Activity-Based Model Systems

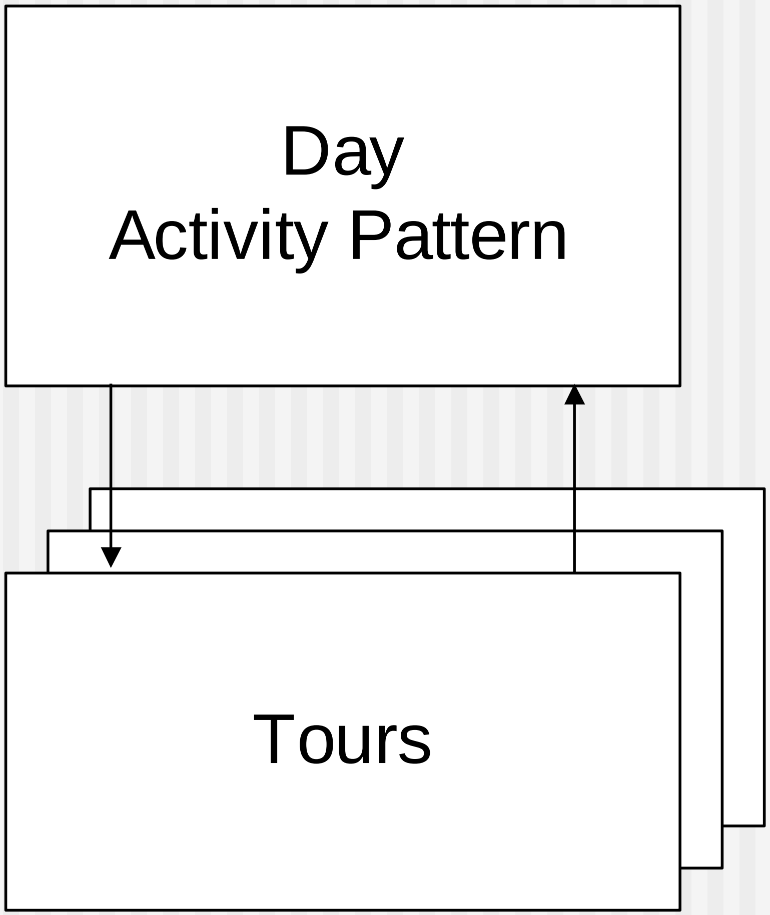
MIT 1.205
November 22, 2013

John L Bowman, Ph.D.
John_L_Bowman@alum.mit.edu
JBowman.net

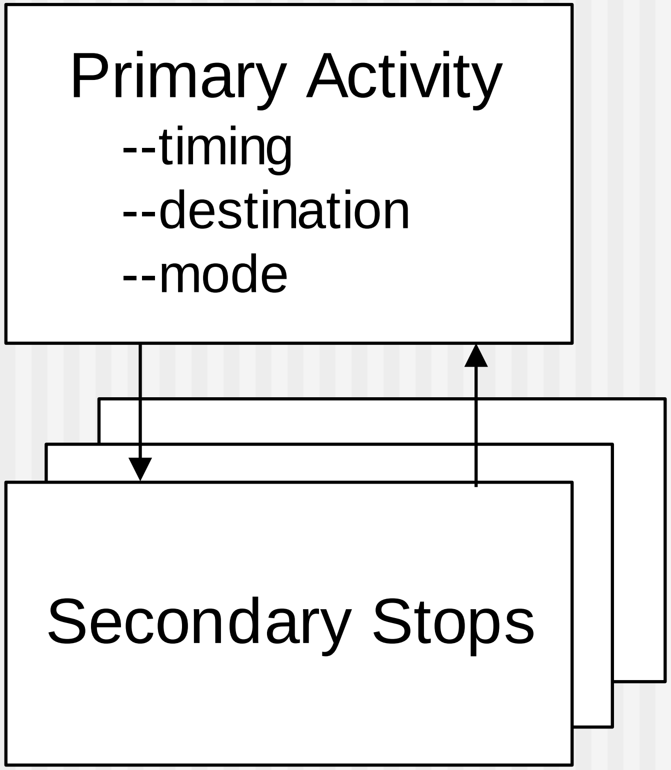
Outline

- Introduction and Basics
- Details
  - Synthetic population and long term models
  - Day models
  - Tour models
  - Fine-grained spatial scale

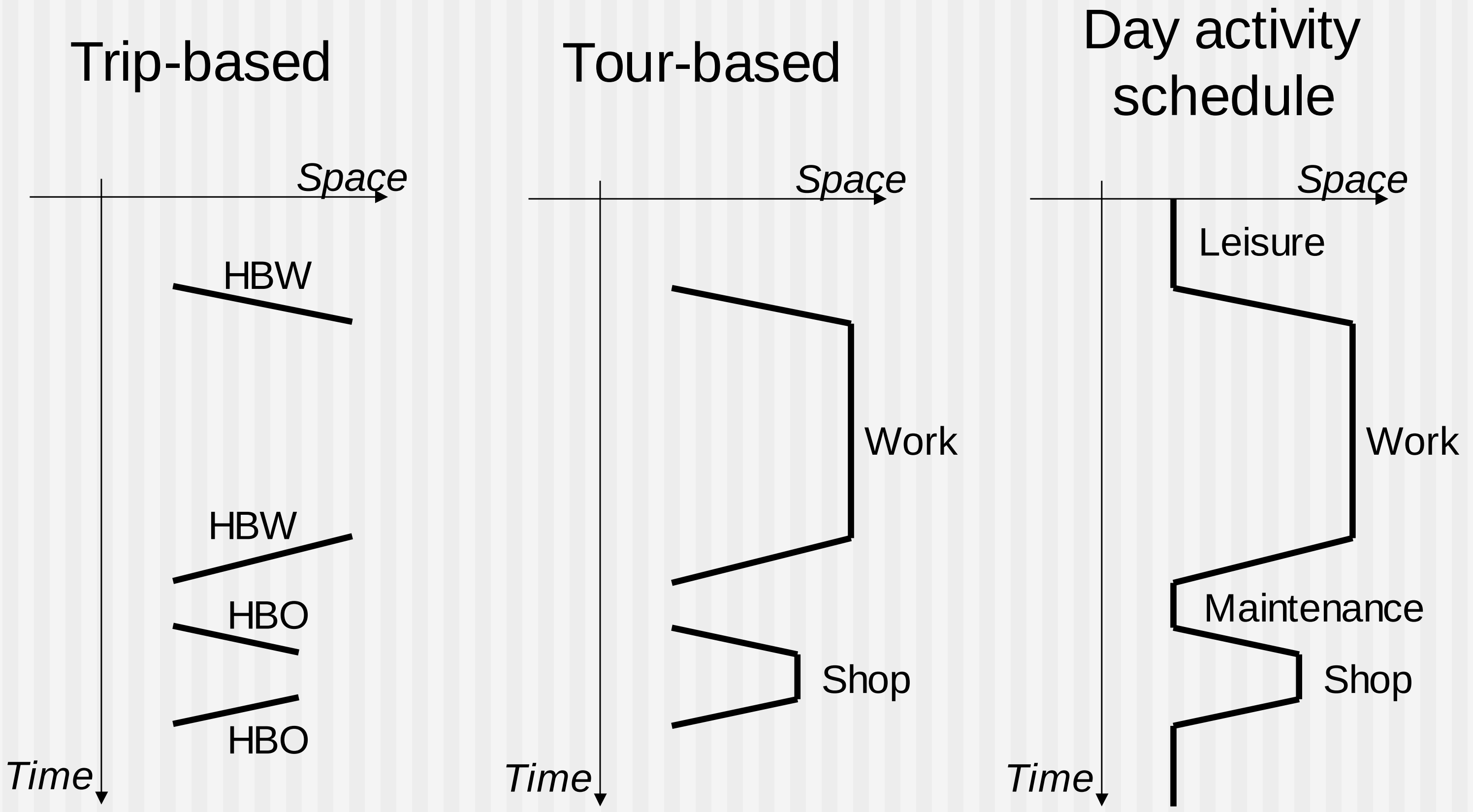
The Day Activity Schedule
(TRB January 1994)



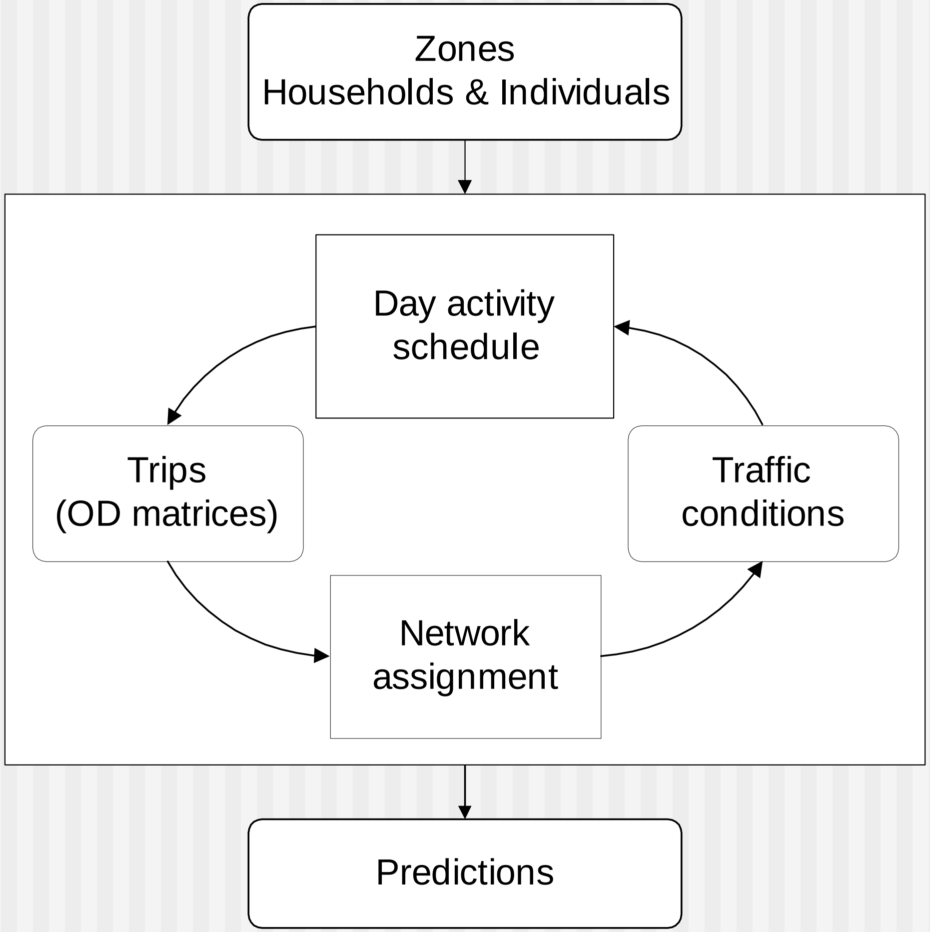
Tours


Primary Activity
--timing
--destination
--mode
Secondary Stops

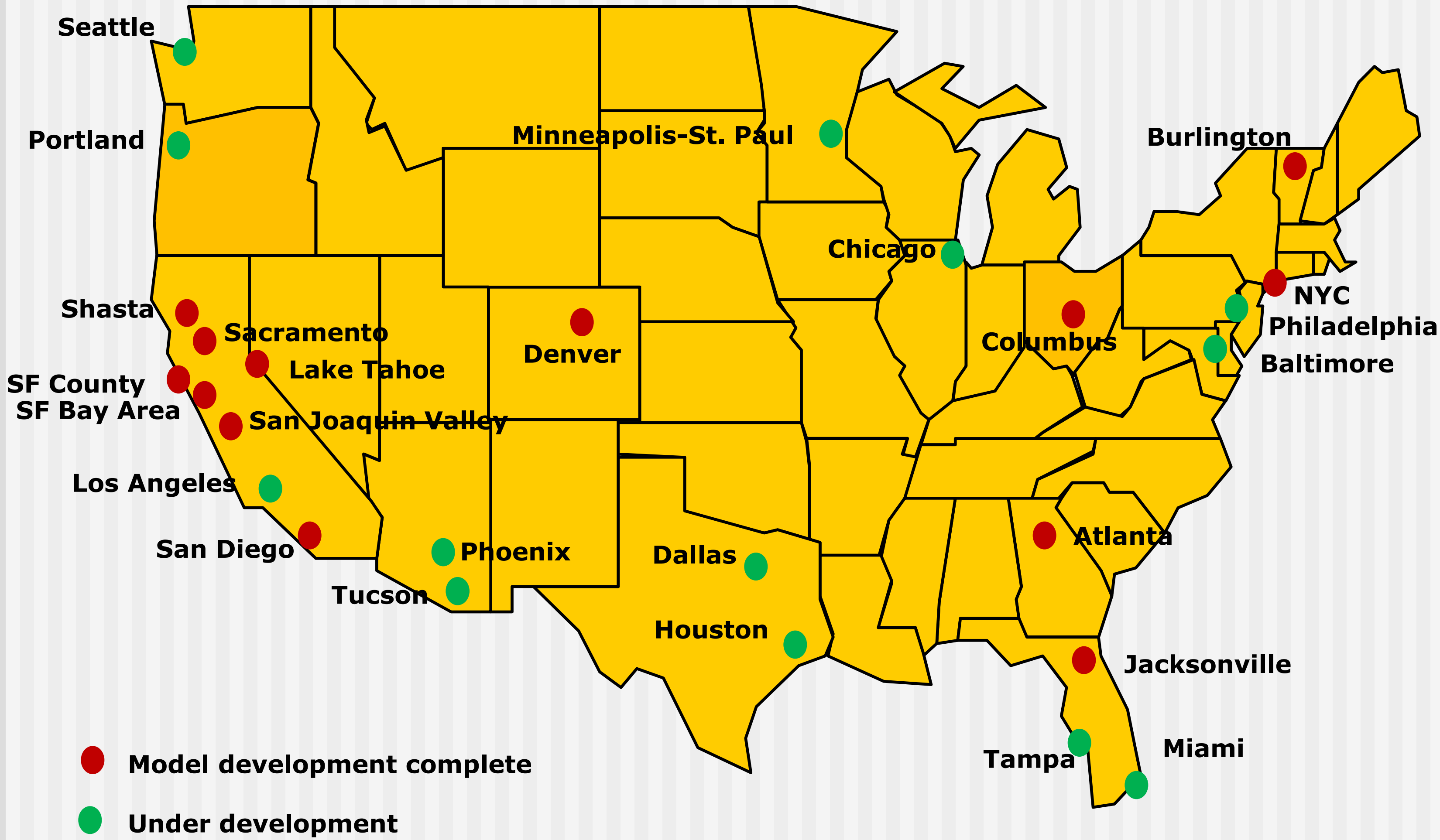
Discrete Choice Approaches



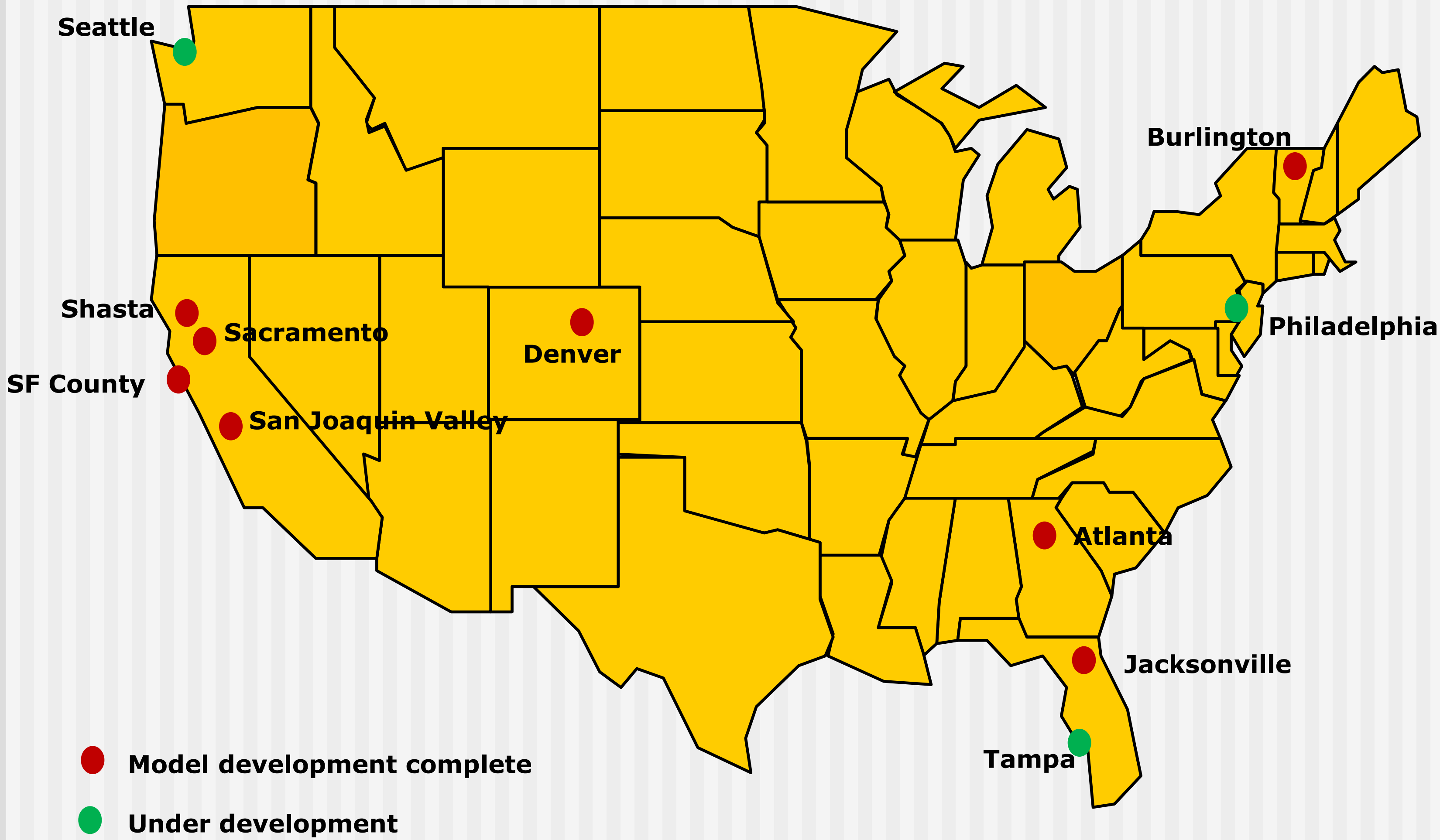
Model Application



AB Models in the U.S. 2013



AB Models in the U.S. 2013



Copenhagen ACTUM Project

- funded by the Danish Strategic Research Council
- led by Danish Technical University
- involves several collaborators
- to develop an advanced activity-based model (COMPAS—Copenhagen Model for Person-Activity Scheduling)

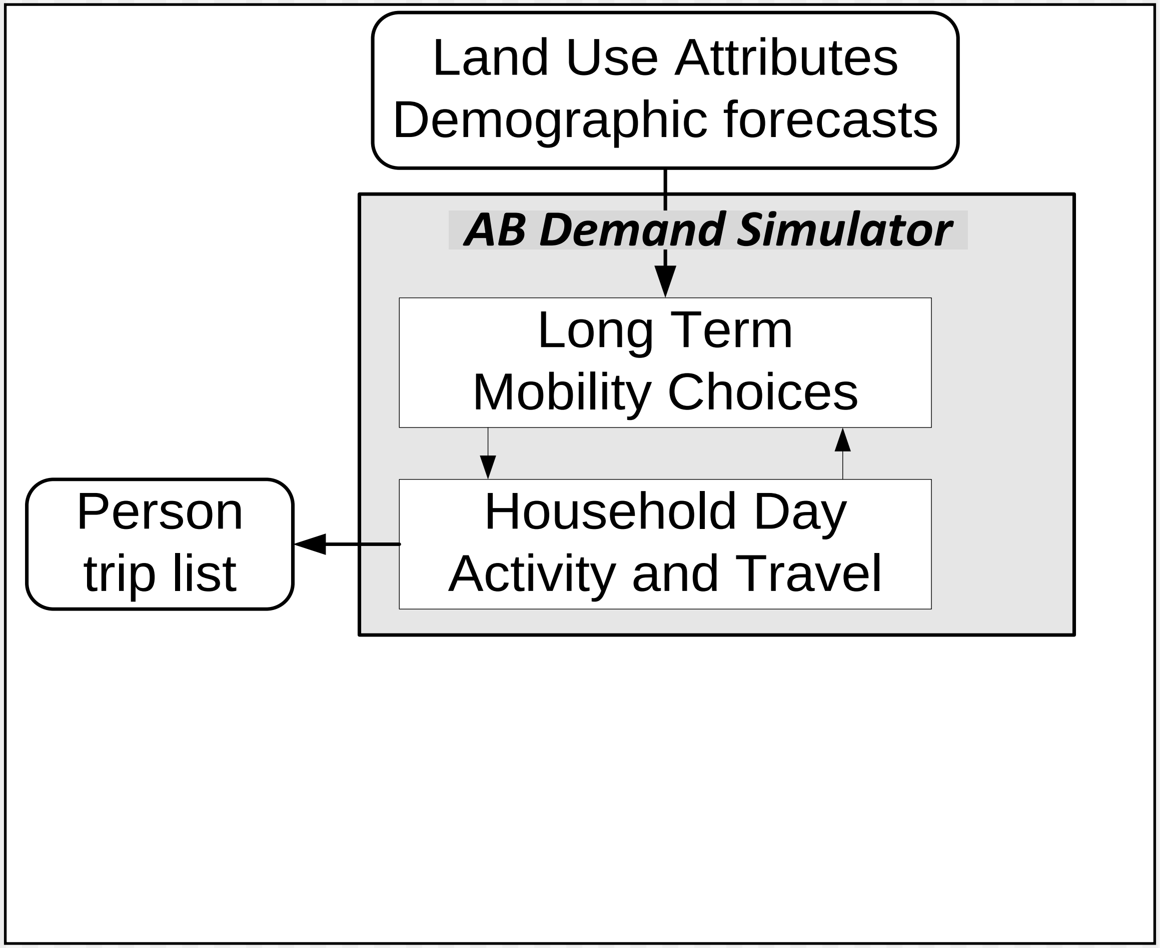
Some good reasons to use AB models

- Time-of-day policy analysis (e.g. road pricing)
- Model "non-home based" trips realistically
- Measure policy impacts on flexibly defined population subsegments
- Improve LoS measurement (and model accuracy) through fine-grained geography
- Evaluate transit fare policies that price by person type

