.97 ***]	-0.049 [-12.864 ***]	-1.702 [-26.691 ***]	-0.408 [-13.502 ***]
p.km_max_T	0.525 [14.299 ***]	0.47 [11.49 ***]	0.098 [26.207 ***]	0.122 [12.369 ***]
p.workTrips_1234	0 [NA]	0.479 [2.177 *]	-0.155 [-5.416 ***]	0.196 [2.814 **]
p.workTrips_5	0 [NA]	0.257 [2.164 *]	-0.166 [-5.095 ***]	0.18 [2.682 **]
p.isMobile_HBW	0.542 [2.959 **]	0 [NA]	0 [NA]	0 [NA]
p.eduTrips_1234	0 [NA]	0.641 [1.685 `]	-0.458 [-5.374 ***]	0.219 [1.928 `]
p.eduTrips_5	0 [NA]	0.424 [1.387]	-0.539 [-3.912 ***]	0.55 [1.881 `]
p.isMobile_HBE	0.585 [2.636 **]	0 [NA]	0 [NA]	0 [NA]
p.workPT_12	0 [NA]	0.844 [4.664 ***]	-0.027 [-11.172 ***]	-0.142 [-5.215 ***]
p.isMobile_RRT	0 [NA]	0 [NA]	2.014 [12.781 ***]	0.557 [4.754 ***]
p.usualCommuteMode_carD	0 [NA]	-1.354 [-2.172 *]	0.096 [4.823 ***]	-0.406 [-2.939 **]
p.usualCommuteMode_carP	0 [NA]	-0.237 [-1.557]	0.686 [3.636 ***]	0 [NA]
p.usualCommuteMode_PT	-0.673 [-2.583 **]	0 [NA]	0.349 [4.562 ***]	0.16 [2.287 *]
p.usualCommuteMode_walk	-1.084 [-2.295 *]	-0.842 [-1.478]	0 [NA]	-0.35 [-2.278 *]
p.usualCommuteMode_cycle	-0.476 [-2.428 *]	-0.996 [-1.777 `]	0.038 [4.314 ***]	0 [NA]

Implementing Mode Set in MITO



Mode Set (Discussion)

Advantages:

- Simple model structures
- Easy to estimate
- Can precisely segment population by mode use

Limitations:

- Requires panel data
- Mode choice sensitivity split between two models

Mode Set

RESTRICTED CHOICE SET

$$U = V + \varepsilon$$

V systematic
ε sampled per ***trip***

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Random Parameters (Mixed) Logit

$$U = V + W + \varepsilon$$

Where:

- V is the **systematic** component of utility (same for everyone)
- W is the **random** component of utility (varies between individuals)
- ε is the i.i.d. error term

W follows any distribution, representing **unobserved variation** in individual preferences

If W follows a discrete distribution, it's called a **latent class logit**

Empirical Findings using Random Parameters Logit

Findings from 6-week MobiDrive panel

- **Cherchi and Chirillo (2014):** Individual tastes for time and cost are relatively stable, repeated trips likely to use the same mode

- **Cherchi et al., (2017):** Intrapersonal variability significant day-to-day, but not week-to-week. Suggests a 7-day survey can be sufficient.

Findings from 4-week Dutch panel

- **Thomas et al., (2019):** Intrapersonal variation mainly for short trips (<2km) and recreation trips. Stable for longer trips and commute trips.

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Implementation for Mixed Logit

$$U_i = V_i + W_i + \varepsilon_i$$

For each alternative,

- V_i estimated as usual (e.g., $V = \beta x$)
- W_i sampled from the specified distribution, ***once per person***
- ε_i sampled from i.i.d. Gumbel (0,1) distribution ***once per decision***

Could better capture **intrapersonal stability** and provide **more informative policy sensitivity**

Why hasn't this been done?

- Random parameters models ideally require **panel data**
- They are difficult to estimate and calibrate
- Probably won't capture all the intrapersonal stability in W

$$U = V + W + \varepsilon$$

Potential solutions to improve stability

Multinomial / nested logit

$U = V + \varepsilon$

V systematic
ε sampled per ***trip***

Fixed error terms

$U = V + \varepsilon$

V systematic
ε sampled per ***person***

- Simple to estimate
- No special data
- Limited flexibility

Preliminary Mode Set Choice

Mode Set

↓

RESTRICTED CHOICE SET

$U = V + \varepsilon$

V systematic
ε sampled per ***trip***

- Simple model structure
- Requires panel data
- Limited sensitivity to mode shift scenarios

Random Parameters

$U = V + W + \varepsilon$

V systematic
W sampled per ***person***
ε sampled per ***trip***

- Incorporates intrapersonal stability
- Requires panel data
- Difficult to estimate & calibrate
- Hasn’t been done (yet)

Discussion

- We increasingly need to model habitual behavior
- Statistical models we use in ABMs are behind empirical literature
- How can we incorporate stability into the ABMs used in practice as well as emerging frameworks (e.g., activity-based models)?

References

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Thank you

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