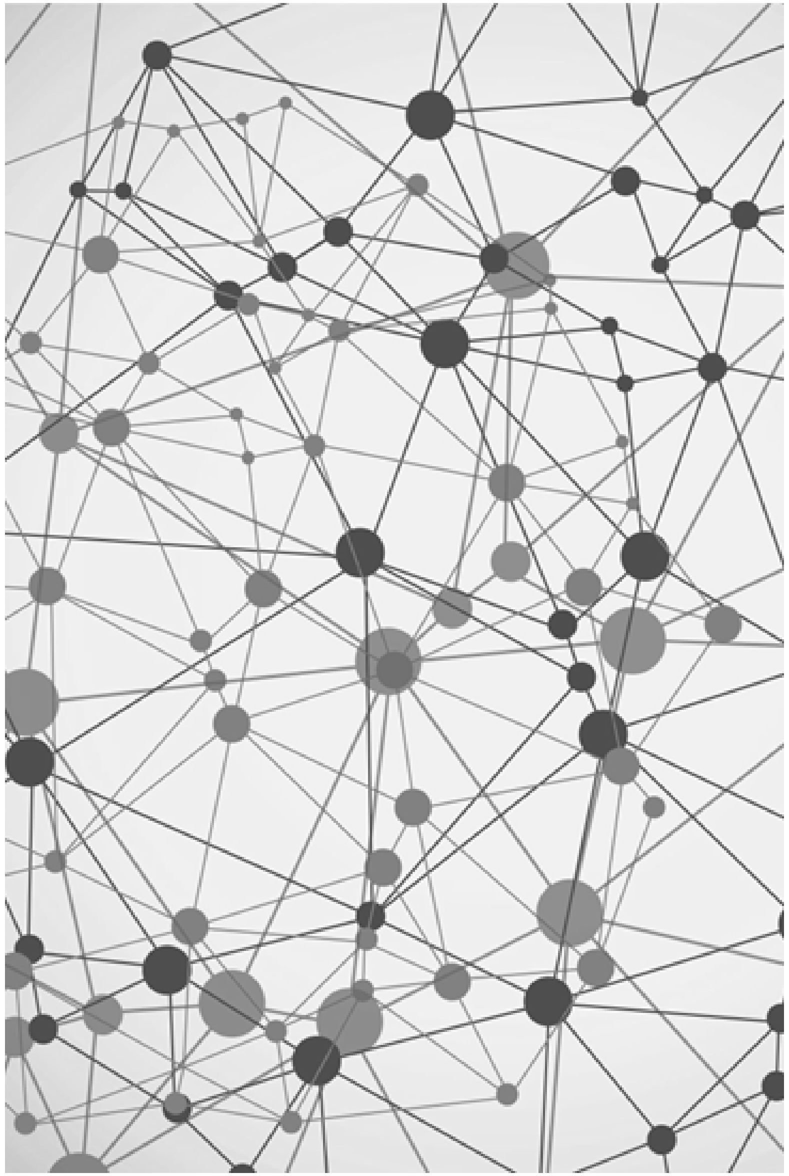

ESTIMATING THE EFFECTS OF LIFE-EVENTS AND CHANGES IN MOBILITY TOOL OWNERSHIP ON MODE CHOICE BEHAVIOUR

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THE BACKGROUND: MODE CHOICE ANALYSIS

Mode Choice analysis as cornerstone of travel behaviour research

Since the 1970's based on RUM discrete choice theory (McFadden 1973; Train 2009)

Mode choice based on *attributes*: travel time, travel cost, etc.

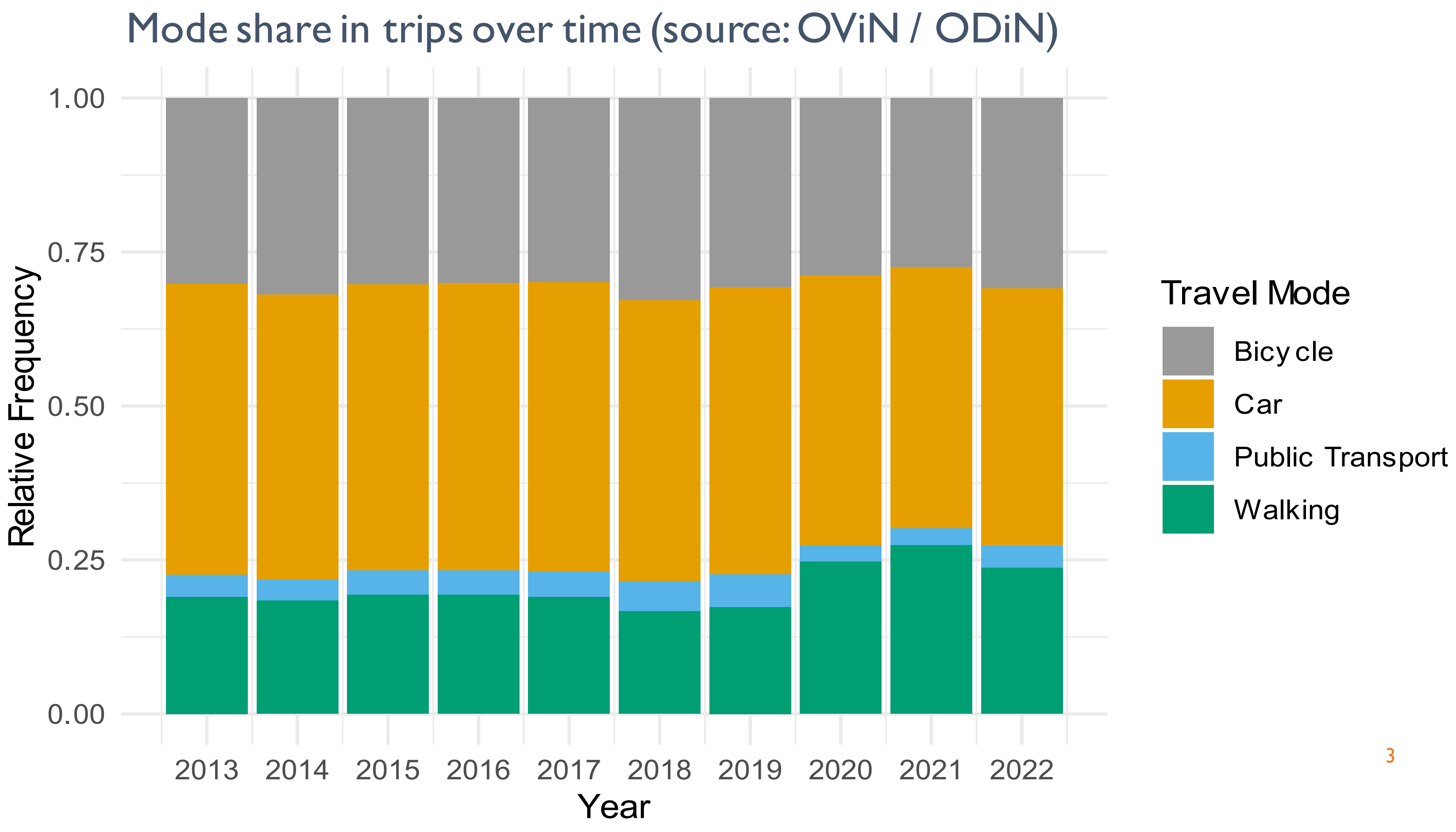
Estimate *preferences* of people with regards to these attributes