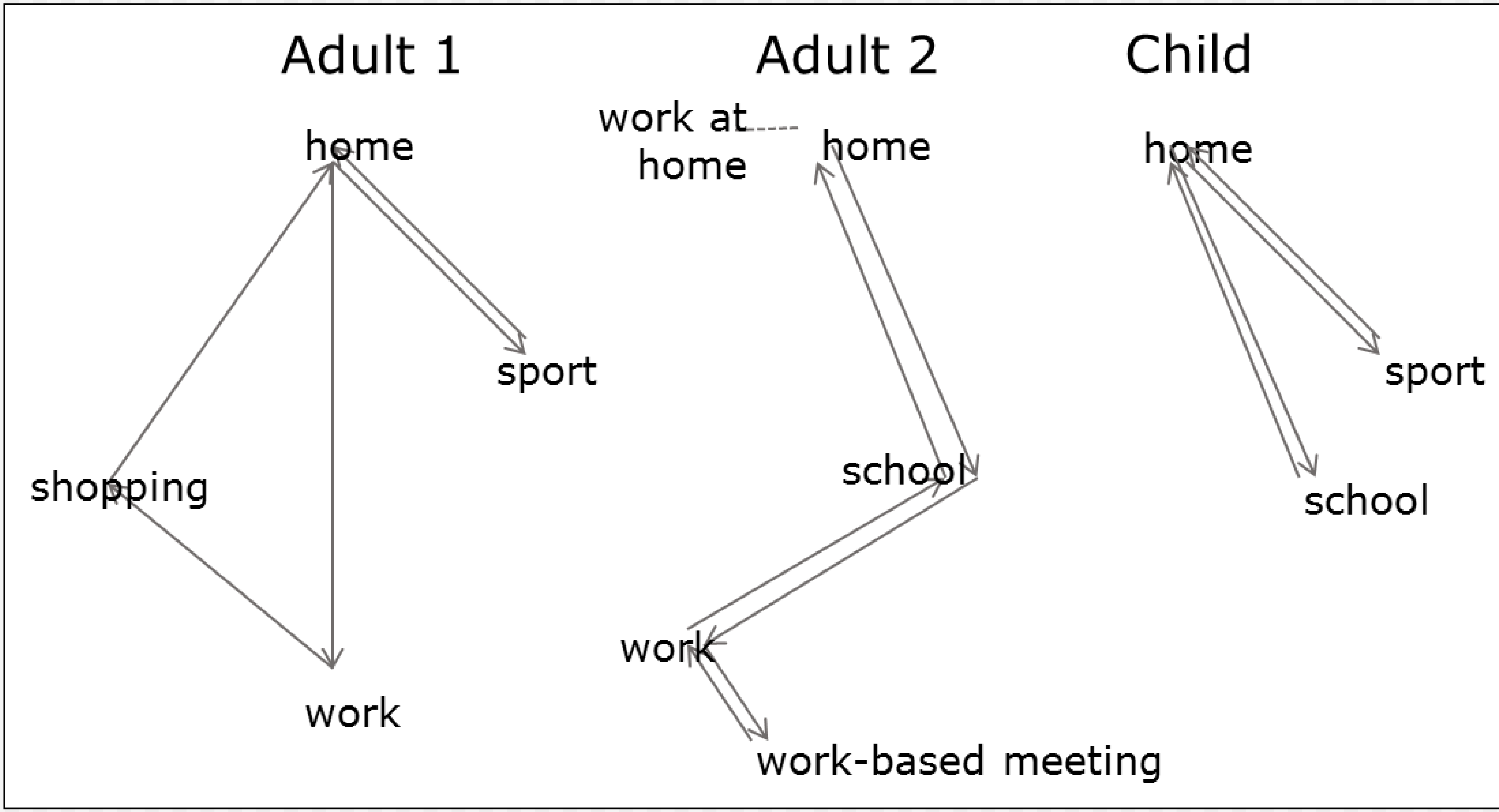
Some good reasons to use AB models (continued)

- Policy analysis related to using autos or bicycles to access transit
- Address the effects of parking policies
- Improve modeling of bicycles
- Approach is intuitively appealing and easy to explain
- Framework lends itself to ongoing enhancements and added capabilities

Demand Microsimulation



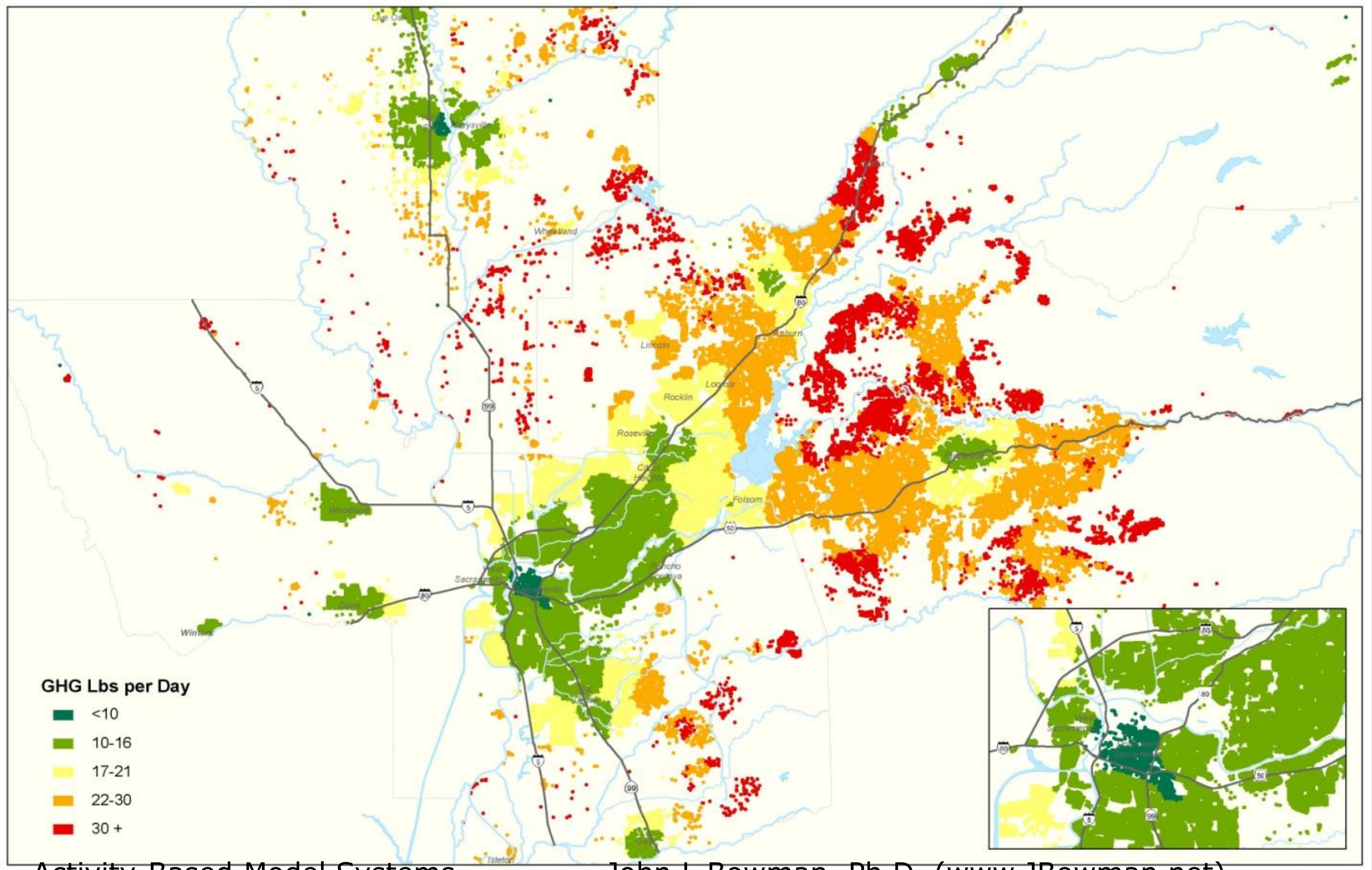
Generate a schedule for each household



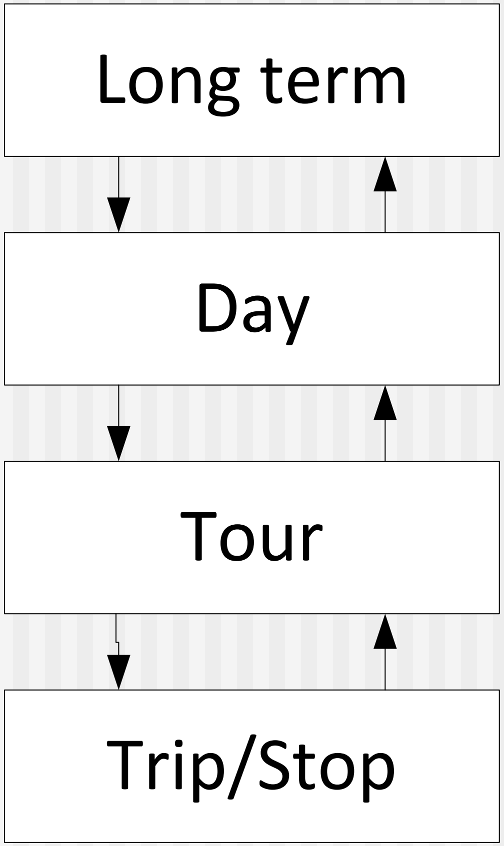
HH/Person/Day/Tour/Trip List

For each…	List includes…
Household	Location, size, vehicles, etc
Person	Age, gender, usual work & school locations, etc
Day	Number of tours and stops
Tour	Purpose, destination, timing, main mode, number of stops
Trip	Origin, destination, origin purpose, destination purpose, mode, departure time, travel time
Joint tour or half tour	Participants and their associated tours

GreenHouse Gas estimates by residence parcel -- Sacramento Area Council of Governments



AB Travel Demand Simulator
Integrated System of Choice Models



Logit Choice Models

$$P_n(i) = \frac{\exp(\beta' X_{in})}{\sum_j \exp(\beta' X_{jn})}$$

Where i and j index discrete alternatives

$P_n(i)$ is the probability that person n chooses alternative i

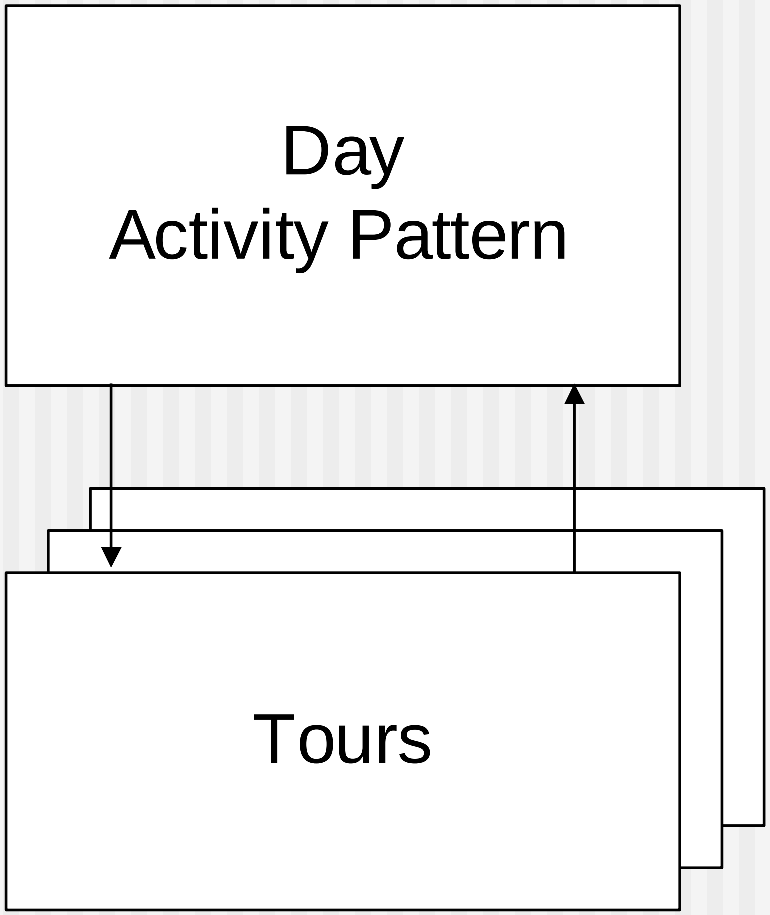
X_{in} is a vector of explanatory variables

β is a vector of coefficients

AB Model Integration

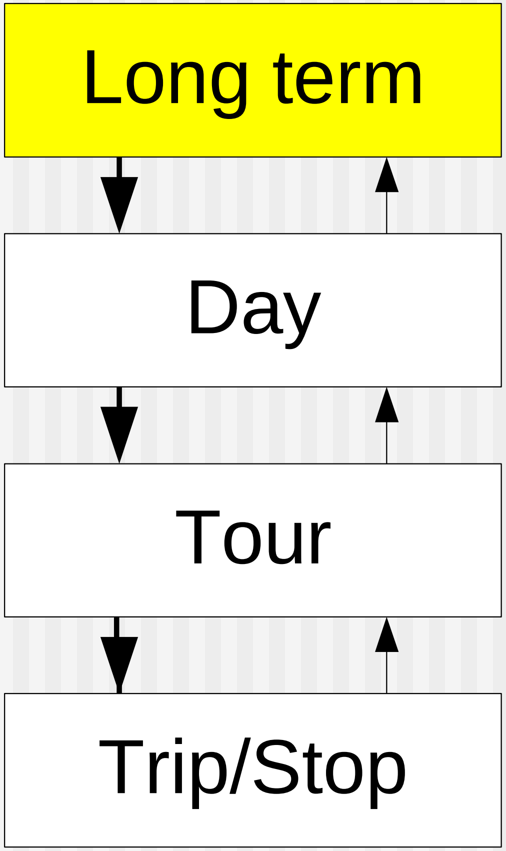
- Downward (conditionality)
- Upward (accessibility)

The Day Activity Schedule
(TRB January 1994)