Typically employed in a <u>static</u> fashion

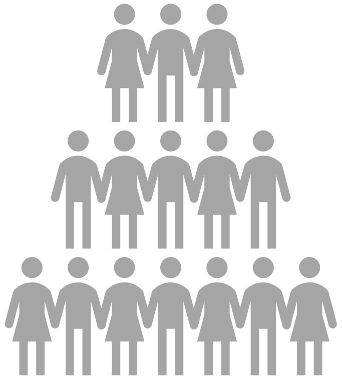
No changes in preferences over time

STABILITY OF PREFERENCES: AGGREGATED

- On an aggregated level, mode choice behaviour is very stable over time



STABILITY OF PREFERENCES: INDIVIDUAL



This aggregated stability might hide *indidual*-level changes over time

Knowing when and why these changes occur can help shift aggregated behaviour

BEHAVIOUR IS NOT ALWAYS STABLE

- Previous studies have looked at effects of:
  - Life-events
  - Changes in mobility tool ownership (cars, bicycles, public transport subscriptions)

- However, they have typically done so using a clustering approach

  Thus, studying *mode use,* rather than *mode choice*

  Unable to show how preferences for attributes change

  Unable to distinguish trip generation from mode choice

Determine the *stability* of mode choice behaviour and attribute-preferences over time