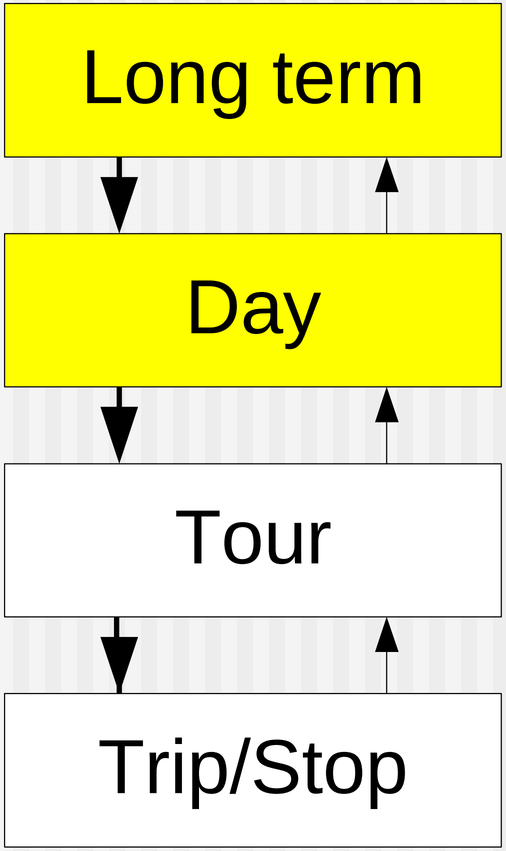
Downward Integration

Lower models take upper outcomes as given



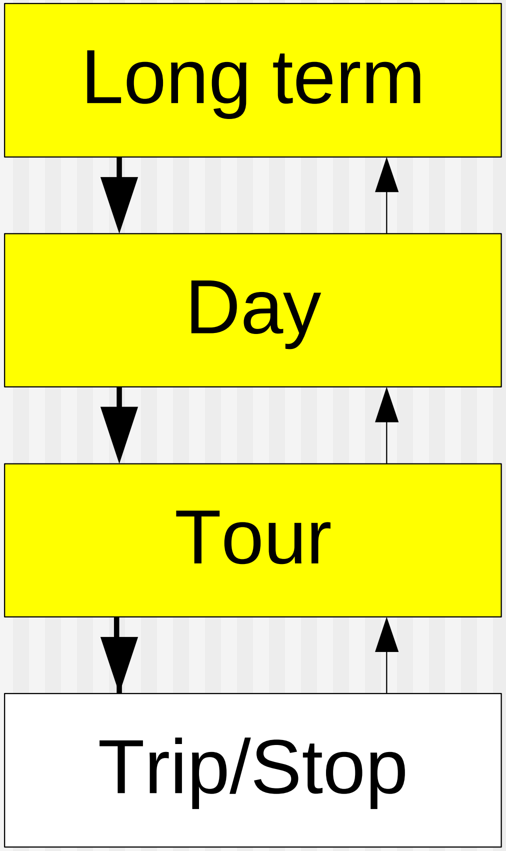
Downward Integration

Lower models take upper outcomes as given



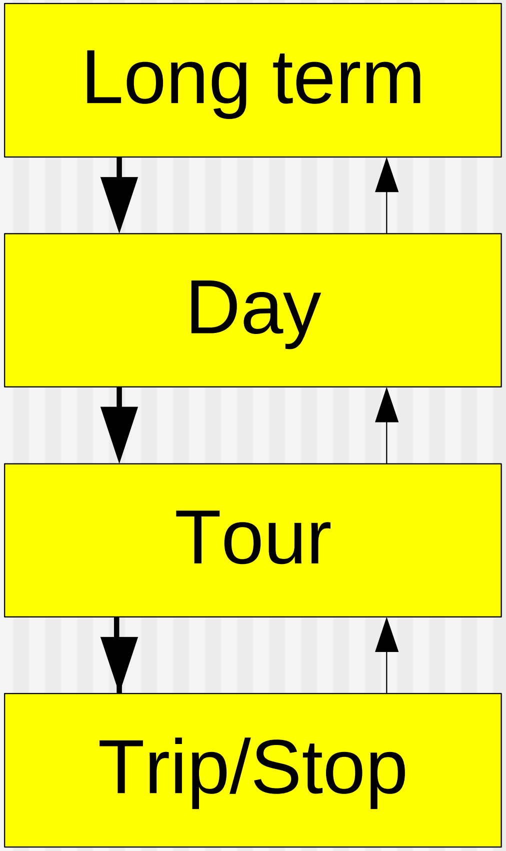
Downward Integration

Lower models take upper outcomes as given



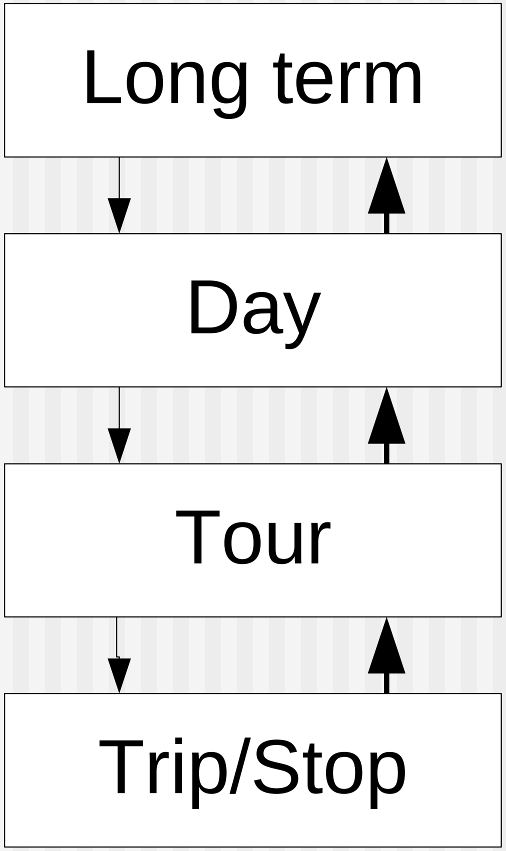
Downward Integration

Lower models take upper outcomes as given



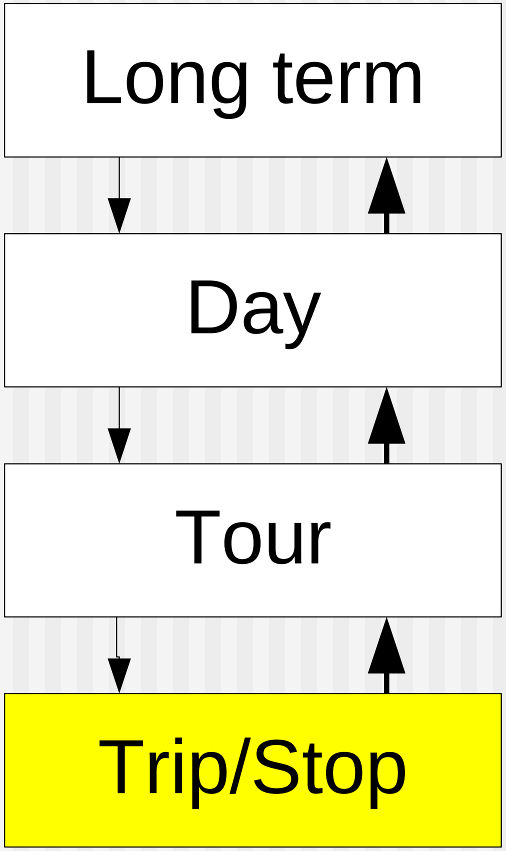
Upward Integration

Upper models should be sensitive to conditions affecting lower models



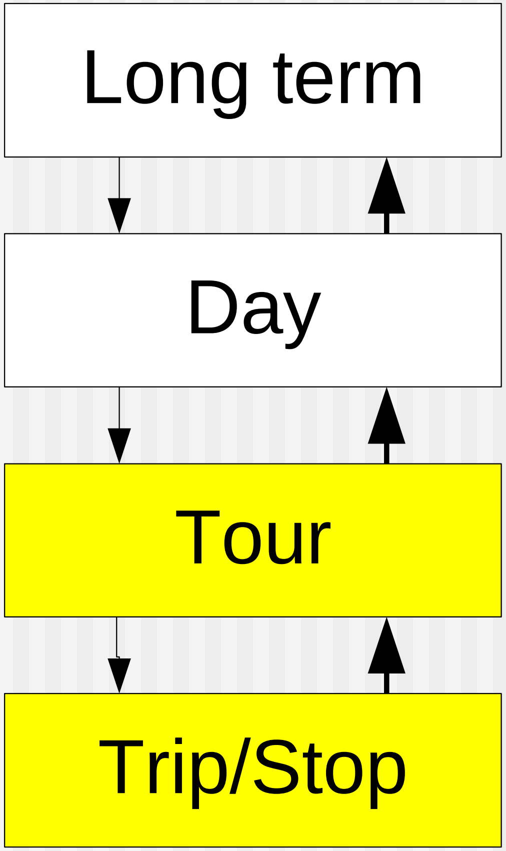
Upward Integration

Upper models should be sensitive to conditions affecting lower models



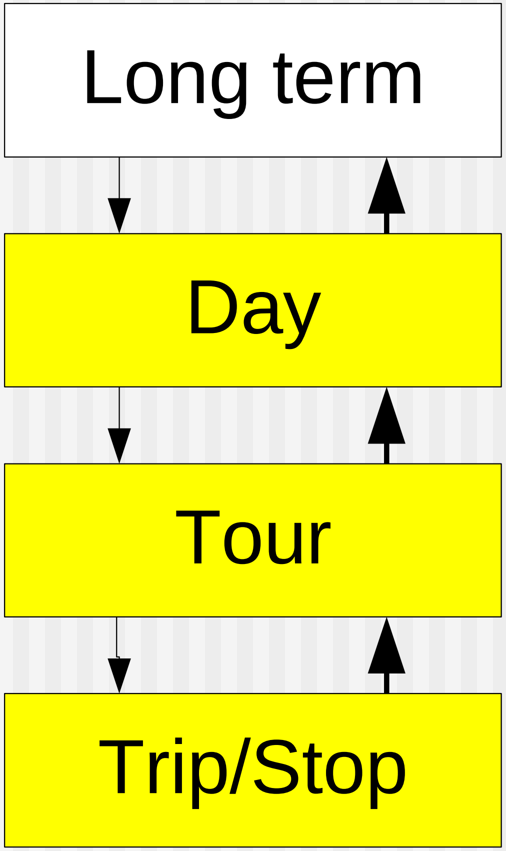
Upward Integration

Upper models should be sensitive to conditions affecting lower models



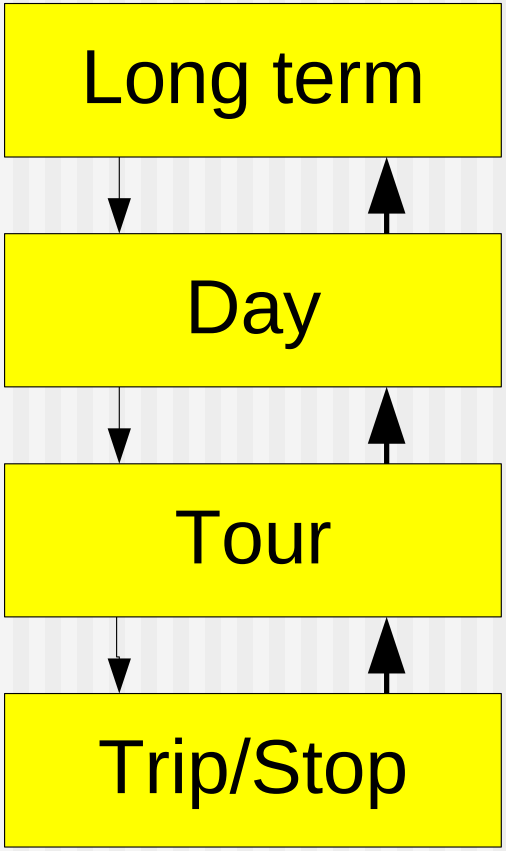
Upward Integration

Upper models should be sensitive to conditions affecting lower models

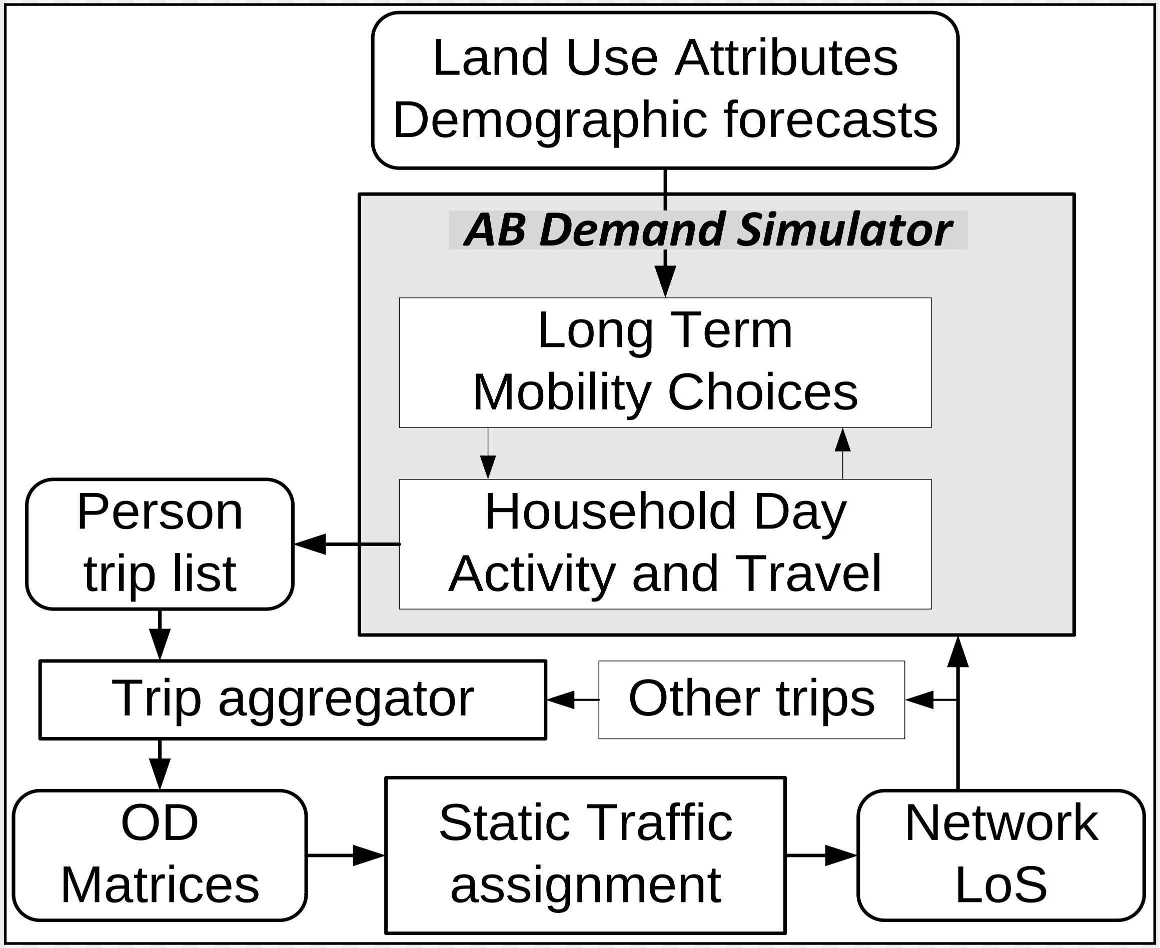


Upward Integration

Upper models should be sensitive to conditions affecting lower models

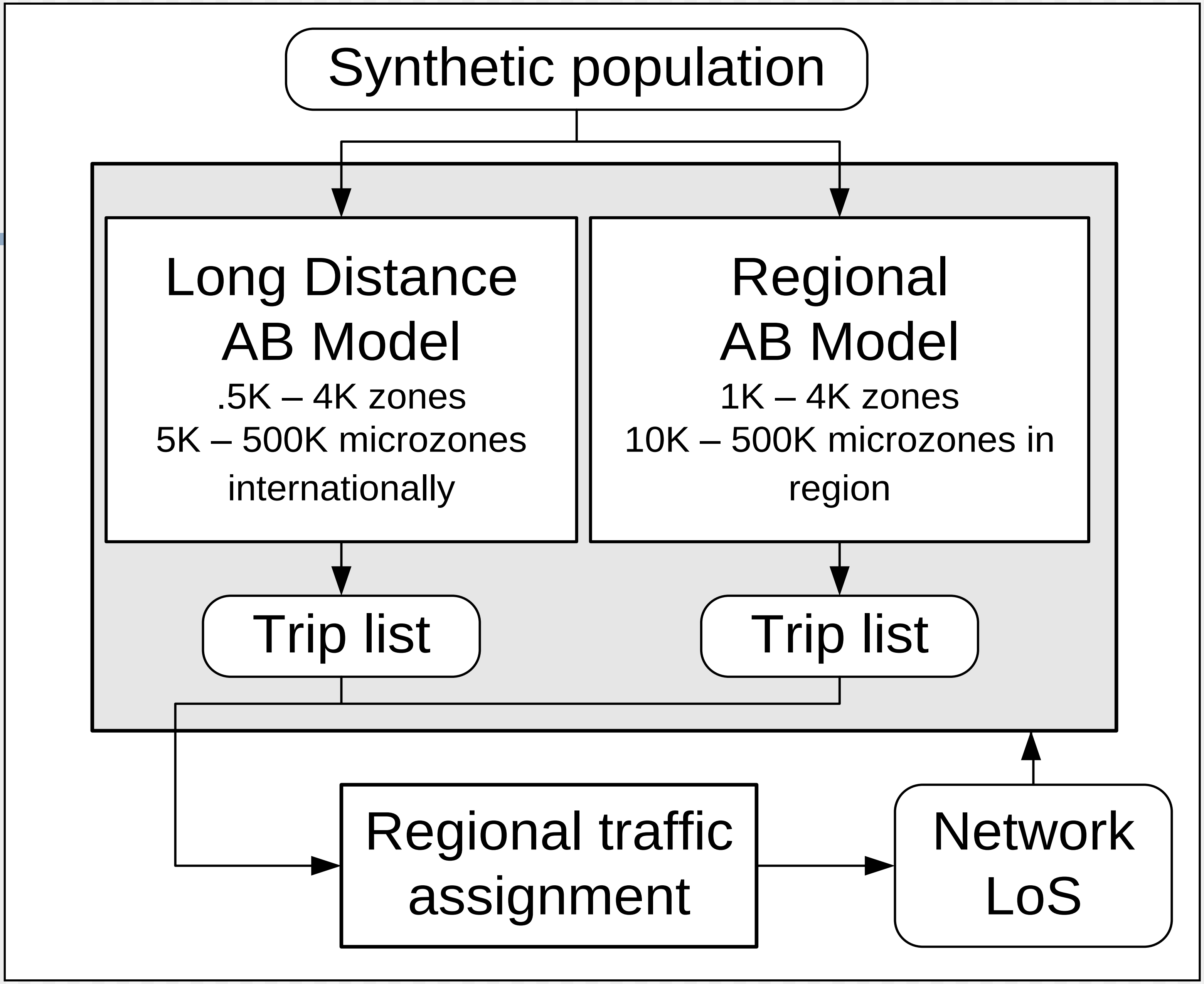


Demand Microsimulation with Aggregate Assignment

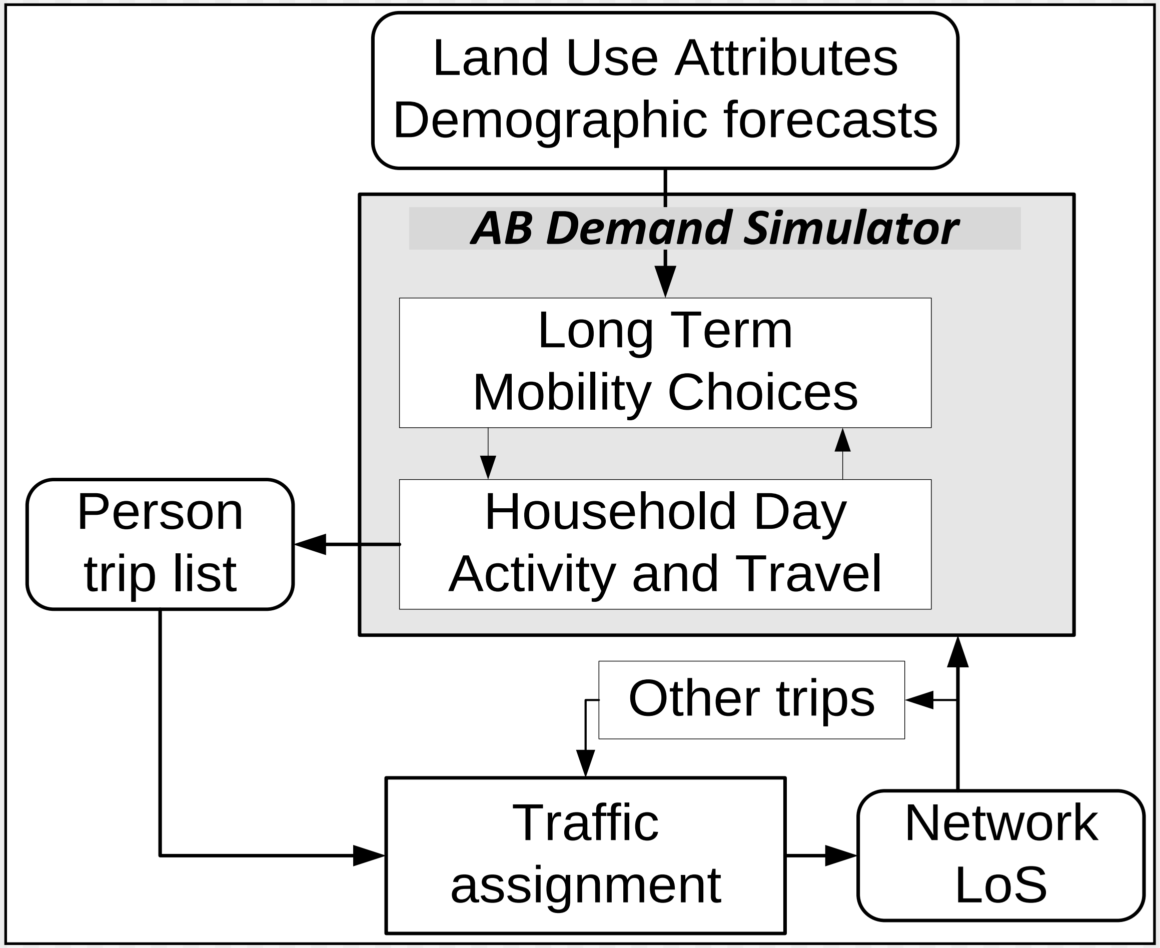


Applications of the activity-based approach

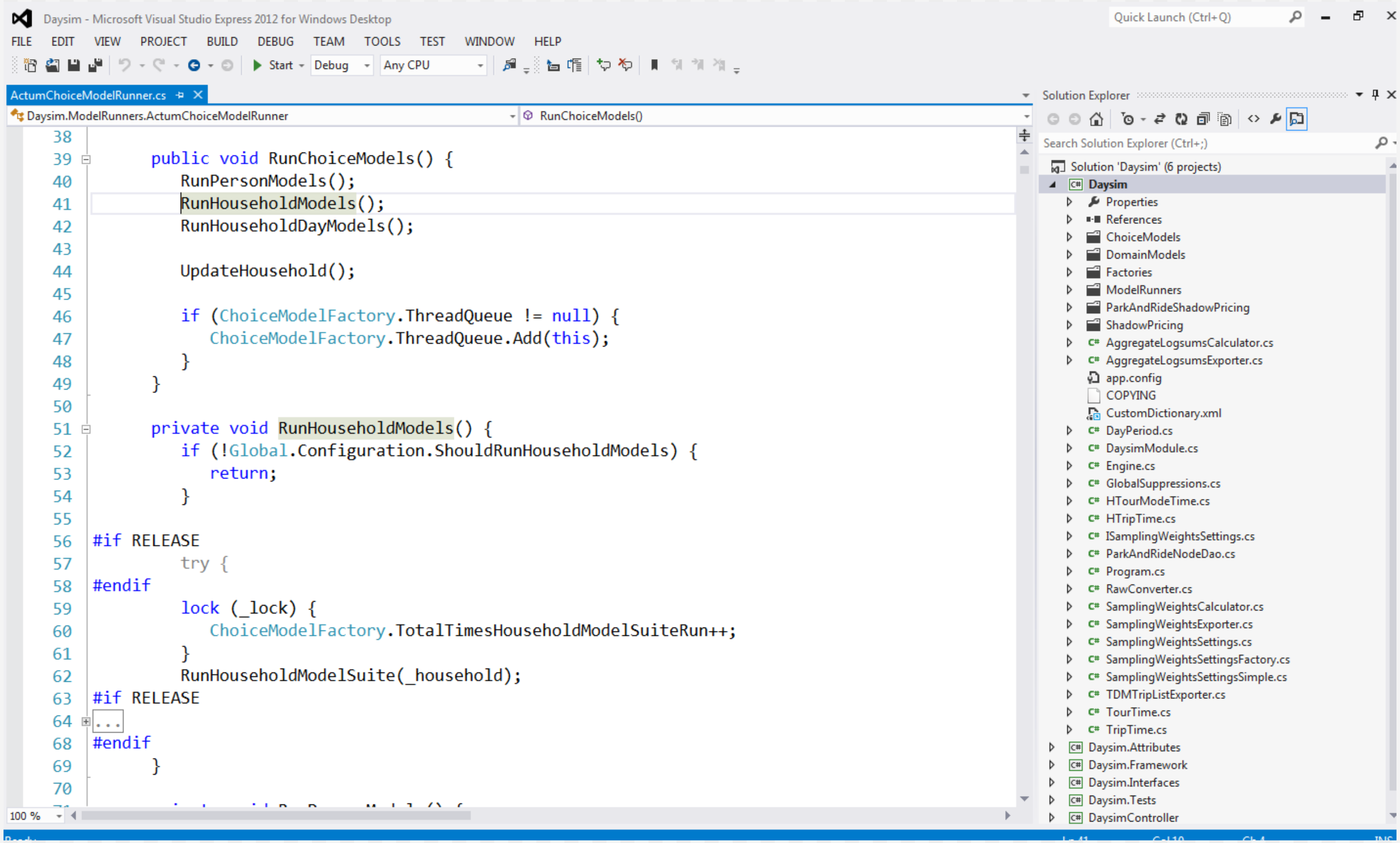
- Regional travel of residents
- Long distance travel of residents
- Regional freight and commercial traffic
- Travel of visitors to a region


Synthetic population
Long Distance
AB Model
.5K – 4K zones
5K – 500K microzones
internationally
Regional
AB Model
1K – 4K zones
10K – 500K microzones in
region
Trip list
Trip list
Regional traffic
assignment
Network
LoS

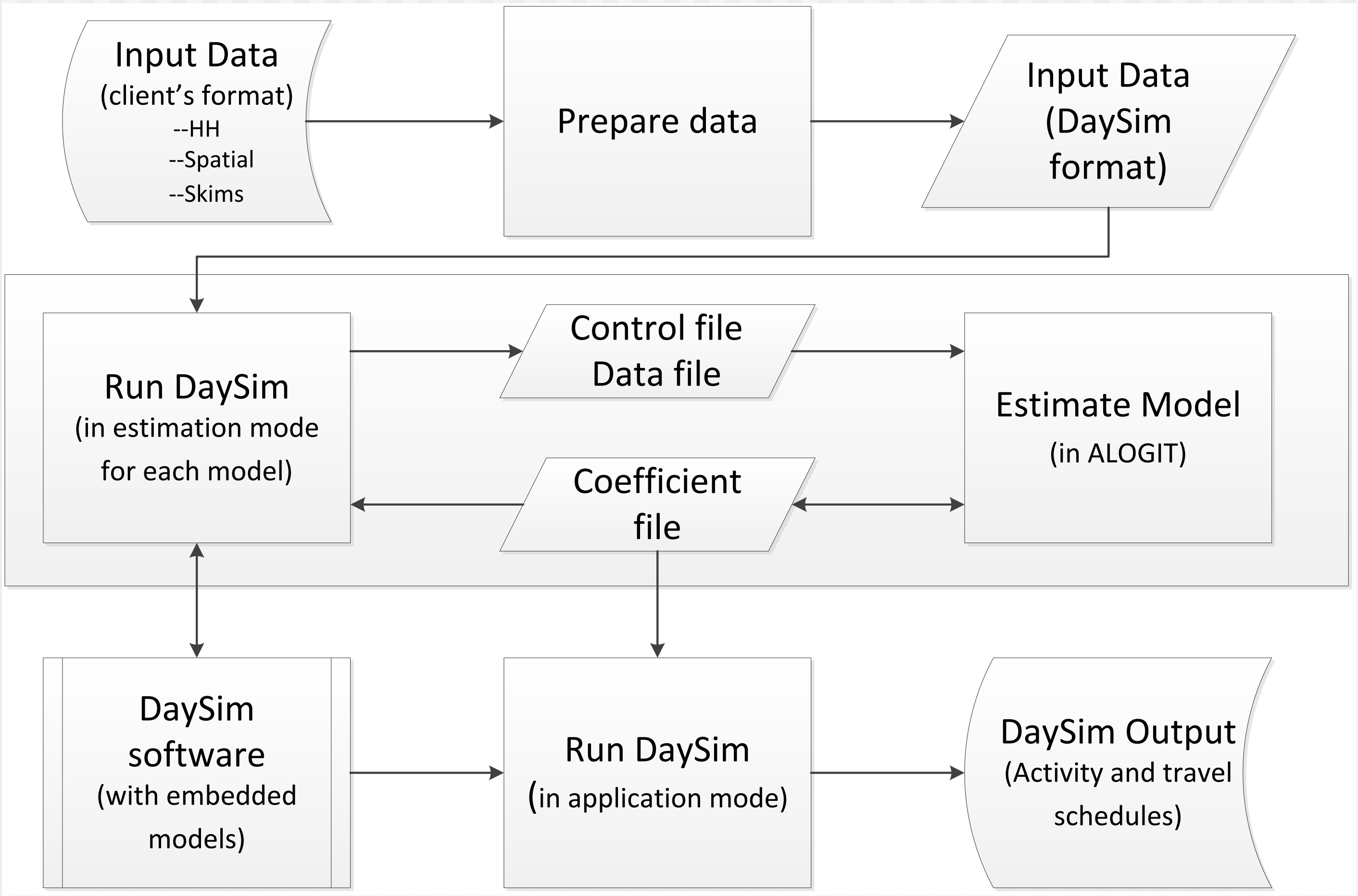
Disaggregate Assignment (COMPAS)