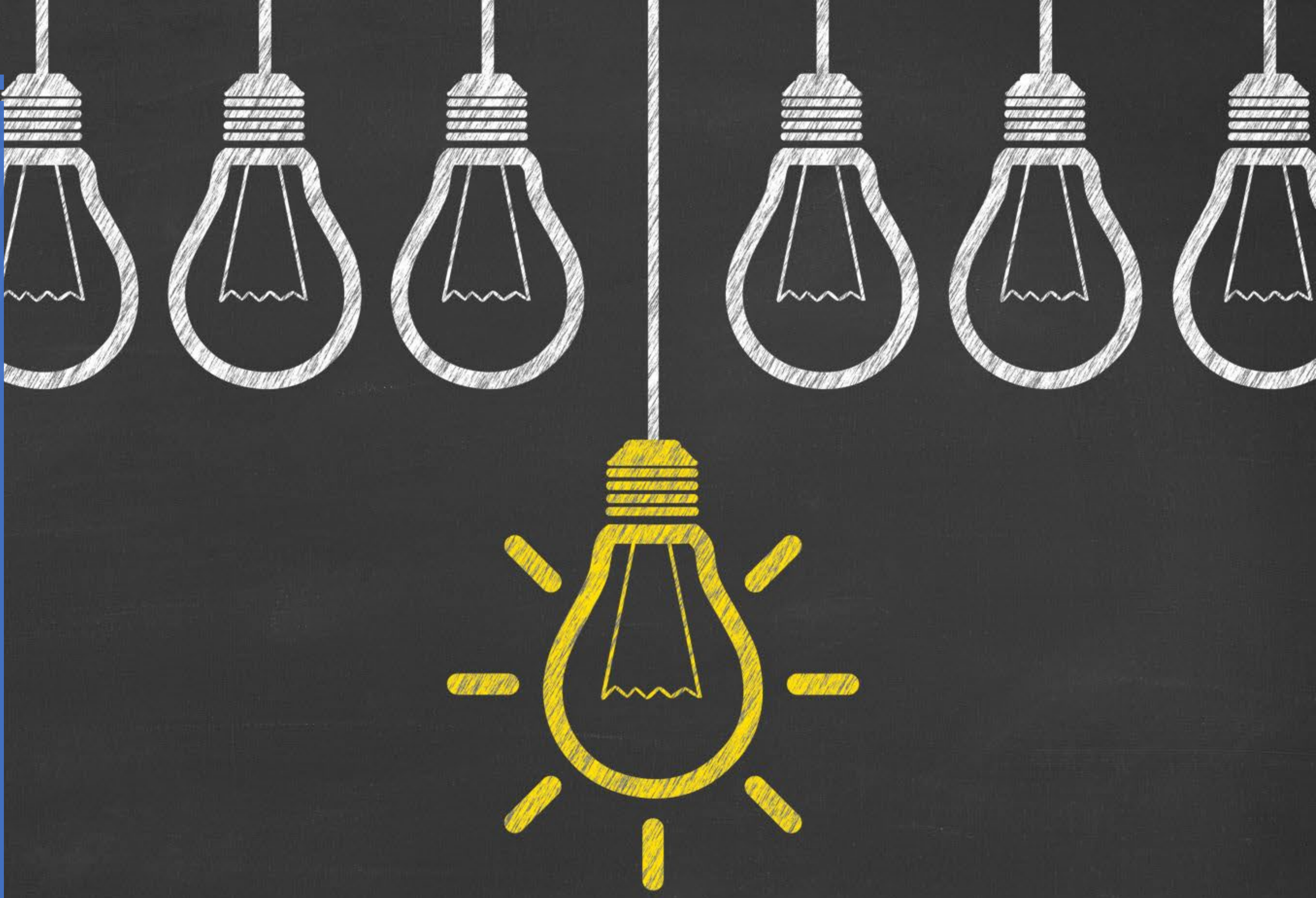
Find when this stability is decreased

- Effects of life-events
- Changes in mobility-tool ownership

RESEARCH OBJECTIVE

RESEARCH METHODS

- Latent Transition Choice Model
- Research Data (MPN)



RESEARCH METHOD

- Latent (Class) Transition Choice Model

  Sometimes also known as ‘Markov choice model’

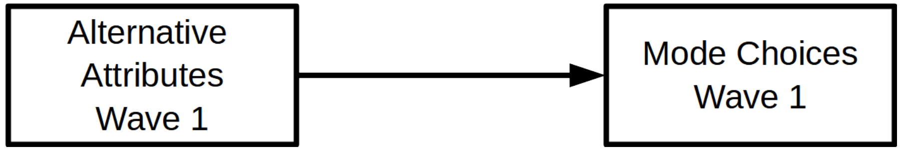
- General idea:

  Separate groups (latent classes)

  Keep the within-group parameters stable over time

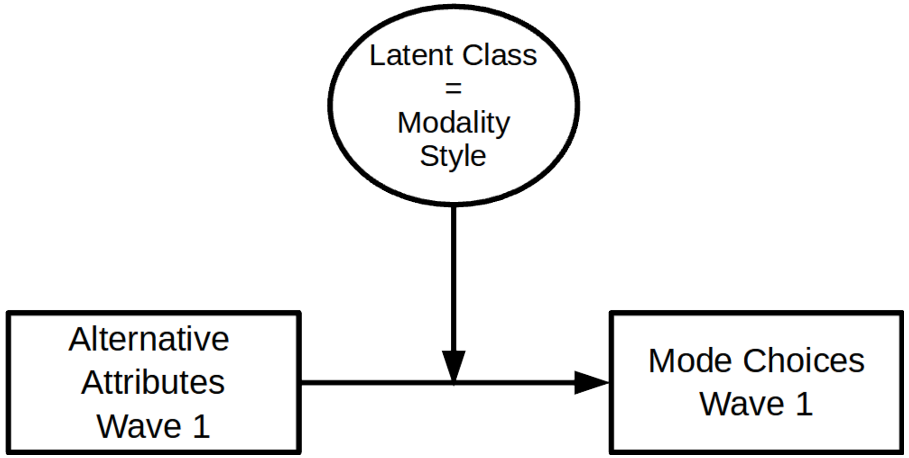
  Let respondents ‘transition’ between the groups

CONCEPTUAL MODEL (1): DISCRETE CHOICE BUILDING BLOCK



- Let mode choice be determined by alternative attributes
- In principle, flexible to specific implementation
  - RUM, RRM
  - nested, mixed, etc.

CONCEPTUAL MODEL (2): LATENT CLASSES

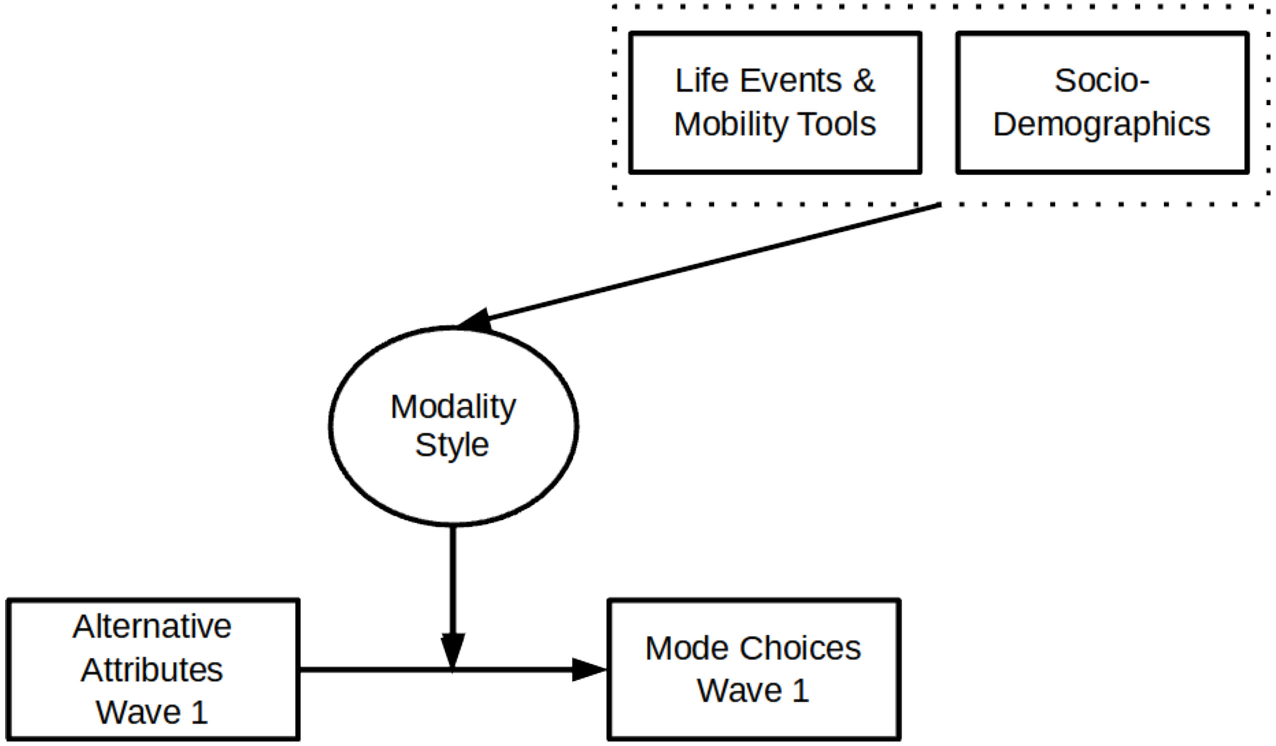


- Specify a latent class choice model
- Each latent class has different *preferences* (~= parameters)
- Interpret the latent classes as modality styles

  Underlying preferences to certain travel modes

  Examples:
  'Car-lover'
  'Bicycle-oriented'

CONCEPTUAL MODEL (3): MEMBERSHIP FUNCTION



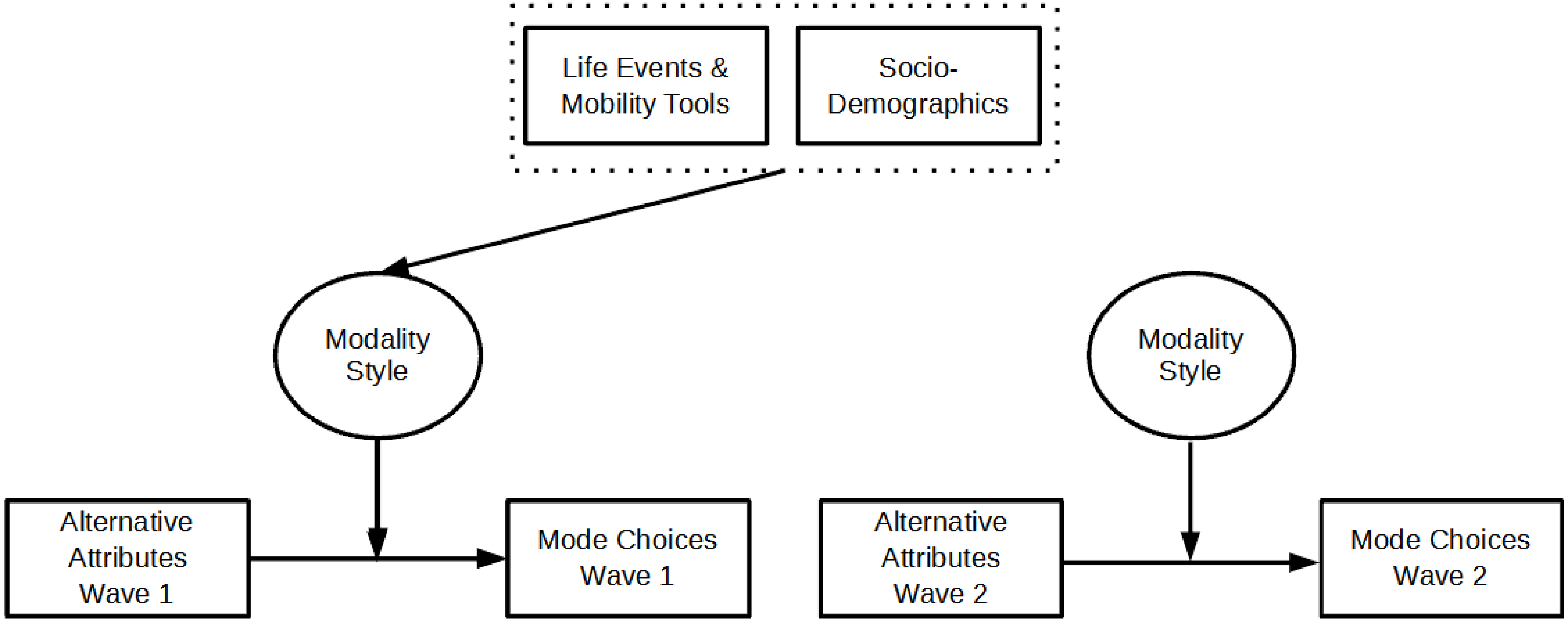
- Let socio-demographics affect class membership
  'Younger people are more likely to be in multimodal class'
- Also add effects of life-events and mobility tool ownership
  'People who change jobs use the car more often'

  'People who own e-bikes are more likely to use the bicycle'