DaySim software is written in C# and distributed with open source license



DaySim software code supports model estimation and application



AB Model Data Requirements

- Household Survey
- Synthetic Population Data
- Zone OD Impedance Matrices
- Zone, microzone or parcel attributes
- All-streets network
- Calibration or pivot application data

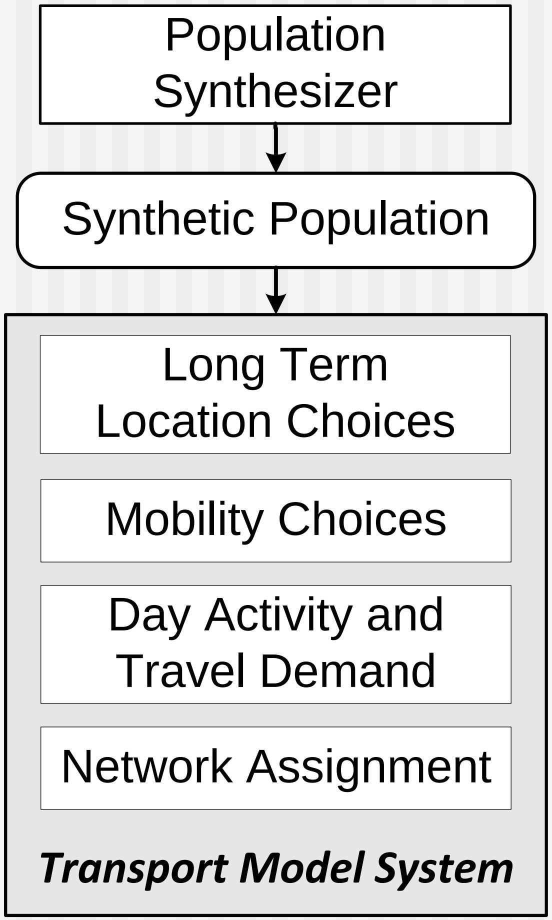
Details

- Synthetic population and long term models
- Day models
- Tour models
- Fine-grained spatial scale

Details

- Synthetic population and long term models
- Day models
- Tour models
- Fine-grained spatial scale

Synthetic Population and Long Term Models



Synthesizing households for one zone using IPF

1. Detailed distribution

	Small HH	Large HH
Low Inc	100	50
High Inc	50	50

2. Control totals

	Small HH	Large HH	
Low Inc			150
High Inc			150
	200	100	

3. Iterative Proportional Fit

	Small HH	Large HH	
Low Inc	111	39	150
High Inc	89	61	150
	200	100	

4. Draw HH from PUMS

(e.g., draw 111 small, low inc HH from zone 1's PUMA)

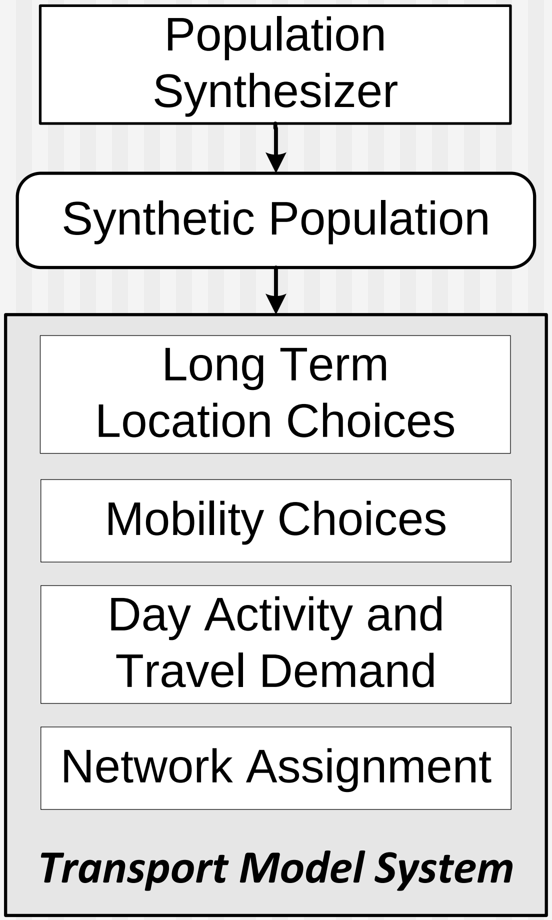
Typical Set of Control Categories for IPF

	Household Categories Defining Cell					
ID	**Income**	**House-holder age**	**HH Size**	**Family**	**Children**	**Number employed**
1	0-20K	15-64 yrs	1	nonfamily	0	0
2	"	"	"	"	"	1
3	"	"	2	nonfamily	0	0
4	"	"	"	"	"	1
5	"	"	"	"	"	2
6	"	"	"	family	0	0
7	"	"	"	"	"	1
8	"	"	"	"	"	2
9	"	"	"	"	1	0
10	"	"	"	"	"	1
11	"	"	"	"	"	2
⋮						
316	100K+	65+ yrs	5+	family	0+	3+

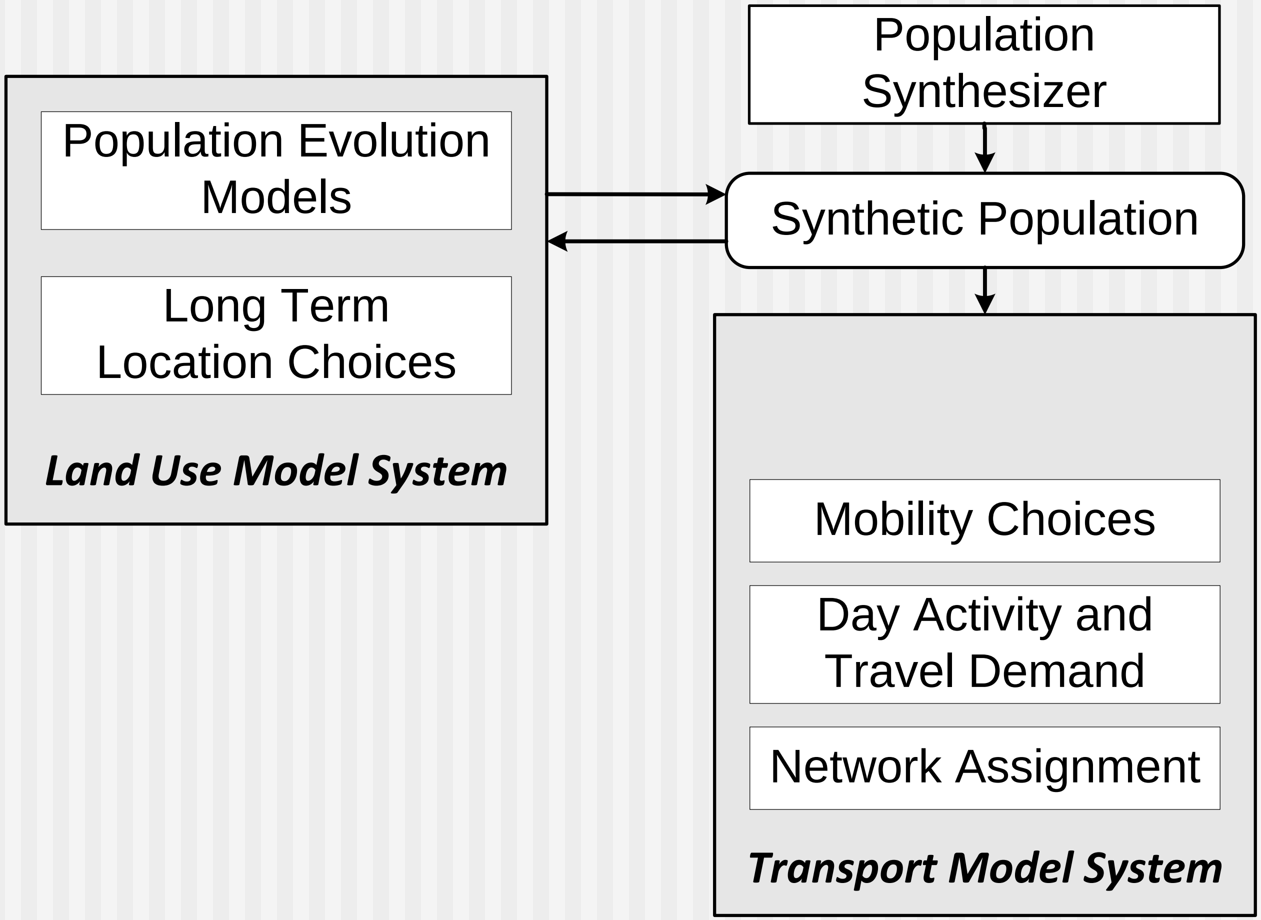
Long term choice models

- Location Choices
  - Usual work location
  - Usual school location
- Mobility Choices
  - Auto ownership
  - Transit pass ownership
  - Pay to park at workplace
  - Usual mode to work

Synthetic Population and Long Term Models



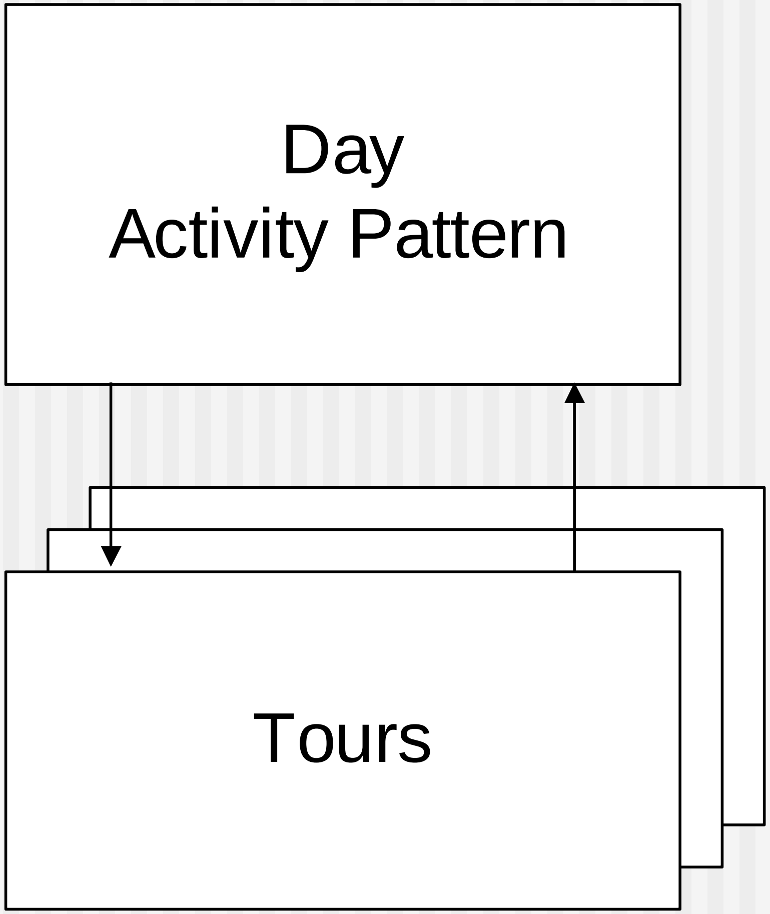
Using a Land Use Model to Evolve the Synthetic Population



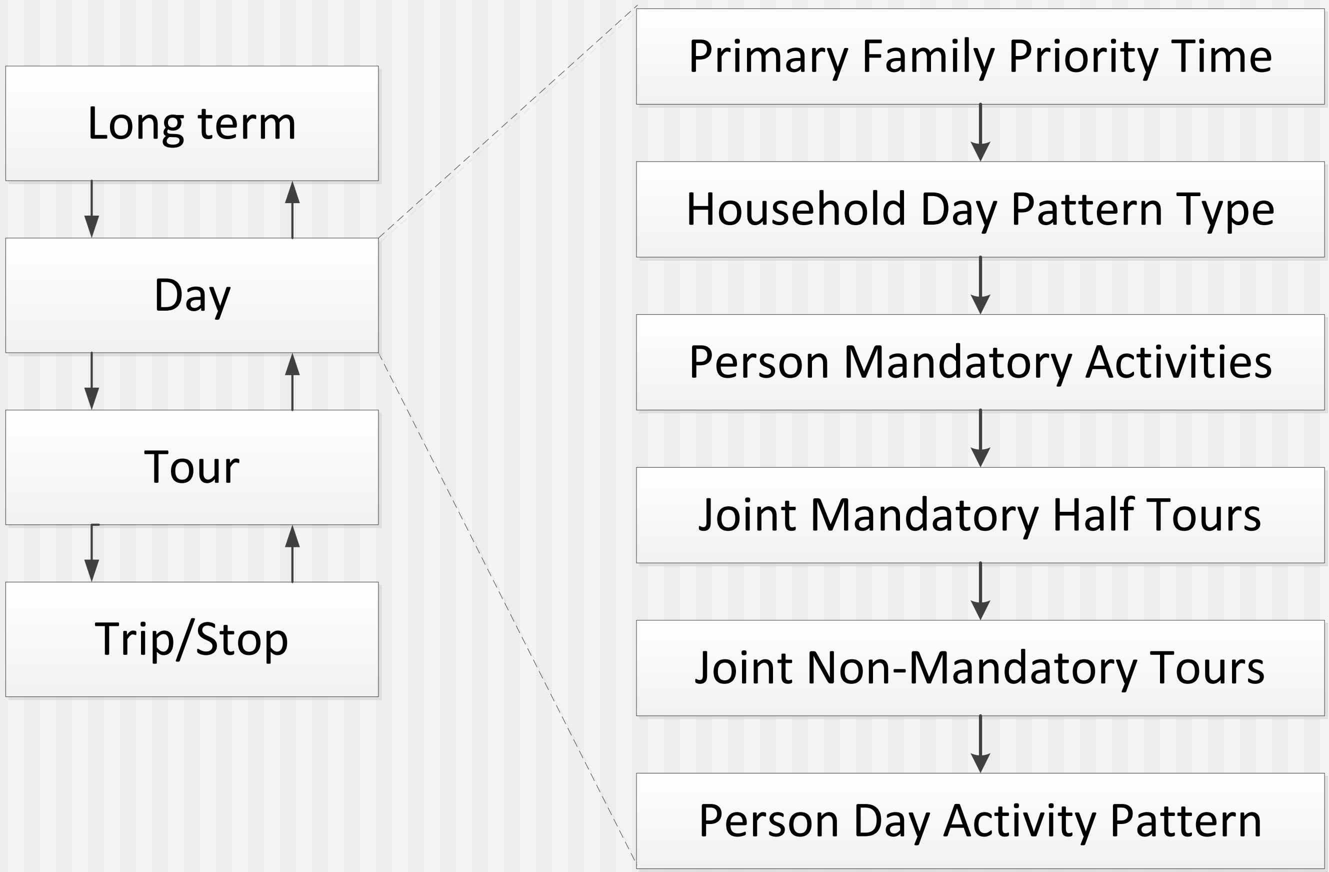
Details

- Synthetic population and long term models
- Day models
- Tour models
- Fine-grained spatial scale

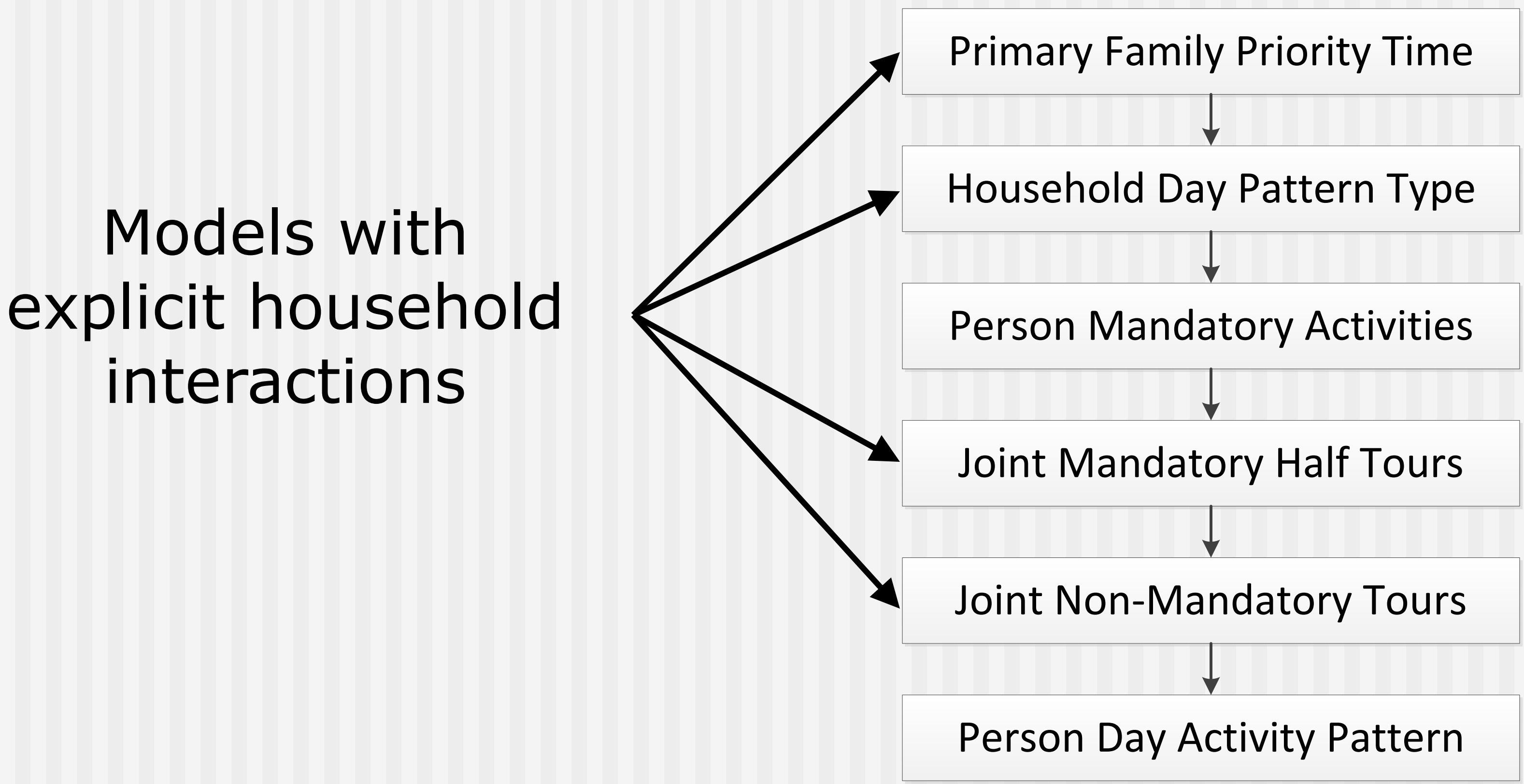
The Day Activity Schedule
(TRB January 1994)



Day Models
with explicit intra-household interactions



Why model joint intra-household interactions?



Why model joint intra-household interactions?

- Yields coherent travel choices among household members

Why model joint intra-household interactions?