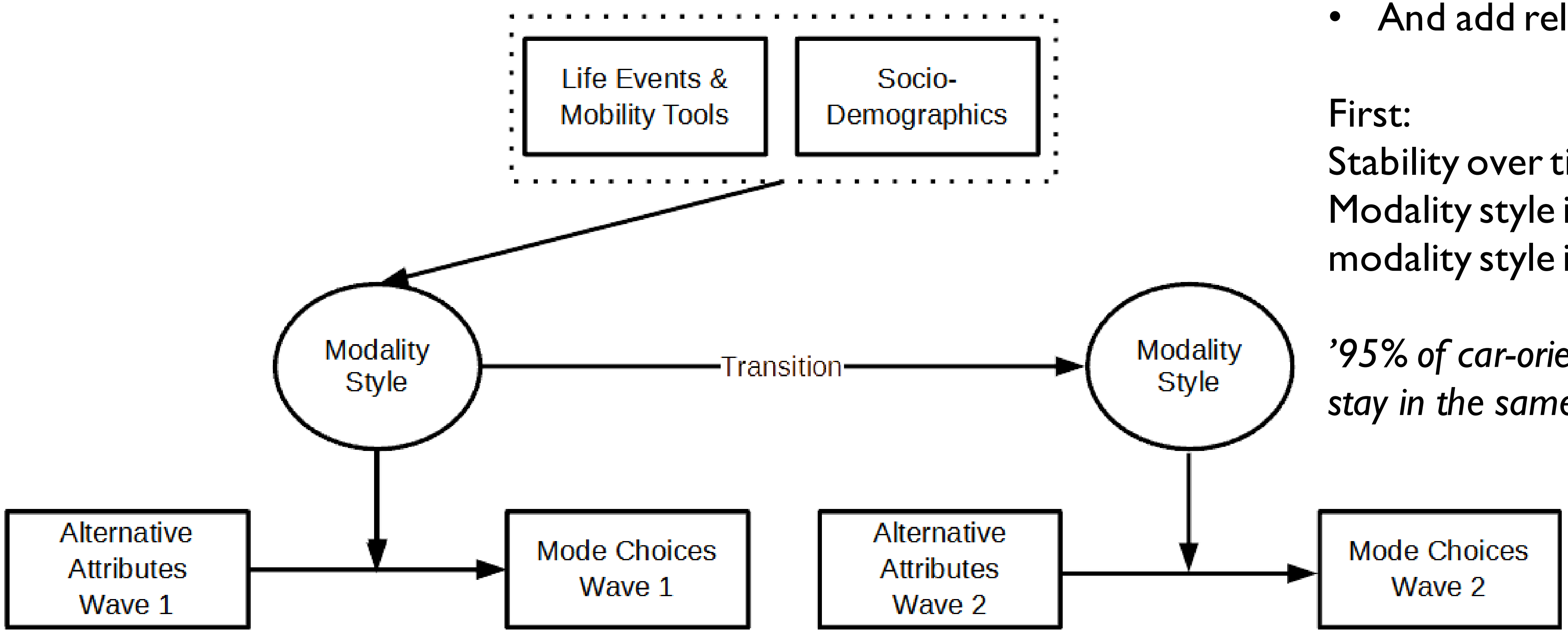
- Note: time is not modeled yet!
  Direction of effects?
  Changes in tool-ownership?

CONCEPTUAL MODEL (4): TOWARDS A TRANSITION MODEL

- So, let's add another wave!



CONCEPTUAL MODEL (4): TOWARDS A TRANSITION MODEL

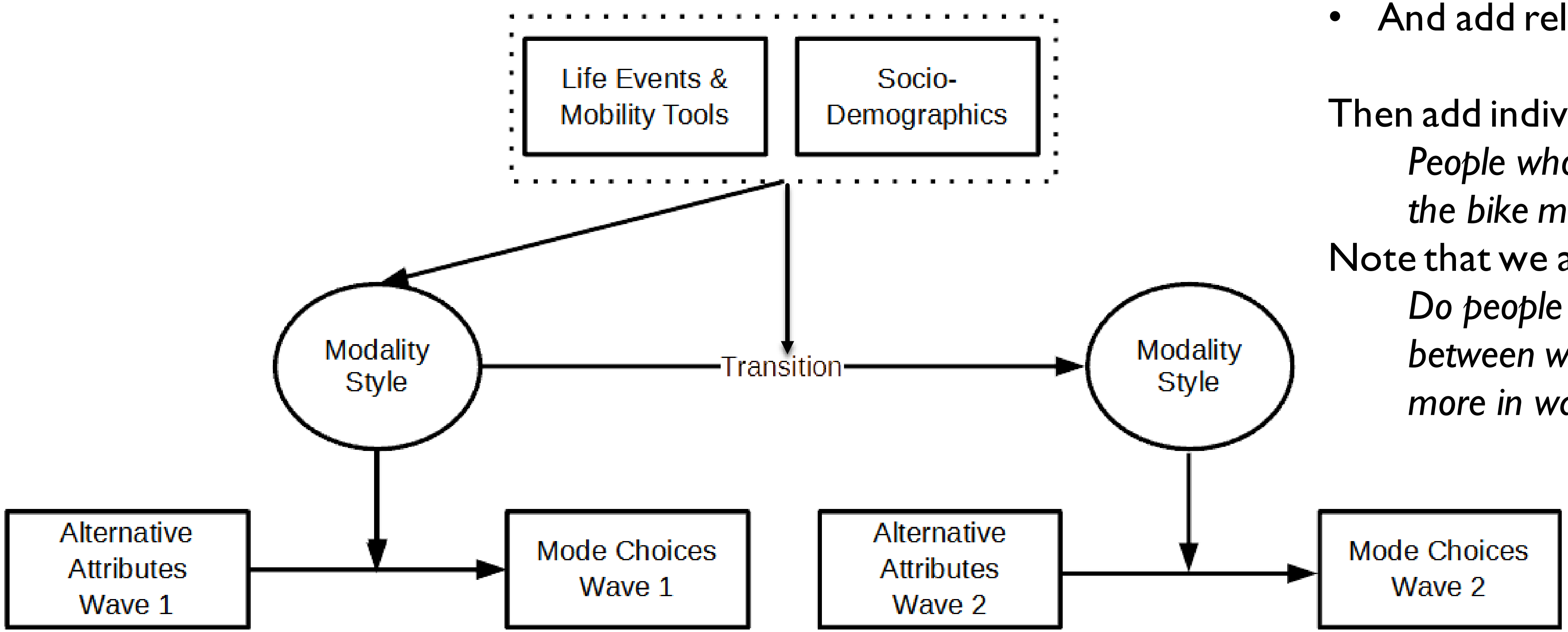


- So, let's add another wave!
- And add relations over time

First:
Stability over time;
Modality style in wave 2 depends on modality style in wave 1

'95% of car-oriented people in wave 1 stay in the same group in wave 2'

CONCEPTUAL MODEL (5): WHO?



- So, let's add another wave!
- And add relations over time

Then add individual characteristics:

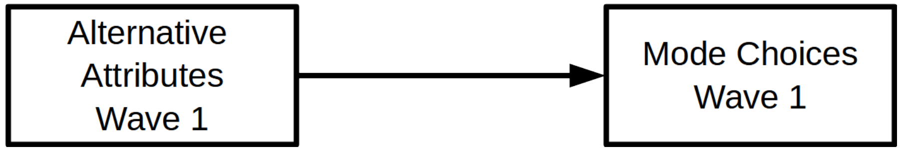
People who buy e-bikes start using the bike more often

Note that we also model 'lead-effects'

Do people who buy e-bikes between wave 1 and wave 2 cycle more in wave 1?

OUR CHOICE MODEL

- Quick word on the specific choice model used in this study
  - Alternative specific travel times (Google Directions API) + travel distance for active modes
  - Correction factor for trips made with multiple people
  - Nested model, with one sub-nest containing public transport, bicycle, walking



RESEARCH DATA (1)

- Need panel data, with alternative-specific information, life-events, and vehicle ownership
  MPN!

- Revealed preference data (real trips!)

- Use a selection of all trips
  - Made with 4 main travel modes: car, public transport, bicycle, and walking
  - Departing from residence
  - <200 km distance
  - Different origin and destination

RESEARCH DATA (2)

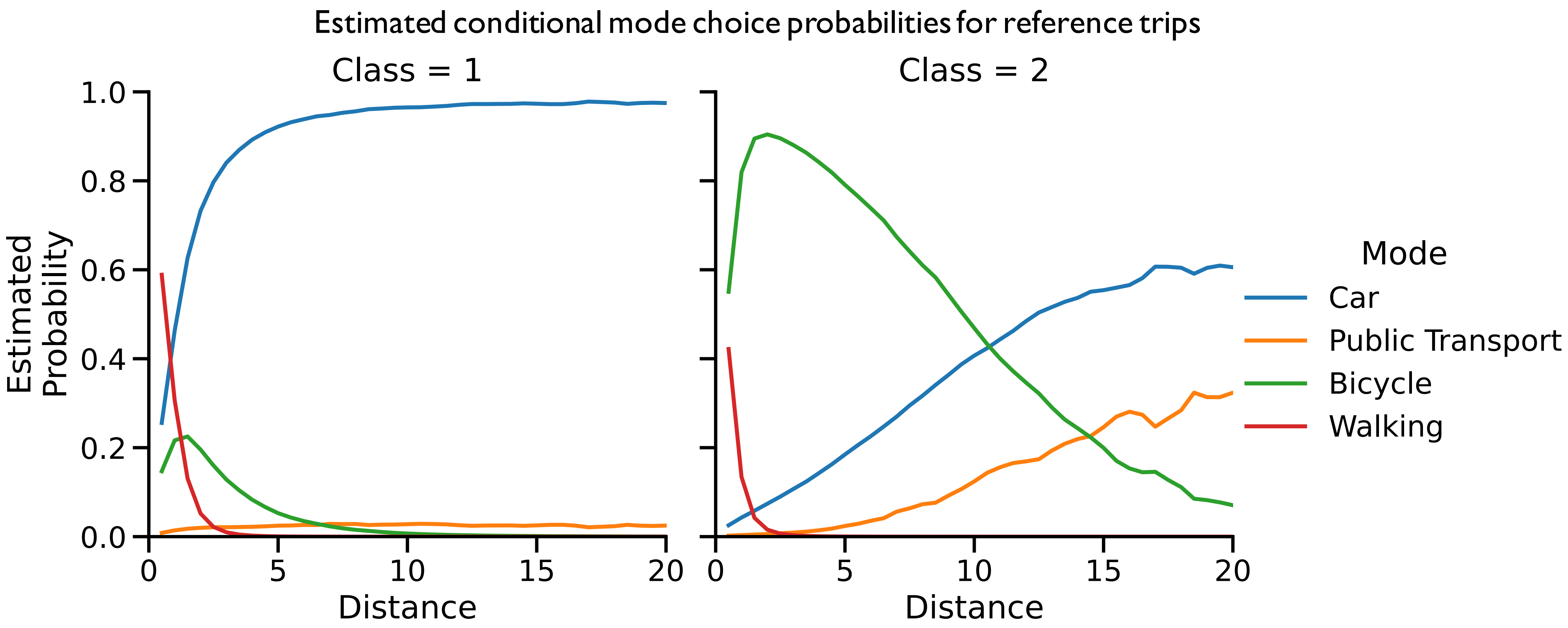
Include respondents who participated in two consecutive waves

Oversample life-events and changes in mobility tool ownership

Final sample consists of ~4000 unique respondents and ~20.000 trips.

RESULTS

- Identify latent classes as modality styles
- Modality styles are inert
- Life-events and changes in mobility tool ownership break inertia