- Yields coherent travel choices among household members
- Joint travel impacts responsiveness to transport policies

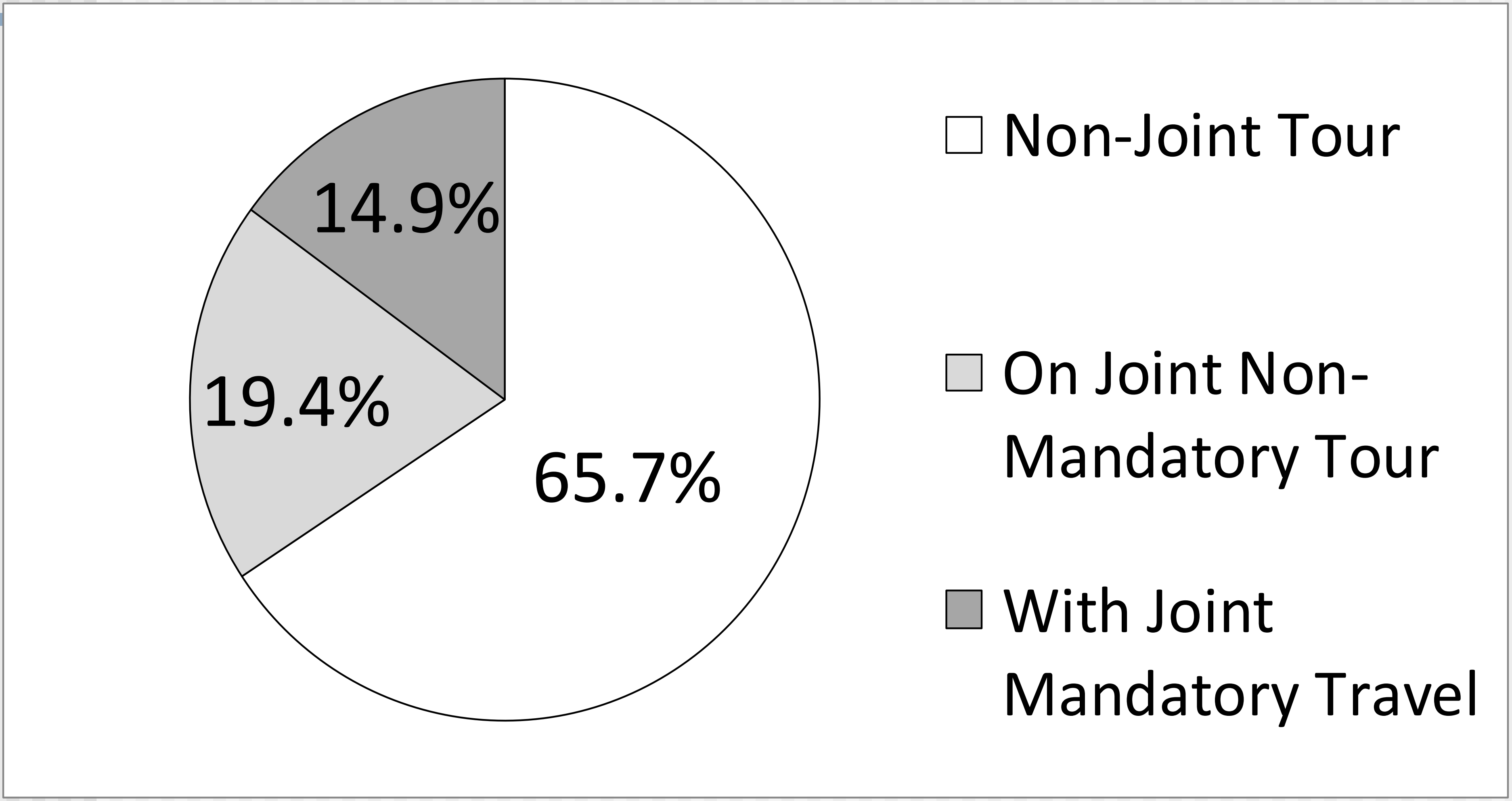
Why model joint intra-household interactions?

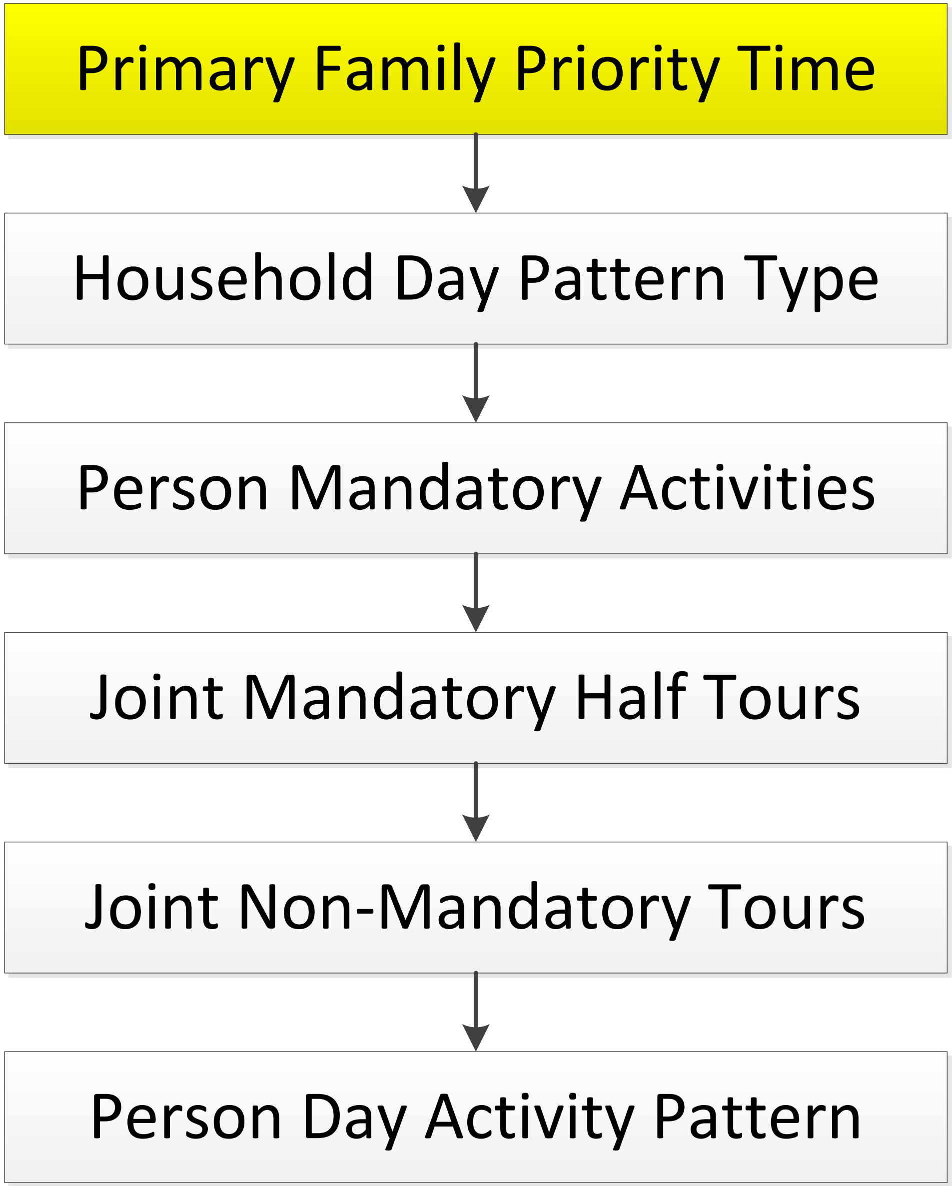
- Yields coherent travel choices among household members
- Joint travel impacts responsiveness to transport policies
- At-home family activities correlate with travel choices

Why model joint intra-household interactions?

- Yields coherent travel choices among household members
- Joint travel impacts responsiveness to transport policies
- At-home family activities correlate with travel choices
- Joint decisions constrain and influence individual choices

Survey Percent of Tours by Joint Type (Seattle)





- Vuk et al (2013)
- Participation Model
  - Shared at-home activity
- Schedule Model
  - Start minute and duration minutes

What is PFPT about? (Vuk, et al, 2013)

- Some families may place a high priority on spending time together
  - schedule other activities around it, even work
  - seems particularly important in Denmark

PFPT definition

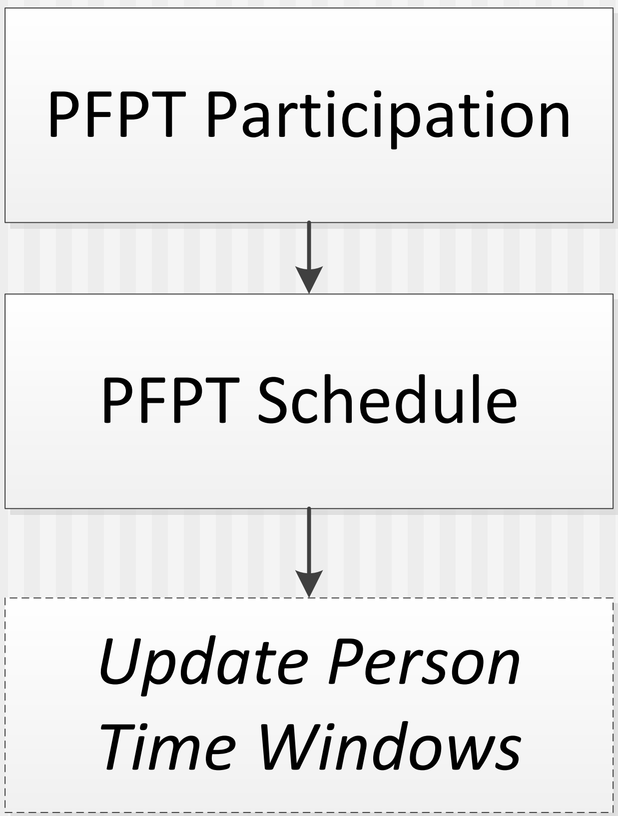
- Shared at-home activity
- All members of household
- At least 20 minutes
- Purpose other then work, school, commerce

- 32% of households with two+ members had PFPT

Copenhagen data

- Travel survey data has been collected for 20+ years
  - diary of travel by one person per household in a weekday
- extended survey was needed to include whole household
  - asked about activities at home with other household members
  - 2209 persons in 801 households

PFPT implementation



- Participation Model
  - Binary choice
- Schedule Model
  - Start time and duration
- The updated time windows constrain subsequent choices

PFPT participation summary statistics

Number observations	644
Degrees of freedom	14
Rho squared (w.r.t. 0)	0.504
Rho squared (w.r.t. constants)	0.451

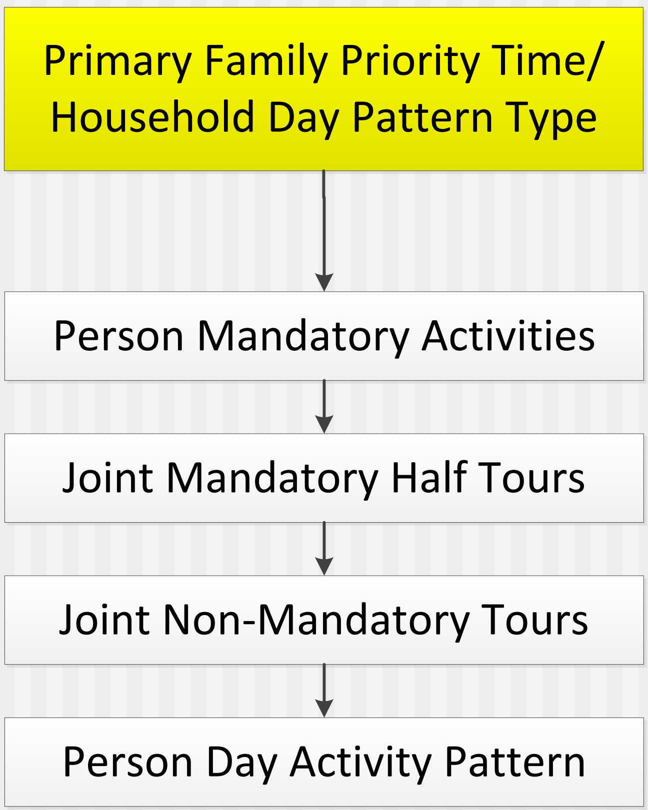
Dummy variables

Variable (PFPT alternative)	Coeff	T Stat
Constant	-1.331	-3.32
HH size 3	-1.164	-3.30
HH size 4+	-1.480	-3.74
Pre-school children	1.151	3.59
One adult + school children	1.168	2.99
Two adults, both working	1.825	4.28
Two adults, 1+ with high education	3.542	10.68
Two adults, one car	-0.458	-1.63
Two adults, 2+ cars	-1.026	-2.20
HH income 3-600,000 DKK	0.619	1.61
HH income 6-900,000 DKK	0.332	0.79
HH income over 900,000 DKK	-0.123	-0.26

Logsums—accessibility to workplaces and at home affect likelihood of PFPT

Variable (PFPT alternative)	Coeff	T Stat
Work tour mode choice logsums for up to two workers	0.134	1.58
At-home non-auto mode-destination logsum	-0.031	-2.38

Alternative structures were tested



Estimated PFPT and Household Day Pattern Type jointly

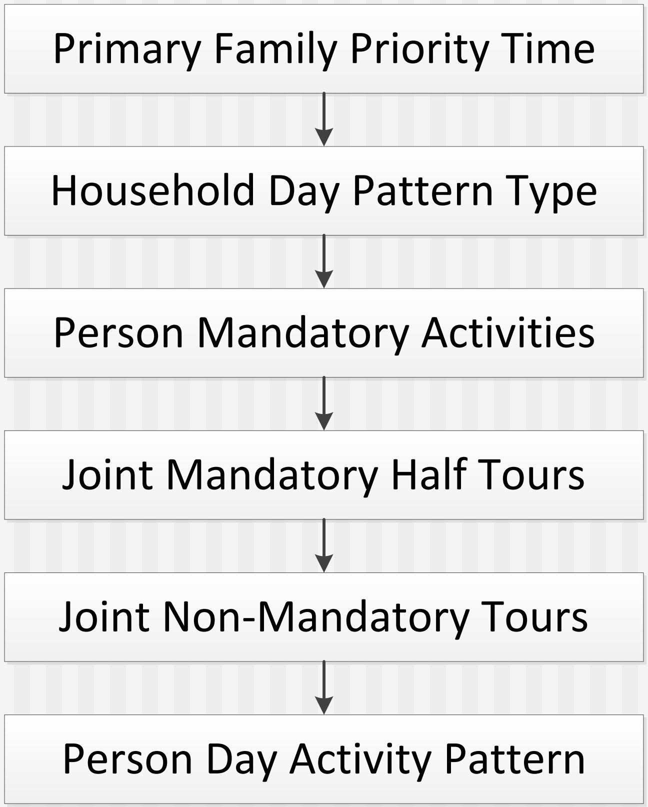
- As MNL
- NL with HH Day Pattern Type conditioning PFPT
- NL with PFPT conditioning HH Day Pattern Type

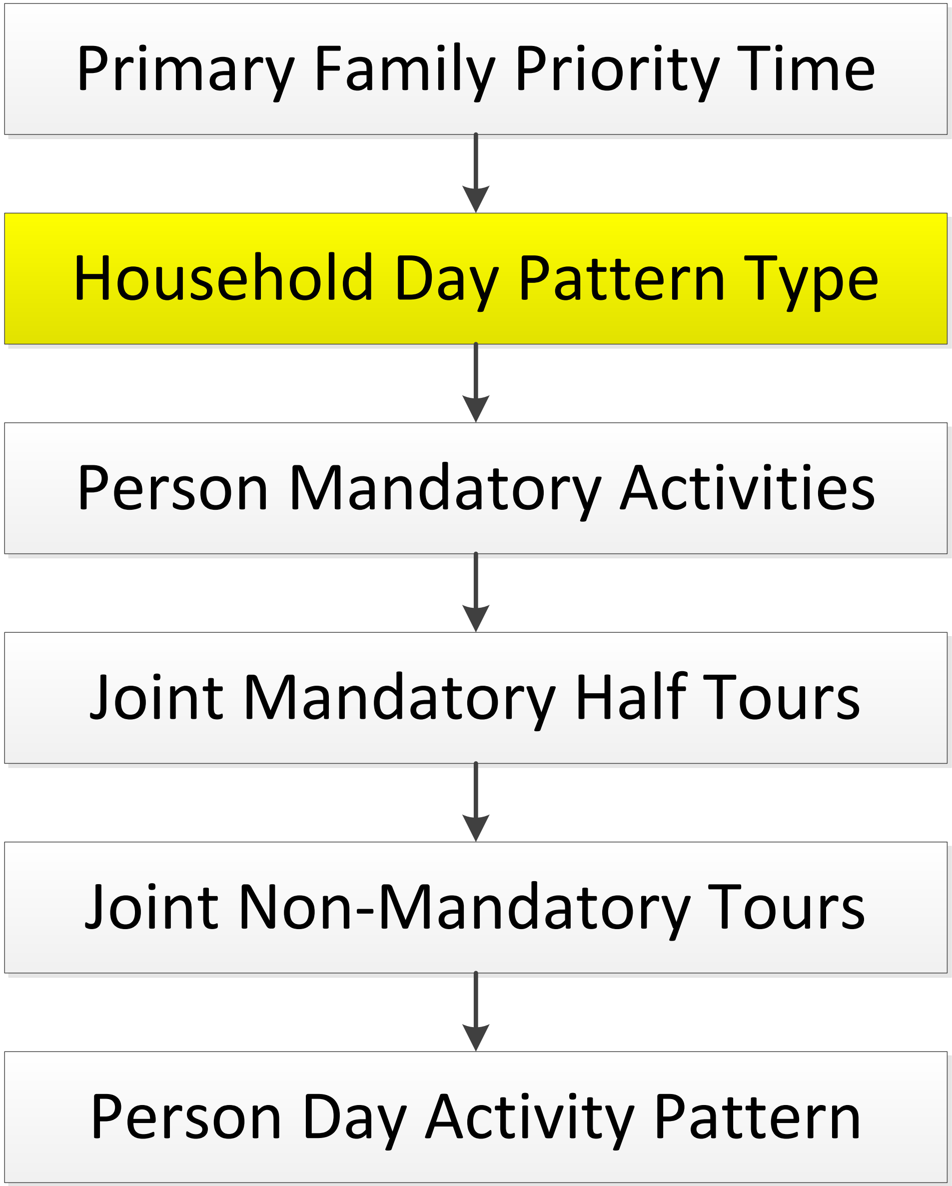
Tests support the hypothesized structure

Model	Log Likelihood	Rho Squared	Nest Theta	ST Error
Log Likelihood (0)	-2606.0			
MNL	-1194.5	.542	1.00	Fixed
NL: Household Day Pattern Type conditions PFPT	-1192.5	.542	1.49	0.27
NL: PFPT conditions Household Day Pattern Type	-1188.5	.544	0.03	0.06

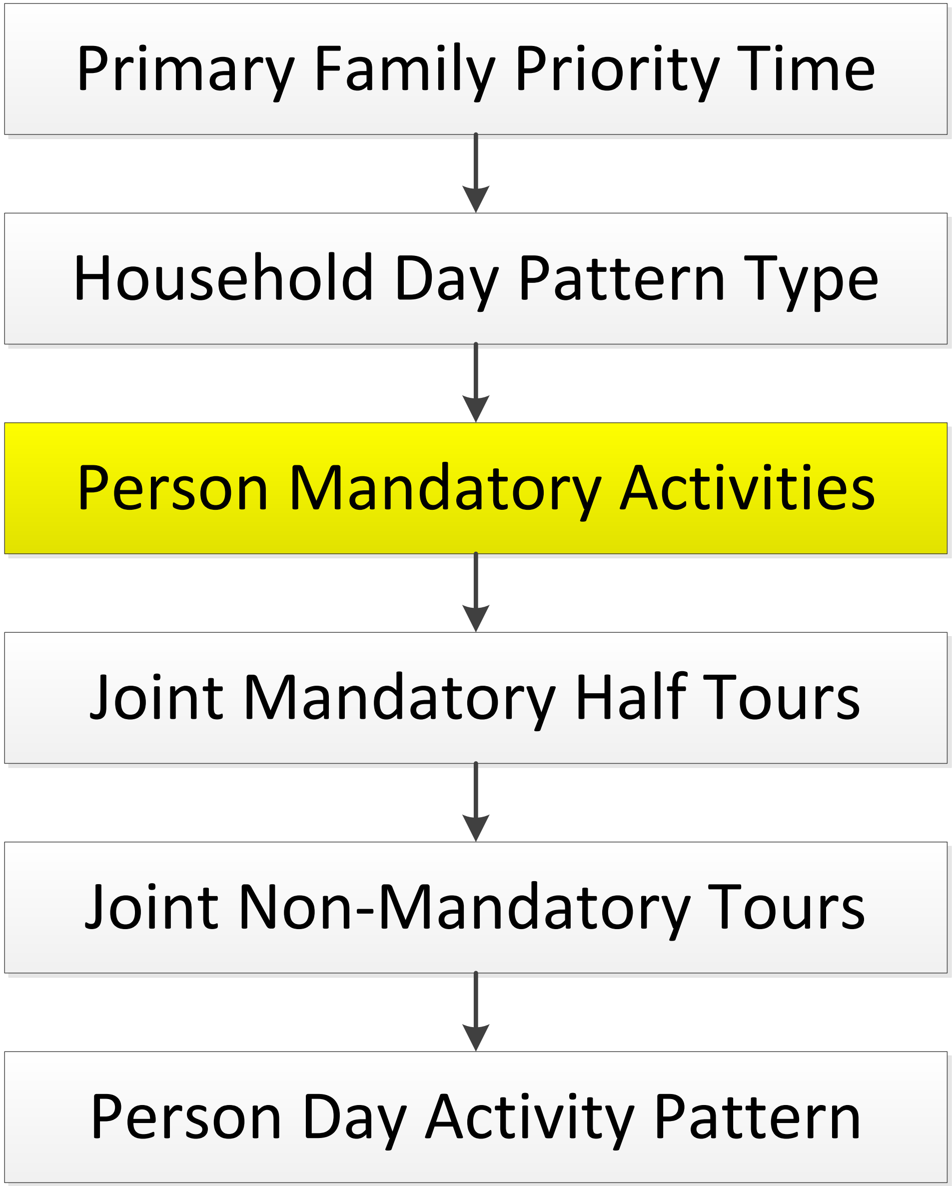
PFPT affects subsequent model components

- ***Time window constraints****—travel activities can't occur during time reserved for PFPT*
- *PFPT workers more likely to take care of personal business on* ***work-based subtours***
- *PFPT households more likely to* ***travel together to work and school***
- *PFPT households more likely to conduct* ***joint tours for non-mandatory purposes***