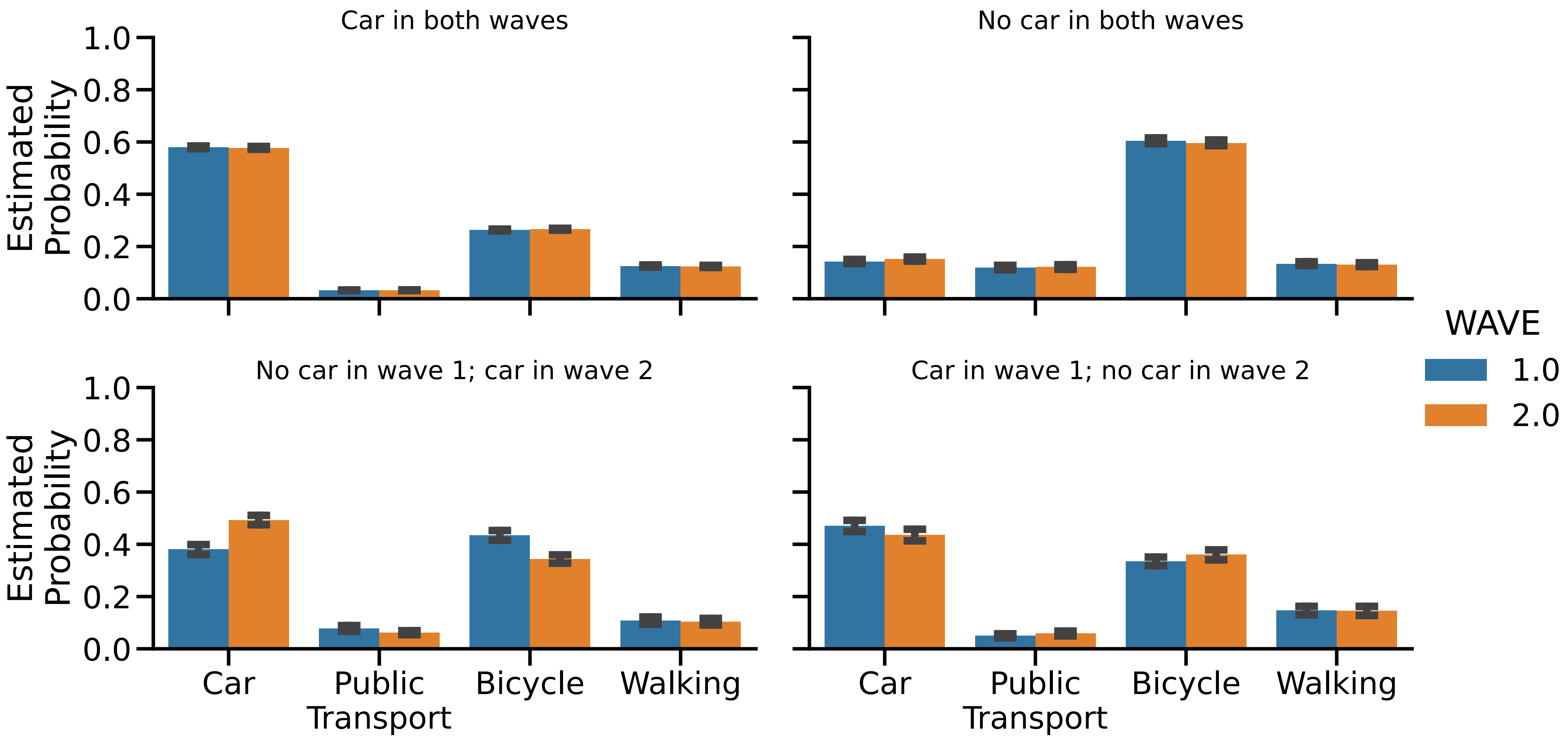
RESULTS (1): IDENTIFY MODALITY STYLES

RESULTS (2): INERTIA OF MODALITY STYLES

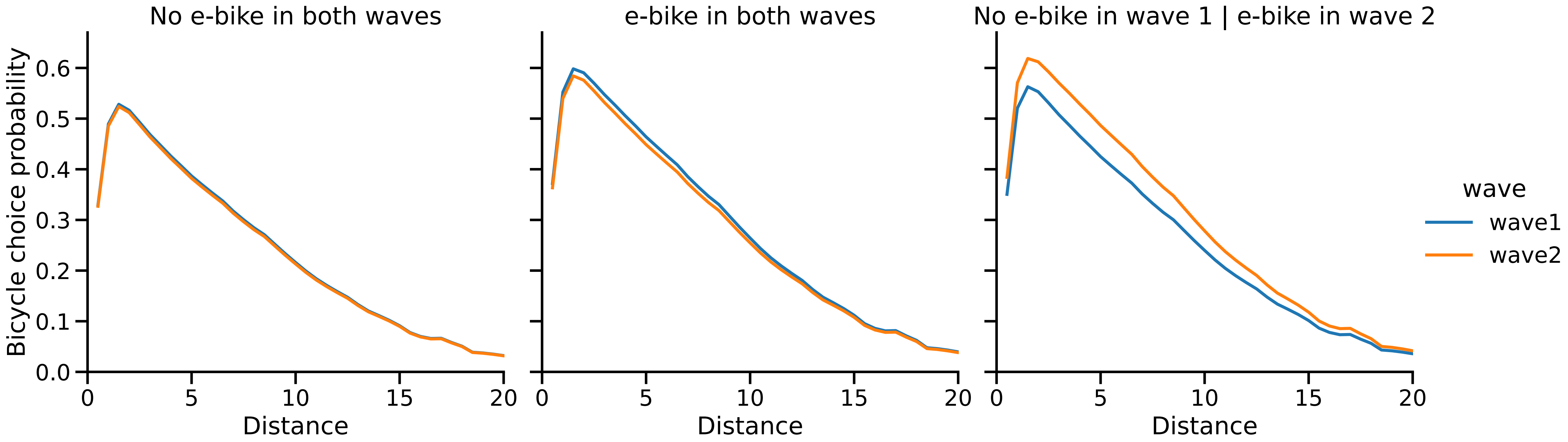
- Both modality styles are in general very stable
- Stability is decreased in presence of life-events / changes in mobility tool ownership

		Average transition matrix		With life-events / changes in mobility tool ownership	
		Wave 2		Wave 2	
		Class 1: Car-oriented	Class 2: Multi-modal	Class 1: Car-oriented	Class 2: Multi-modal
Wave 1	**Class 1: Car-oriented**	0.924	0.0759	0.884	0.116
	Class 2: Multi-modal	0.0821	0.918	0.112	0.888