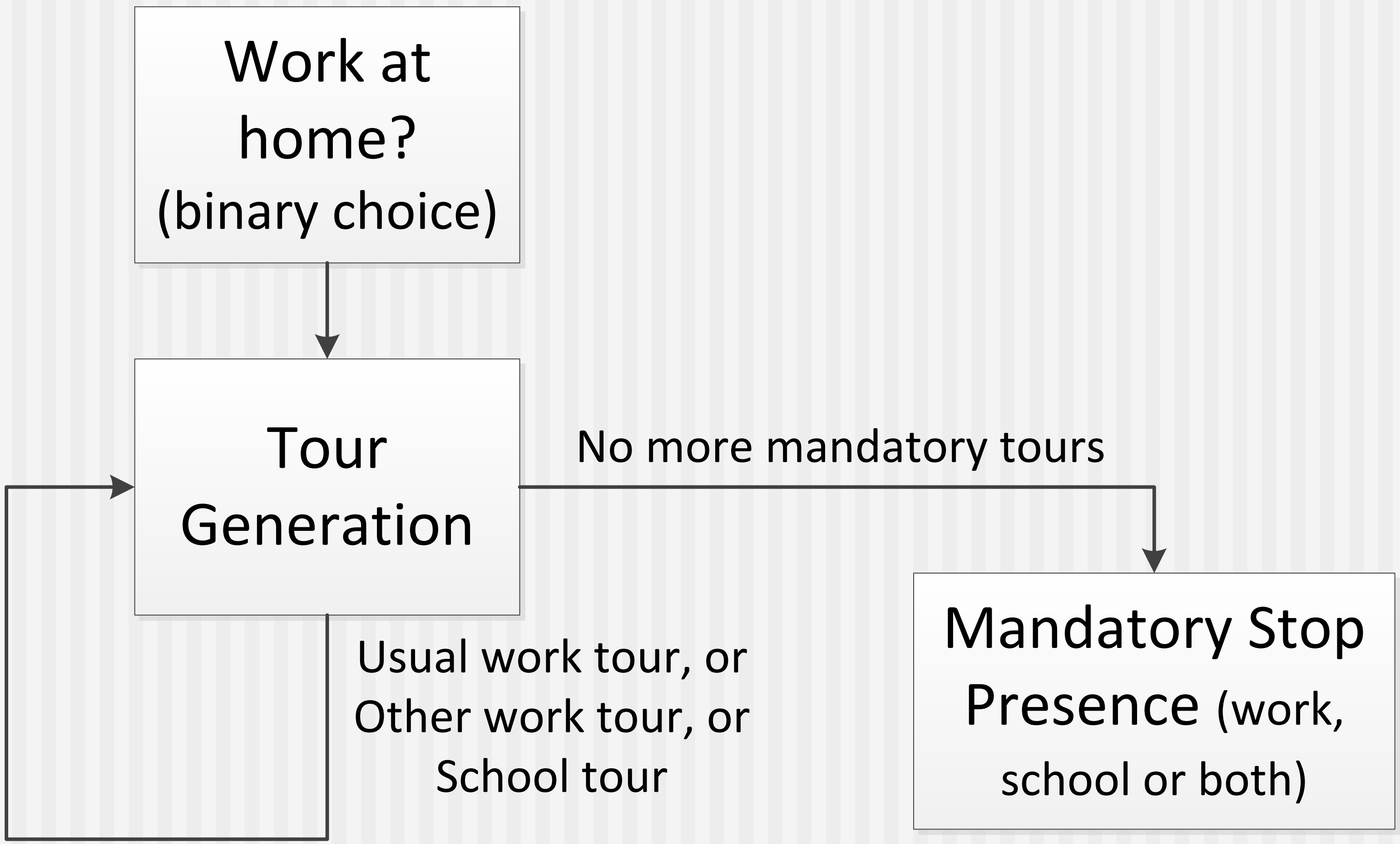


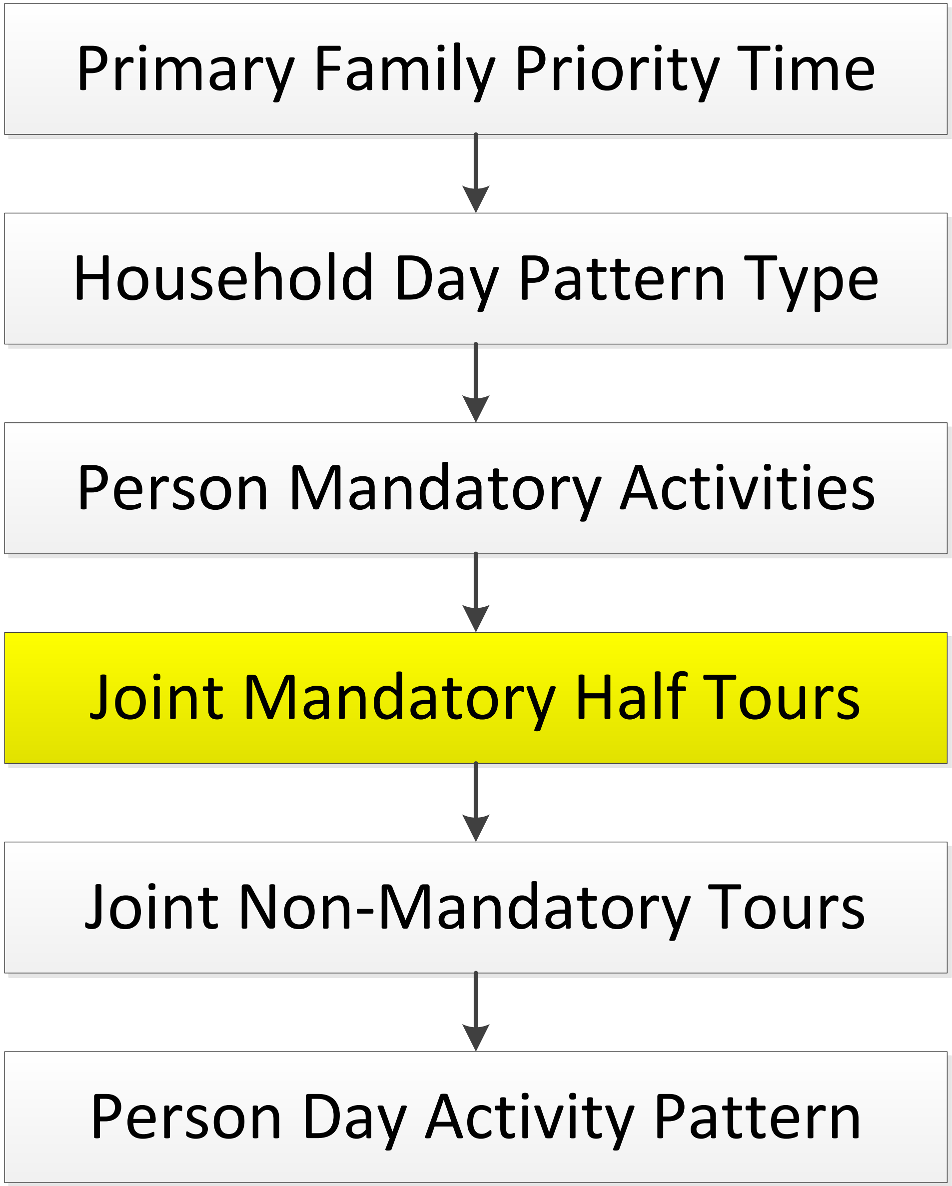
- Based on Bradley & Vovsha (2005)
- Joint for up to five HH members
- Up to three pattern type alternatives per person
  - Mandatory on tour
  - Non-mandatory on tour
  - At home all day



- Work at Home Model
- Mandatory Tour Generation Model
- Mandatory Stop Presence Model

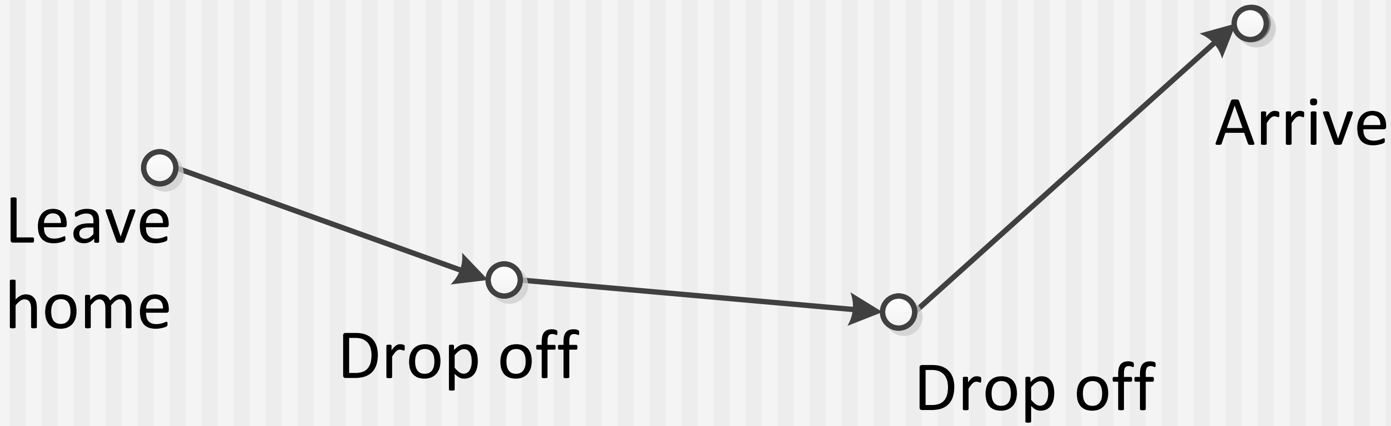
Modeling Person Mandatory Activities



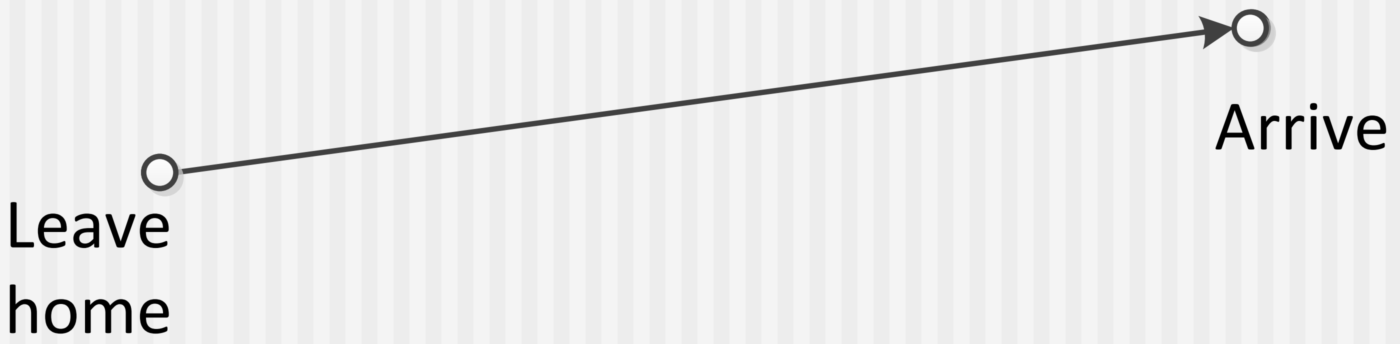


- Shared travel to work and school
- Joint Half Tour Generation Model
  - Fully joint or partially joint
- Participation Model
  - Jointly for up to five persons

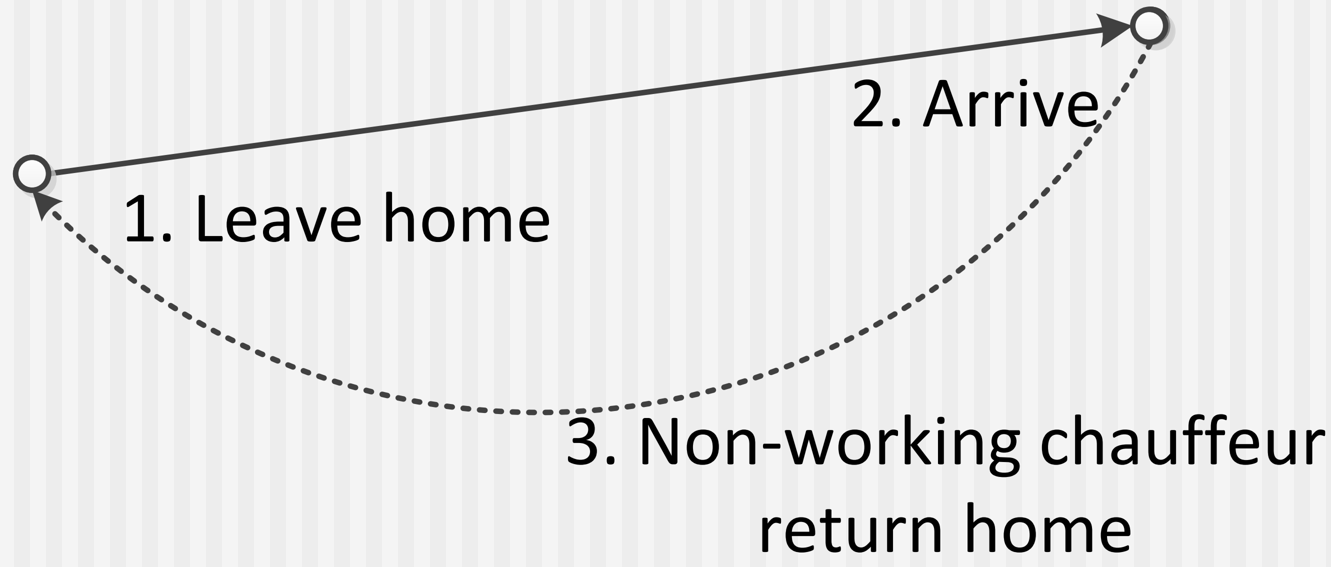
Partially Joint Half Tour
(**To** Work and/or School)



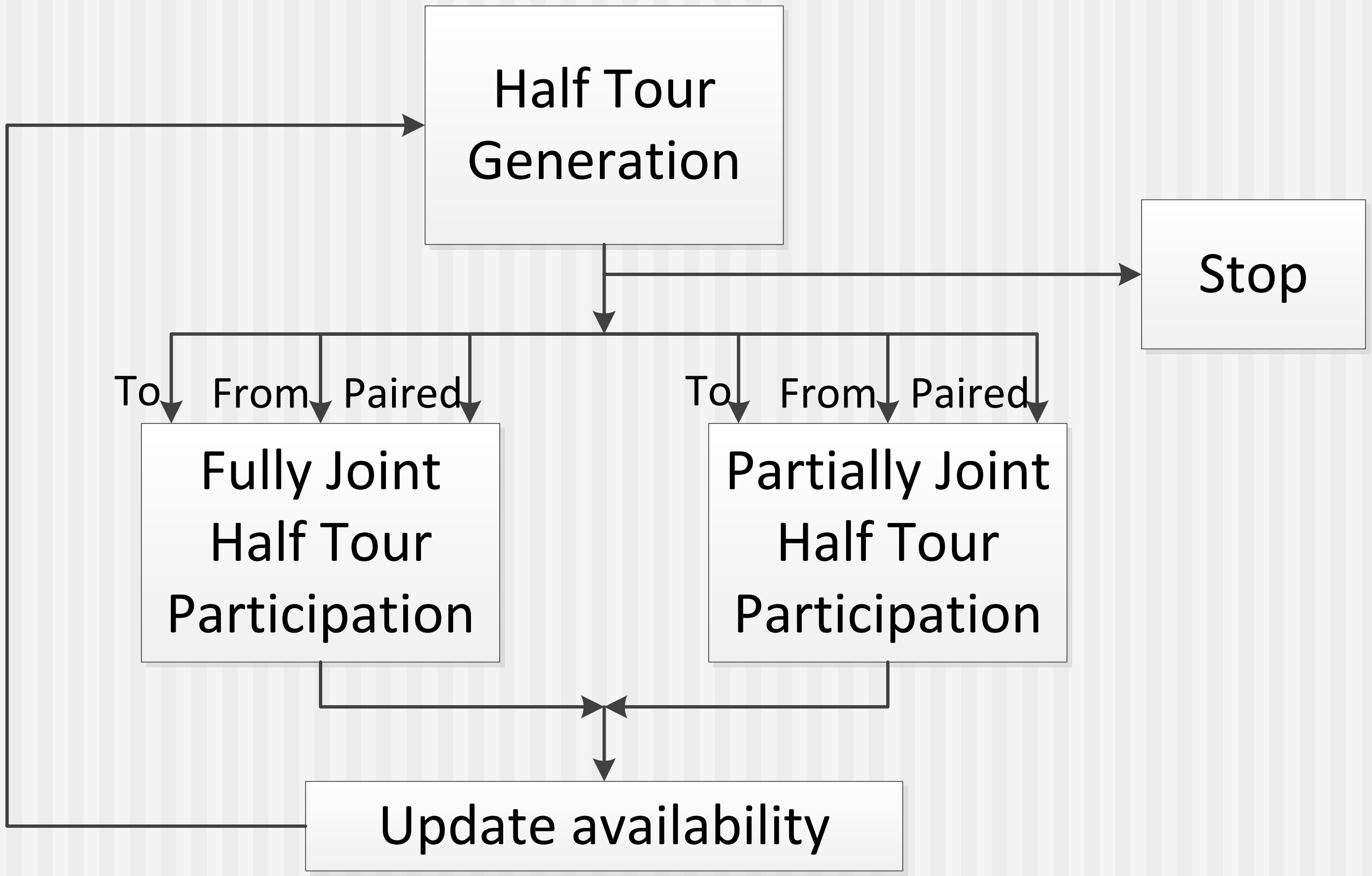
Fully Joint Half Tour
(**To** Work or School)

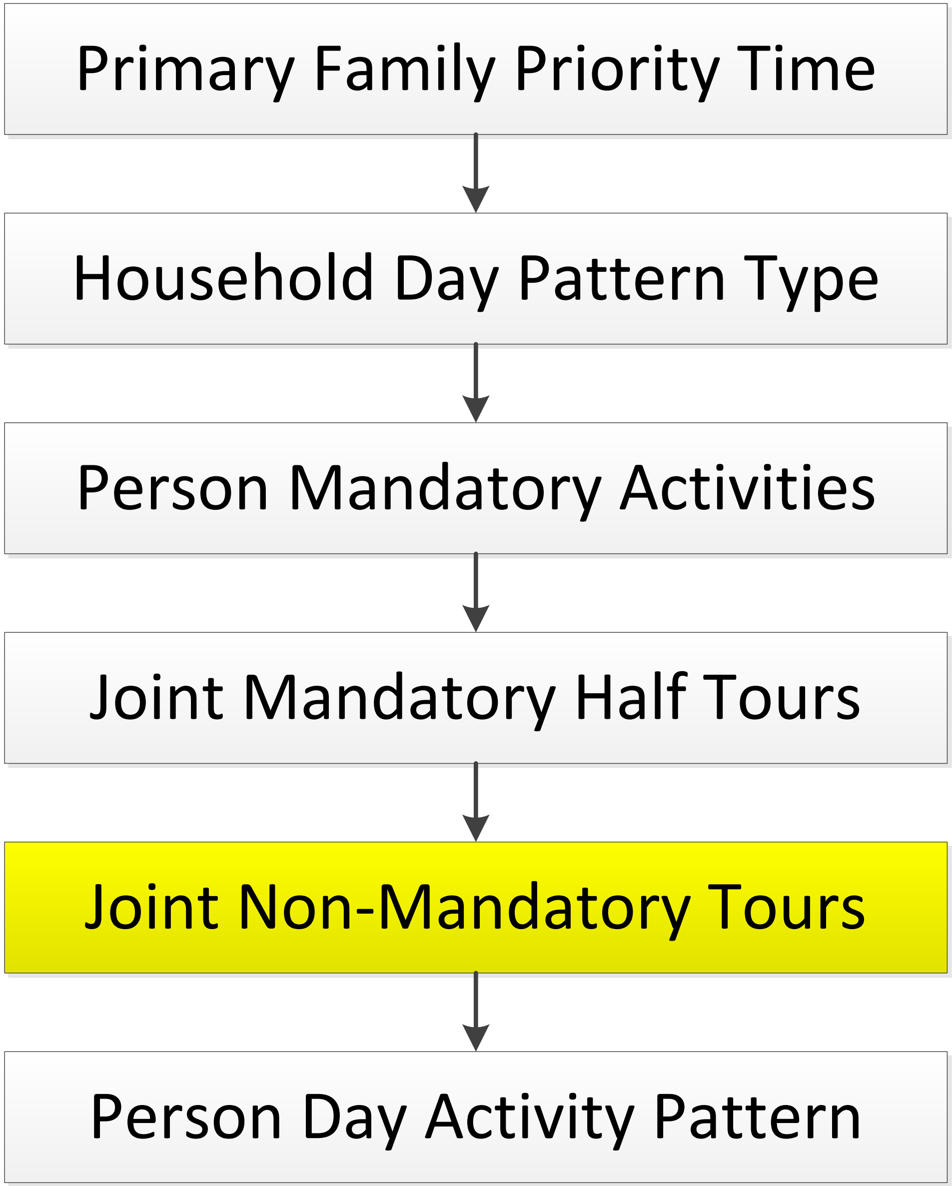


Fully Joint Half Tour
(**Chauffeured To** Work or School)



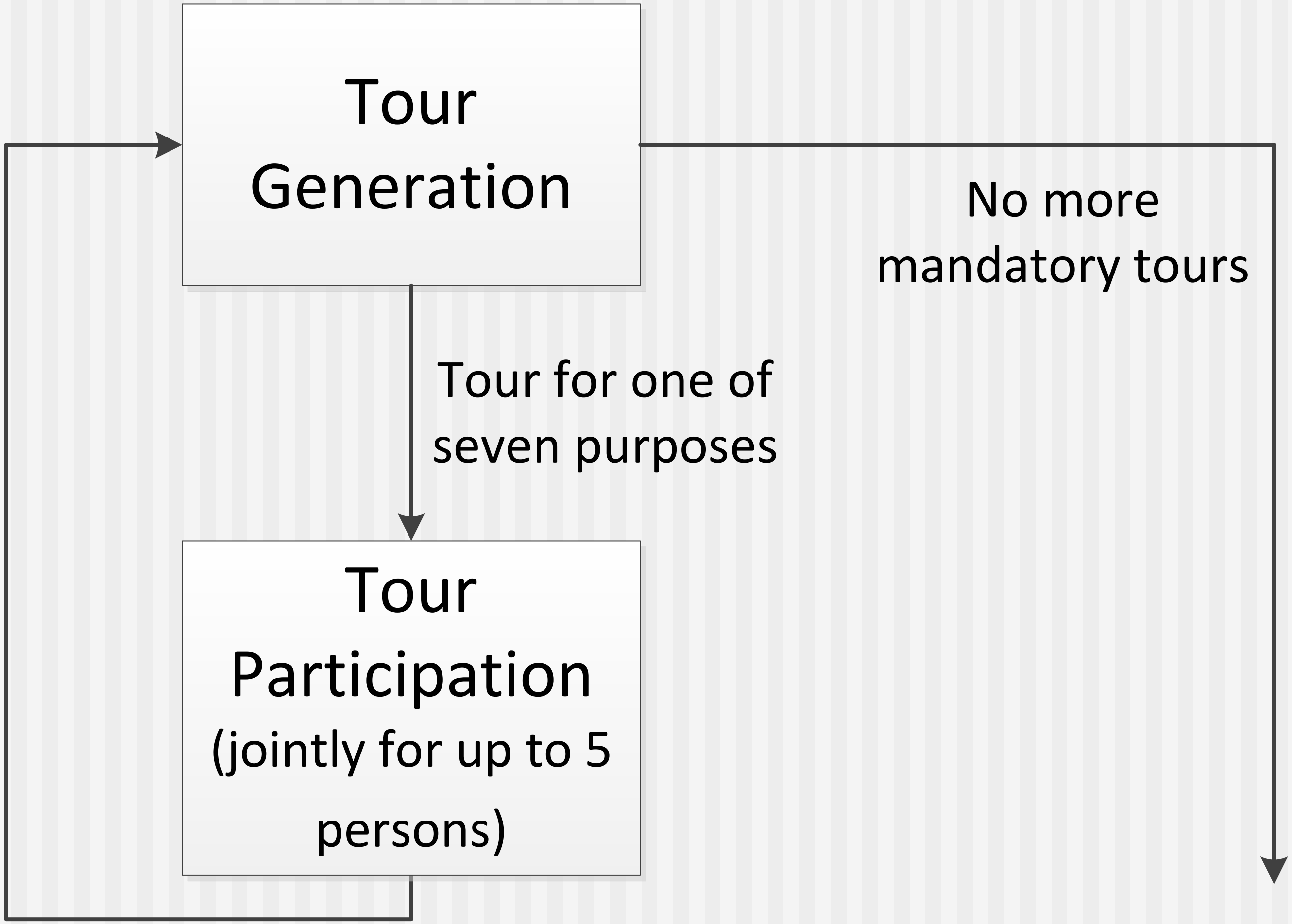
Modeling Joint Half Tours

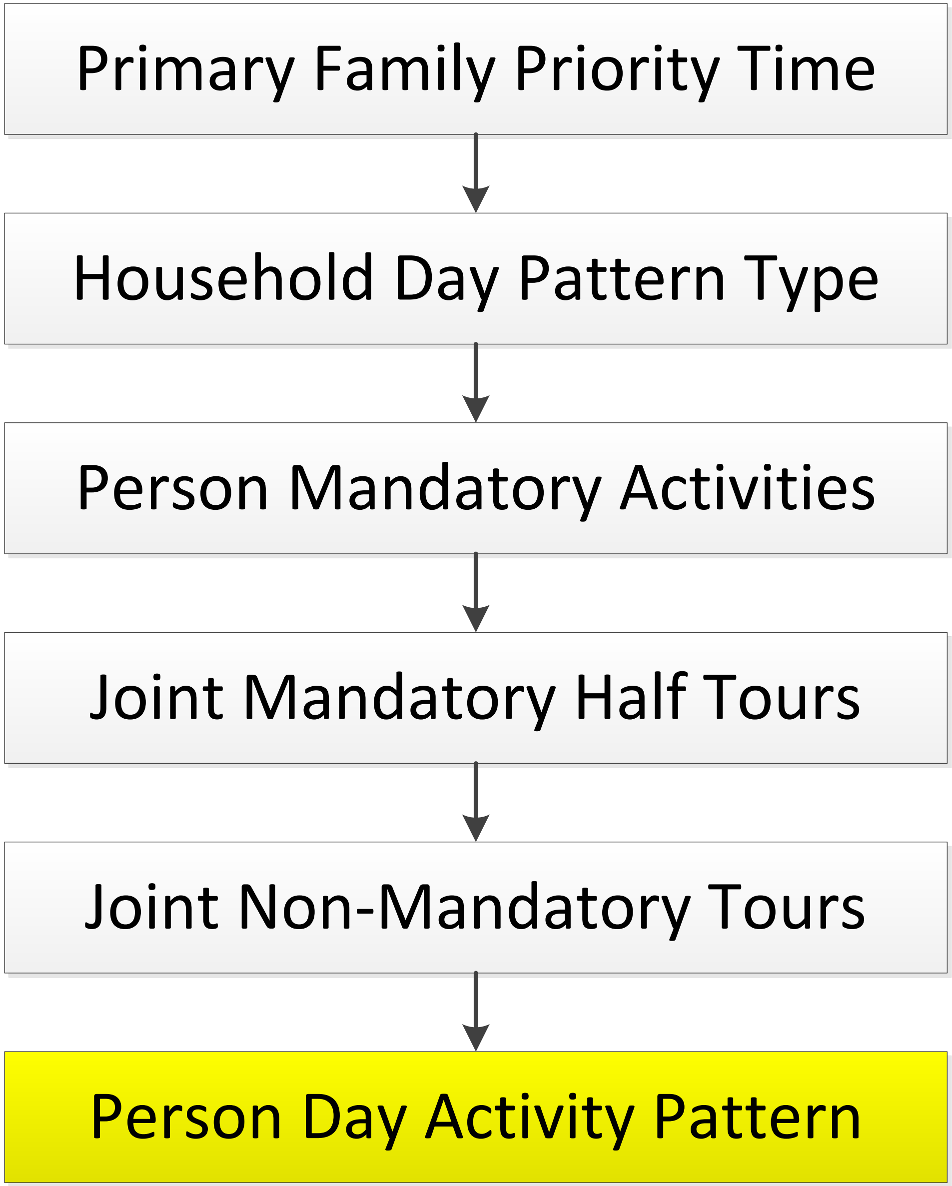




- Shared travel for non-mandatory activity
- Joint Tour Generation Model
- Participation Model
  - Jointly for up to five persons

Modeling Joint Non-Mandatory Tours





- Person Day Pattern Model
  - Presence in day of…
    - tour purposes
    - intermediate stop purposes
- Tour Generation Model
  - Exact number of tours for each purpose

Person Day Pattern

- Presence or absence in day of…
  - tours for each purpose
  - intermediate stops for each purpose
- Purposes:
  - Work, business, school
  - Escort, personal business, shop, meal, social, recreation, medical

Choice Set (Seattle) has 3051 alternatives

- Include combinations of:
  - 7 binary tour purpose variables
  - 7 binary stop purpose variables
  - This would yield 2^14 = 16384 alternatives
- Remove extremely rare combinations:
  - Number of tour purposes > 3
  - Number of stop purposes > 4
  - Number tour purposes plus number stop purposes > 5
- Allows interactions between tours, stops and purposes to be modeled explicitly

Summary Estimation Results (Seattle)

Number observations	17353
Number alternatives	3051
Estimated Coefficients	**364**
Likelihood (0)	-120337
Likelihood (C)	-61203
Likelihood (Final)	-50180
Rho-Squared (w.r.t. C)	**.180**
Rho-Squared (w.r.t. 0)	.583

Utility Term Categories

Category	Example
Activity Purpose Presence	Dummy for Full Time Worker with shopping **tour(s) and/or stop(s)**
Tour Purpose Presence	Mixed use density for pattern with **one or more tours** of any purpose
Stop Purpose Presence	Constant for presence of **one or more** social **stops**
Ln(# tour purposes)	**Log(number tour purposes)** for a retired person
Ln(# stop purposes)	**Log(number stop purposes)** for female with children under 5
Tour and Stop Combos	Constant for pattern with one or more work tours and one or more escort stops

Estimated Coefficients

	Activity Purpose Presence*	Tour Purpose Presence	Stop Purpose Presence	Ln(# tour purposes)	Ln(# stop purposes)	Tour and Stop Combos
Constants		7	7			116
Person characteristics	71	1	2	13	13	
Household characteristics	77	1	1	11	11	
Neighborhood characteristics		2	2	2	2	
Day				2	2	
Logsums						10
Nuisance**	7					

*Activity purpose is present if there is at least one tour or intermediate stop with that purpose
**For diaries completed by a proxy

Logsums on **work days**

	Patterns with additional tour purpose(s) Tour Coeff (T stat)	Patterns with intermediate stops Stop Coeff (T stat)
Work tour mode choice logsum	-0.014 (-0.66)	0.036 (2.13)
At-home mode-destination logsum	0.042 (2.17)	0.033 (2.30)

Logsums on **work days**

	Patterns with additional tour purpose(s) Tour Coeff (T stat)	Patterns with intermediate stops Stop Coeff (T stat)
Work tour mode choice logsum	-0.014 (-0.66)	0.036 (2.13)
At-home mode-destination logsum	0.042 (2.17)	0.033 (2.30)

Logsums on **work days**

	Patterns with additional tour purpose(s) Tour Coeff (T stat)	Patterns with intermediate stops Stop Coeff (T stat)
Work tour mode choice logsum	-0.014 (-0.66)	0.036 (2.13)
At-home mode-destination logsum	0.042 (2.17)	0.033 (2.30)

Logsums on **work days**

	Patterns with additional tour purpose(s) Tour Coeff (T stat)	Patterns with intermediate stops Stop Coeff (T stat)
Work tour mode choice logsum	-0.014 (-0.66)	0.036 (2.13)
At-home mode-destination logsum	0.042 (2.17)	0.033 (2.30)

Logsums on **work days**

	Patterns with additional tour purpose(s) Tour Coeff (T stat)	Patterns with intermediate stops Stop Coeff (T stat)
Work tour mode choice logsum	-0.014 (-0.66)	0.036 (2.13)
At-home mode-destination logsum	0.042 (2.17)	0.033 (2.30)

Logsums on **school days**

	Patterns with additional tour purpose(s) Tour Coeff (T stat)	Patterns with intermediate stops Stop Coeff (T stat)
School tour mode choice logsum	-0.014 (-0.19)	0.627 (7.74)
At-home mode-destination logsum	0.090 (3.84)	-0.007 (-0.37)

Logsums on **school days**

	Patterns with additional tour purpose(s) Tour Coeff (T stat)	Patterns with intermediate stops Stop Coeff (T stat)
School tour mode choice logsum	-0.014 (-0.19)	0.627 (7.74)
At-home mode-destination logsum	0.090 (3.84)	-0.007 (-0.37)

Logsums on **school days**

	Patterns with additional tour purpose(s) Tour Coeff (T stat)	Patterns with intermediate stops Stop Coeff (T stat)
School tour mode choice logsum	-0.014 (-0.19)	0.627 (7.74)
At-home mode-destination logsum	0.090 (3.84)	-0.007 (-0.37)

Logsums on
on-tour non-commute days

	Patterns with additional tour purpose(s) Tour Coeff (T stat)	Patterns with intermediate stops Stop Coeff (T stat)
At-home mode-destination logsum	0.077 (4.61)	0.000 (0.02)

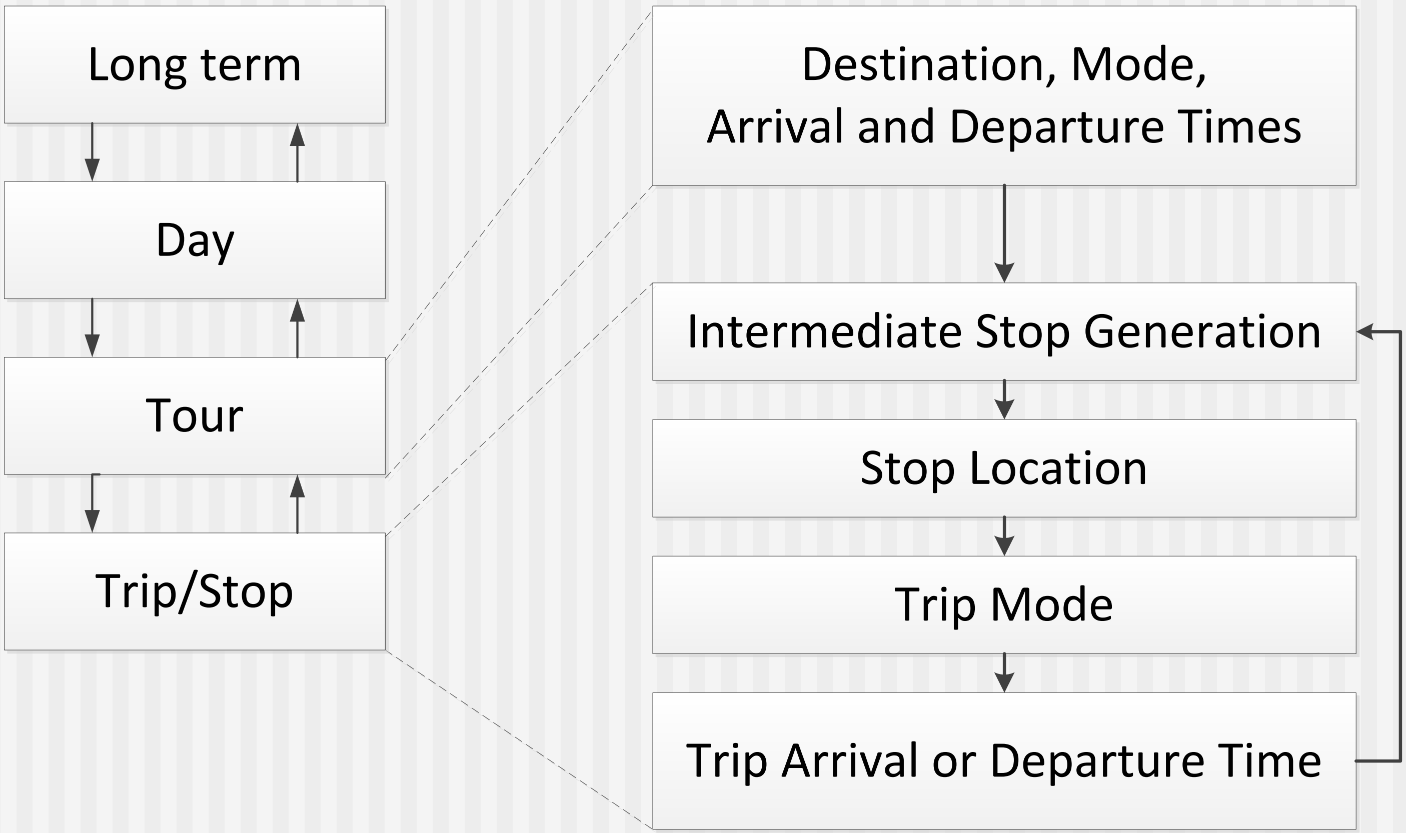
Logsums on **on-tour non-commute days**

	Patterns with additional tour purpose(s) Tour Coeff (T stat)	Patterns with intermediate stops Stop Coeff (T stat)
At-home mode-destination logsum	0.077 (4.61)	0.000 (0.02)

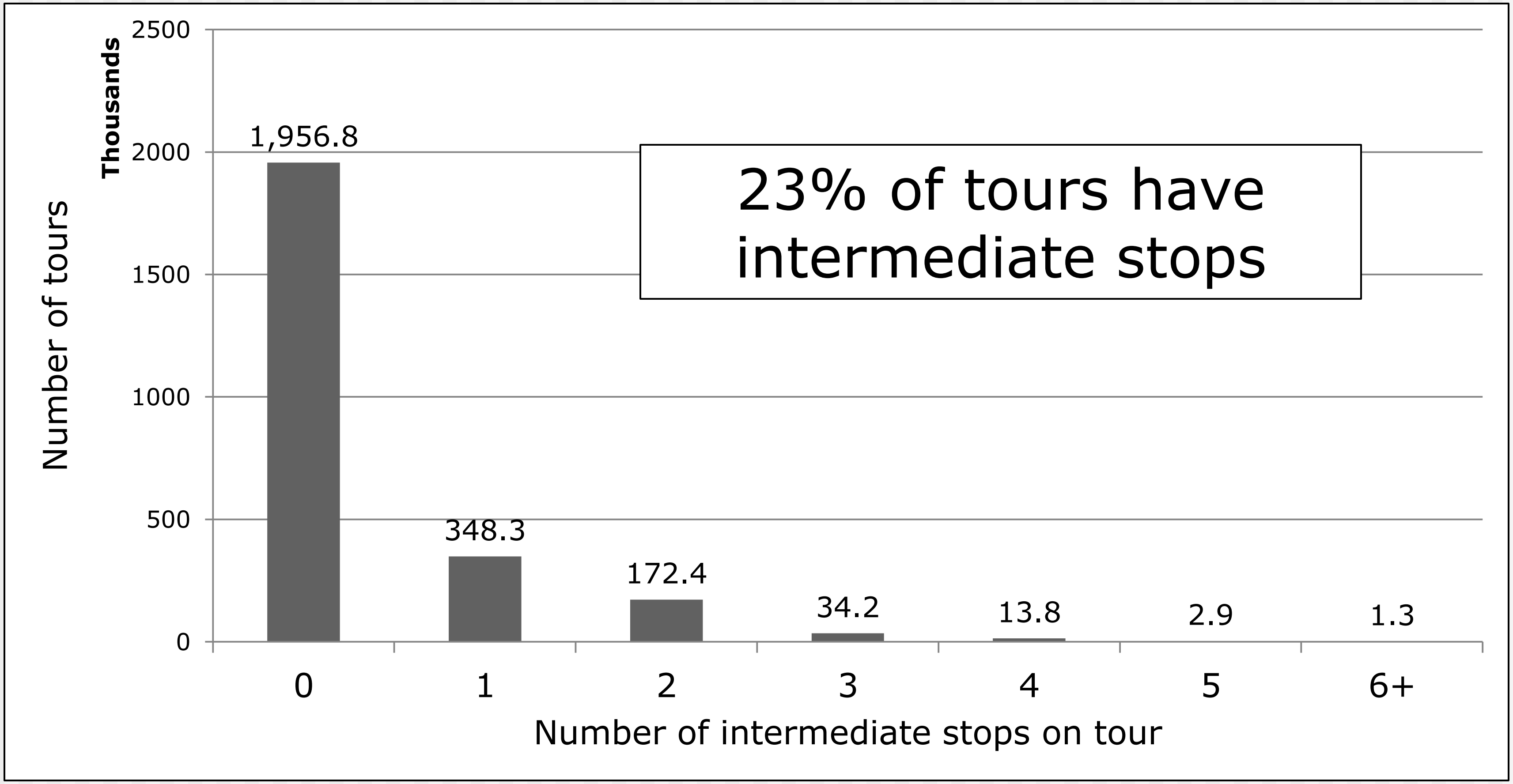
Details

- Synthetic population and long term models
- Day models
- Tour models
- Fine-grained spatial scale

Simulating one tour



DaySim Base Year Intermediate Stops on Tours (Copenhagen)



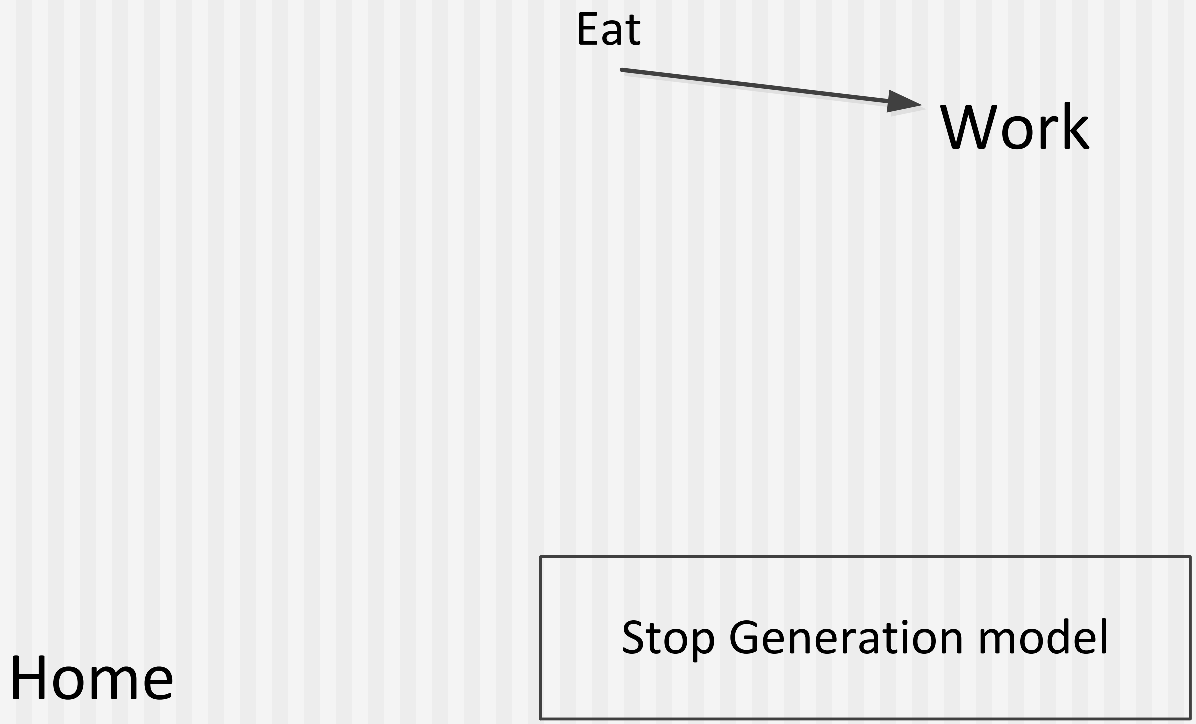
Simulating the trips on a half tour

Work

Home

Start with known tour outcomes
--purpose
--destination
--main tour mode
--arrival and departure time periods
Model stops on each half tour

Generate a stop for some purpose (or not) ….