RESULTS (3): EFFECTS OF CAR OWNERSHIP



RESULTS (4): EFFECTS OF E-BIKE OWNERSHIP



CONCLUSIONS

CONCLUSION (1): BENEFITS OF THE MODEL

- Latent Transition Choice Model

  Provides a better fit to the data

  Allows for estimation of effects of life-events on choice probabilities

    Changes in preferences with regards to attributes

  Explicitly incorporates time

CONCLUSION (2): SUBSTANTIVE CONCLUSIONS

- Owning or not owning a car is important determinant of car use

  Asymmetry: gaining a car has larger effect than losing one

  Lead-effects: people who use a car more often will then buy a car

  Higher sensitivity to travel time (and travel distance for active modes)

- E-bike ownership increases bicycle use

  Reductions in public transport and car use

  Lower sensitivity to travel time and travel distance

CONCLUSION (3): SUBSTANTIVE CONCLUSIONS

- Small / no effects of the life-events we investigated

  Contradicts earlier mode use studies

  Perhaps effects are mostly related to trip generation / travel patterns?

  Or effects run through mobility tool ownership?

  We do find significant lead-effects

LIMITATIONS

Model is finicky:

how robust are results to outliers?

Still difficult to fully establish direction of causality

Relatively small sample size with changes in life-events

NEXT STEPS

Add other mobility tools:

Household car ownership

Public transport cards and subscriptions (OV-kaart)

Access to car (unlimited, in coordination, etc.)

Change to electric car

Compare findings with cluster model and contrast results

Modeling changes in mobility tool ownership in their own right

A WORD ON THE MPN

- Unique dataset, not just for the Netherlands but worldwide
- Ability to estimate choice models using revealed preference data

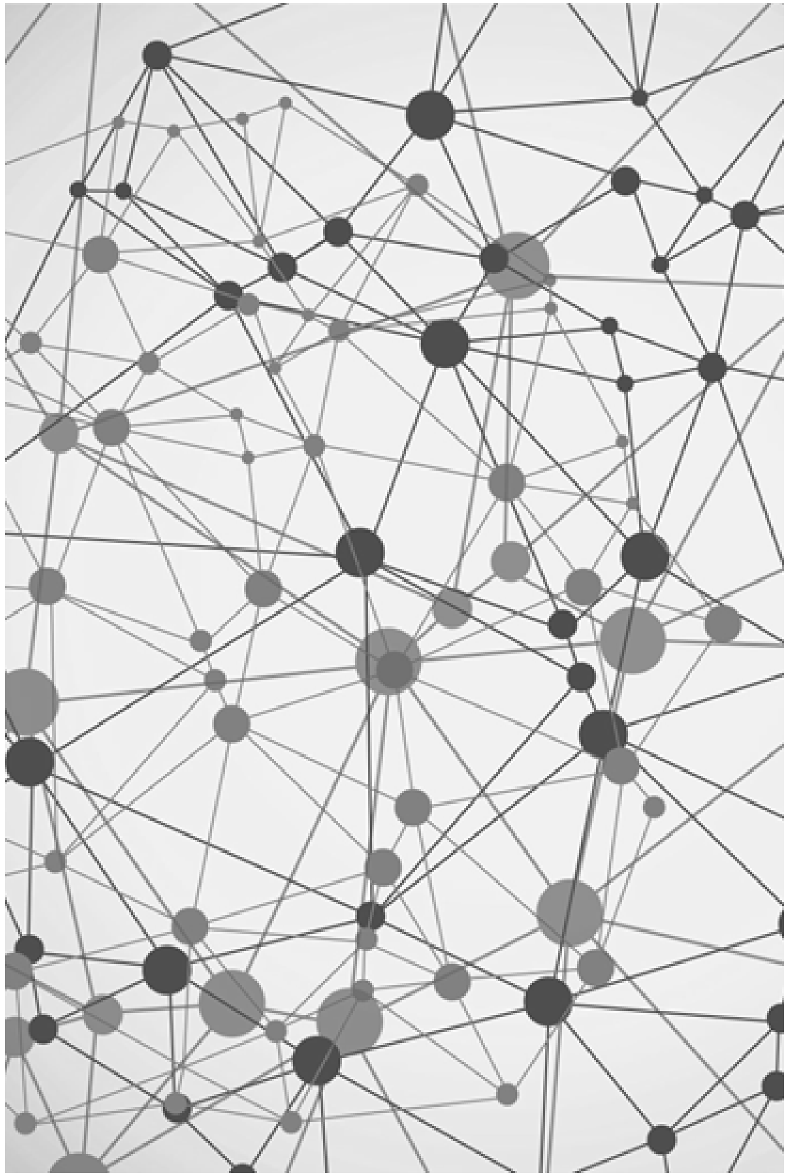
  Enough information on individuals to work on choice set formation

  Alternative specific travel times
- Panel data enables estimation of richer models, providing relevant information

  Direction of effects, lead-effects, effects of changes in independent variables, etc.

- Still 'normal' downsides of revealed preference data (correlations, extrapolation)

  Life-events / changes in mobility tools are rare events and sample size is just about OK



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	Model 1	Model 2	Model 3	Model 4
	latent class model	latent class model. change size across waves	latent transition model. No covariates	latent transition model. With covariates
	Within-sample model fit			
Est. parameters	20	21	22	55
LL_β	-17 023	-17 023	-16 946	-16 602
Mean LL_β per person	-0.603	-0.603	-0.600	-0.586
ρ^2 eq. shares	0.518	0.518	0.520	0.530
LL_β diff	-	0	77	344
	Out of sample validation			
LL_β per obs. In sample	-0.606	-0.606	-0.605	-0.592
LL_β per obs. Out of sample	-0.604	-0.604	-0.600	-0.590
% Diff.	-0.59%	-0.59%	-0.71%	-0.42%

RESULTS (EXTRA): DOES LCTCM FIT BETTER?