…then the stop location…

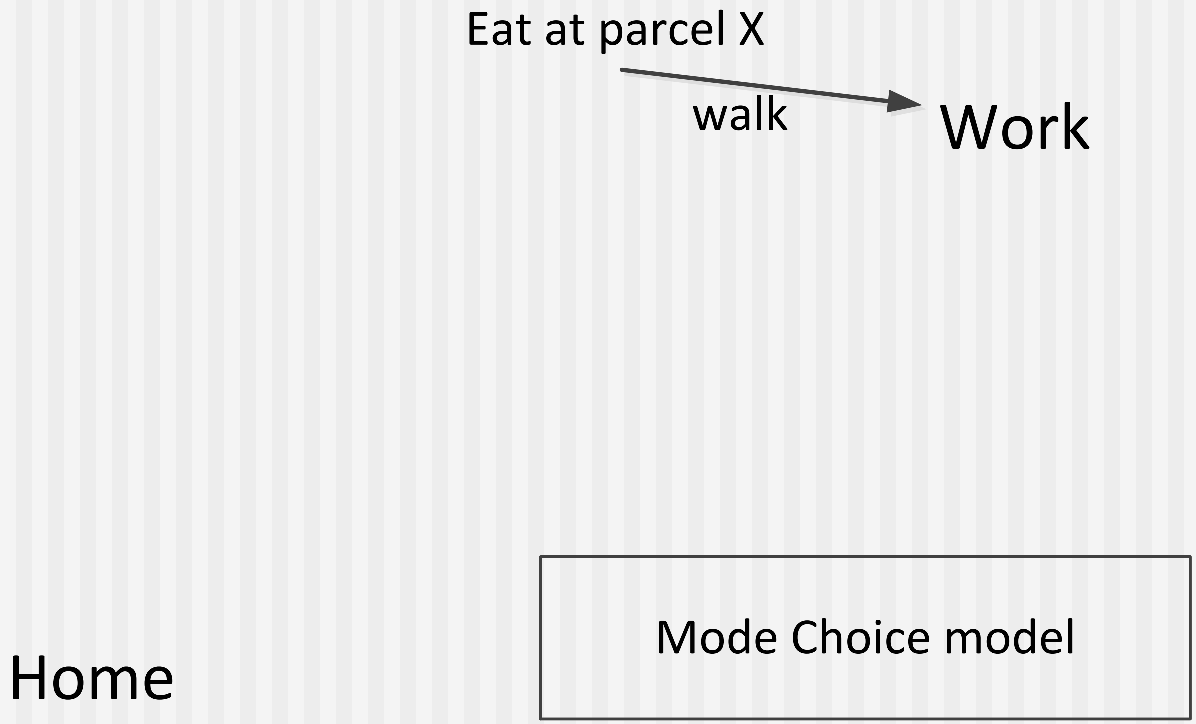
Eat at parcel X

Work

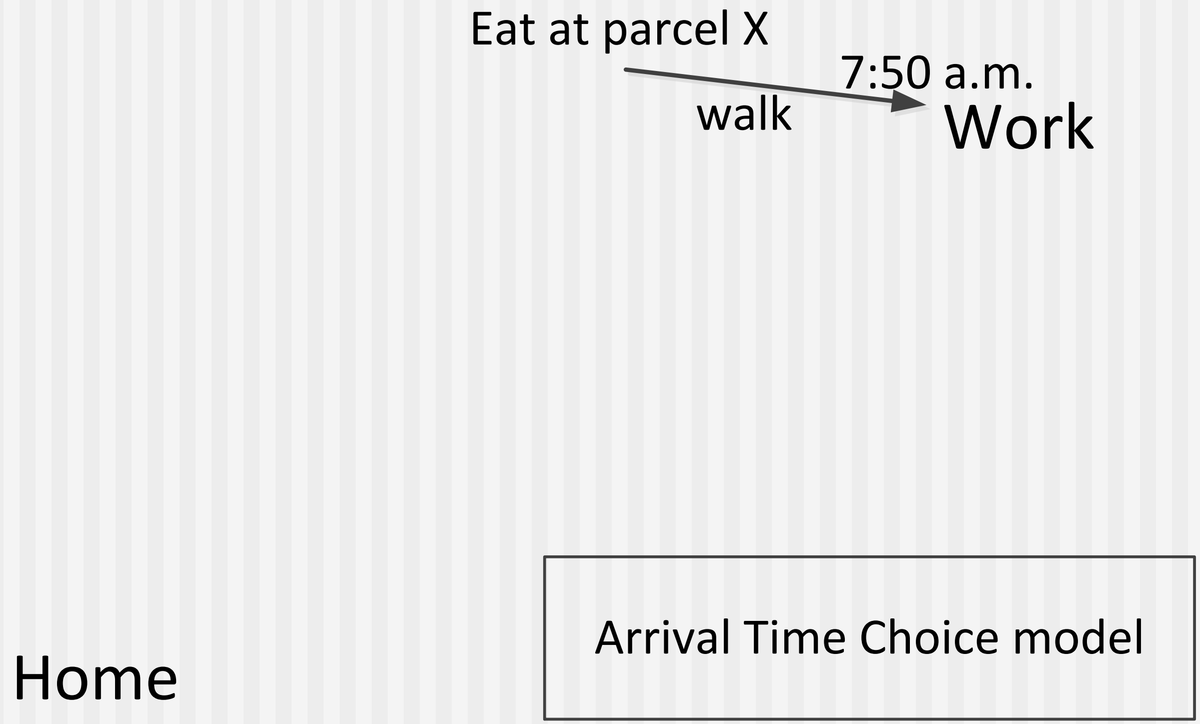
Home

Location Choice model

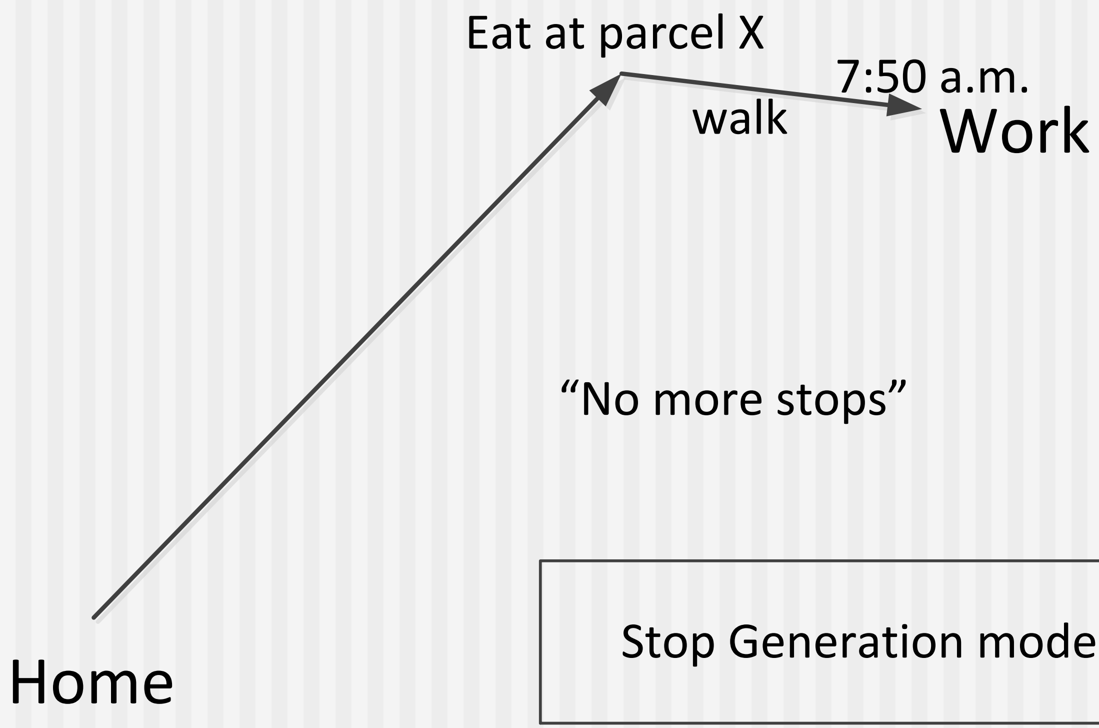
…then the trip mode…



…and the arrival time.



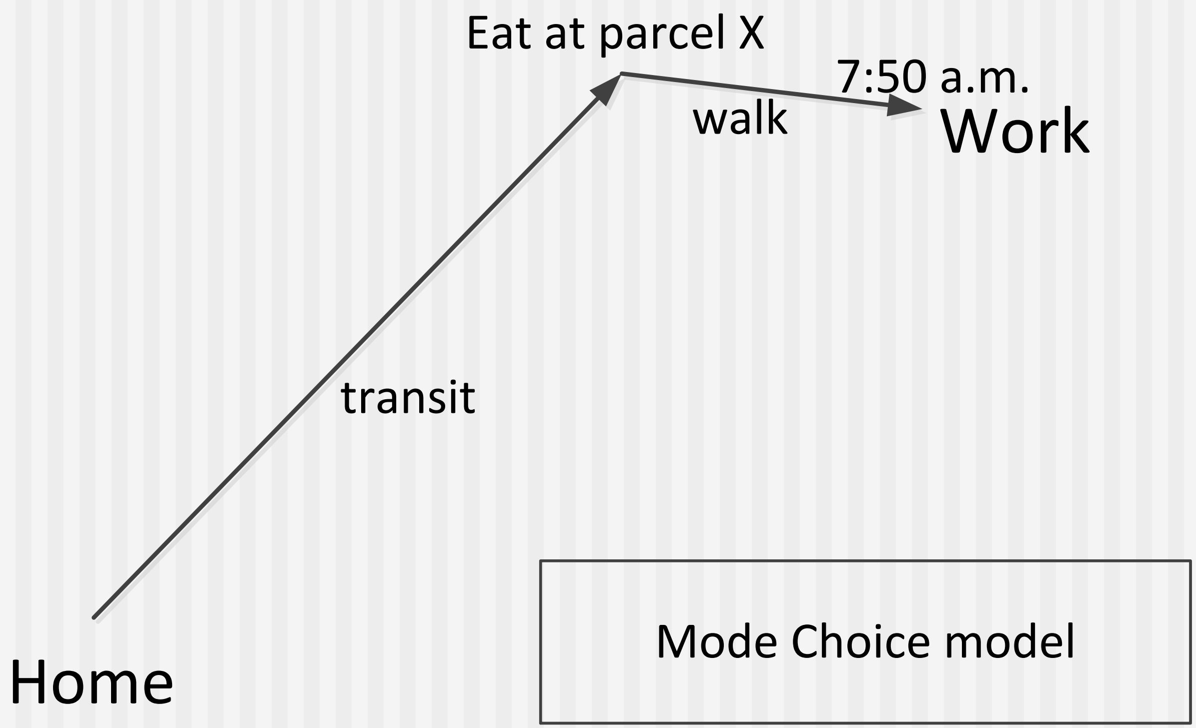
Generate another stop? (not this time)



"No more stops"

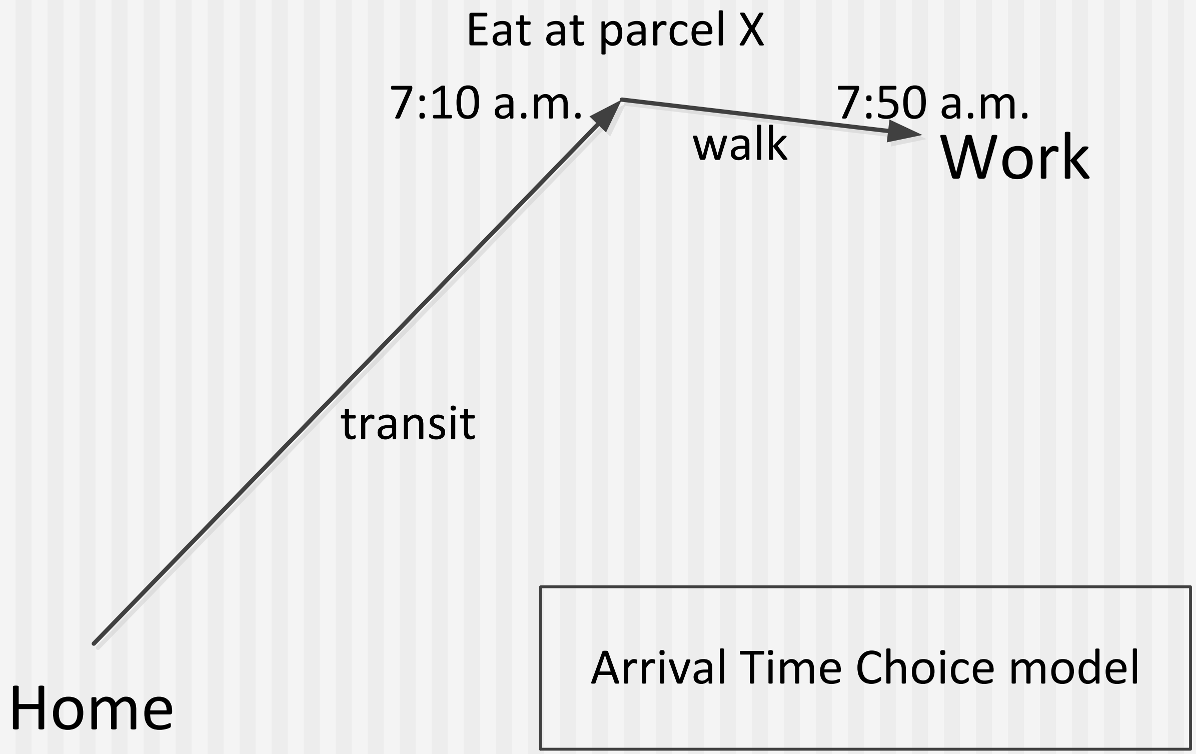
Stop Generation model

For the ‘last’ trip in the half tour model mode choice…

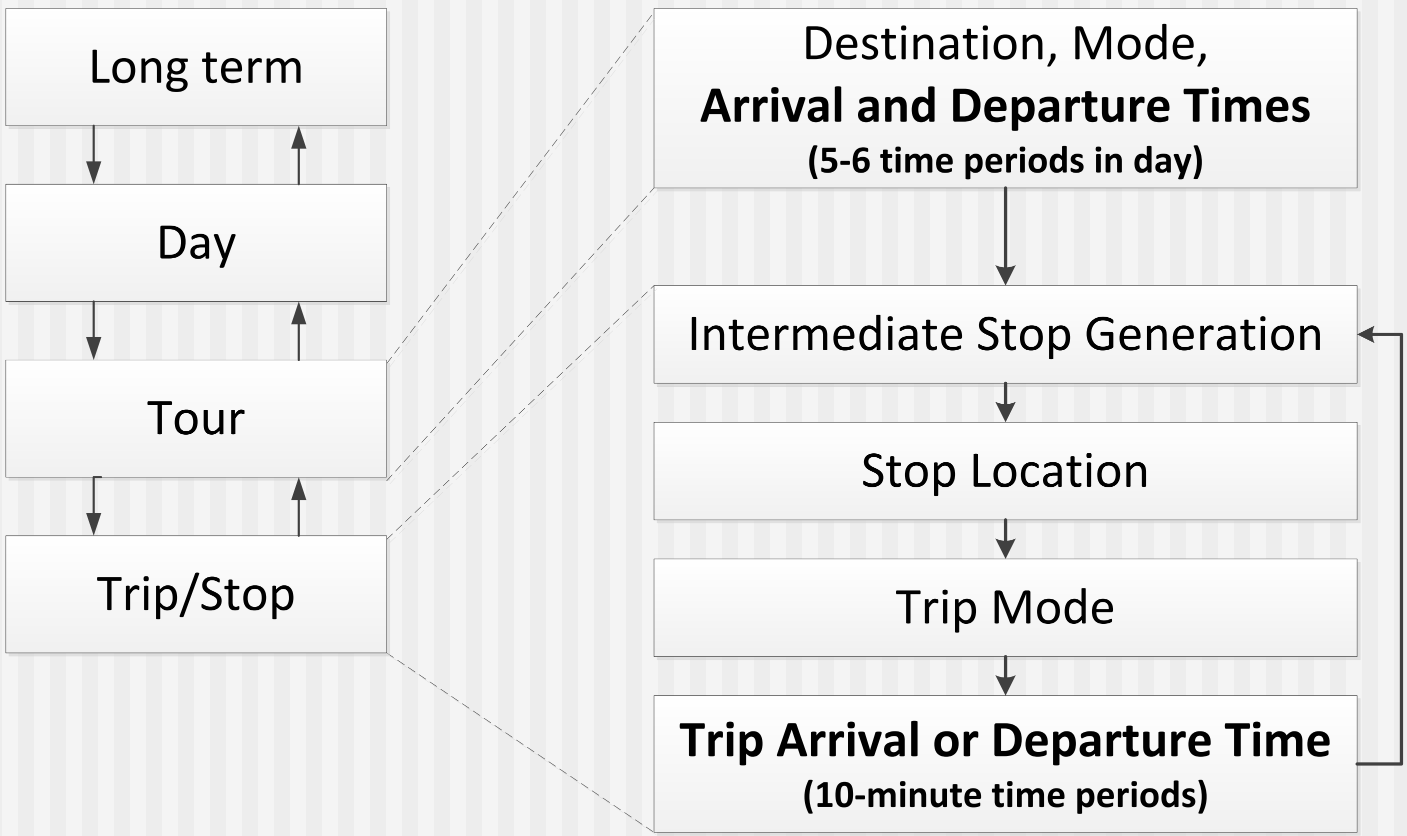


…and arrival time.

Then repeat for the second half tour



Time of day component



Discrete Choice Model Formulation for Tour Time of Day
(Vovsha and Bradley, 2004)

- Logit model
- Joint choice of:
  - Arrival Time at tour destination
  - Departure time from tour destination
  - (Derived) Total duration of activity at tour destination

Analog Between Discrete Choice and Hazard Duration Models

Duration Model

$$P(t) = \lambda(t) \prod_{s=1}^{t-1} \left[1 - \lambda(s)\right]$$

Discrete Choice Model

$$P(t) = \frac{\exp(V_t)}{\sum_s \exp(V_s)}$$

Constrain the outcomes to be equal:

$$\frac{P(t+1)}{P(t)} = \frac{\lambda(t+1) \times \left[1 - \lambda(t)\right]}{\lambda(t)} = \exp(V_{t+1} - V_t)$$

Particular case: constant hazard

$$1 - \lambda = \exp(V_{t+1} - V_t)$$

Utility function

$$V_t = \sum_k \beta_{kt} x_{kt}$$

Generic coefficients & shift variables

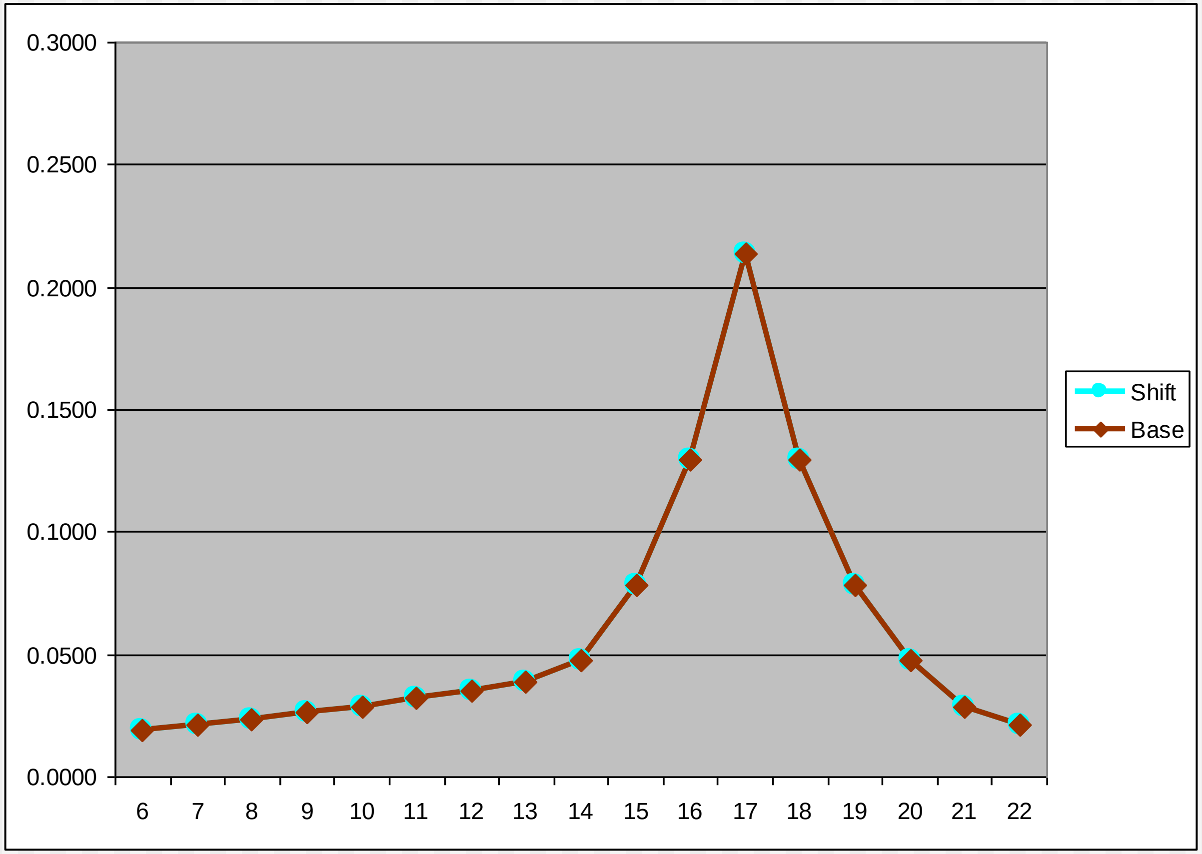
$$\beta_{kt} = \beta_k$$

$$x_{kt} = t \times x_k$$

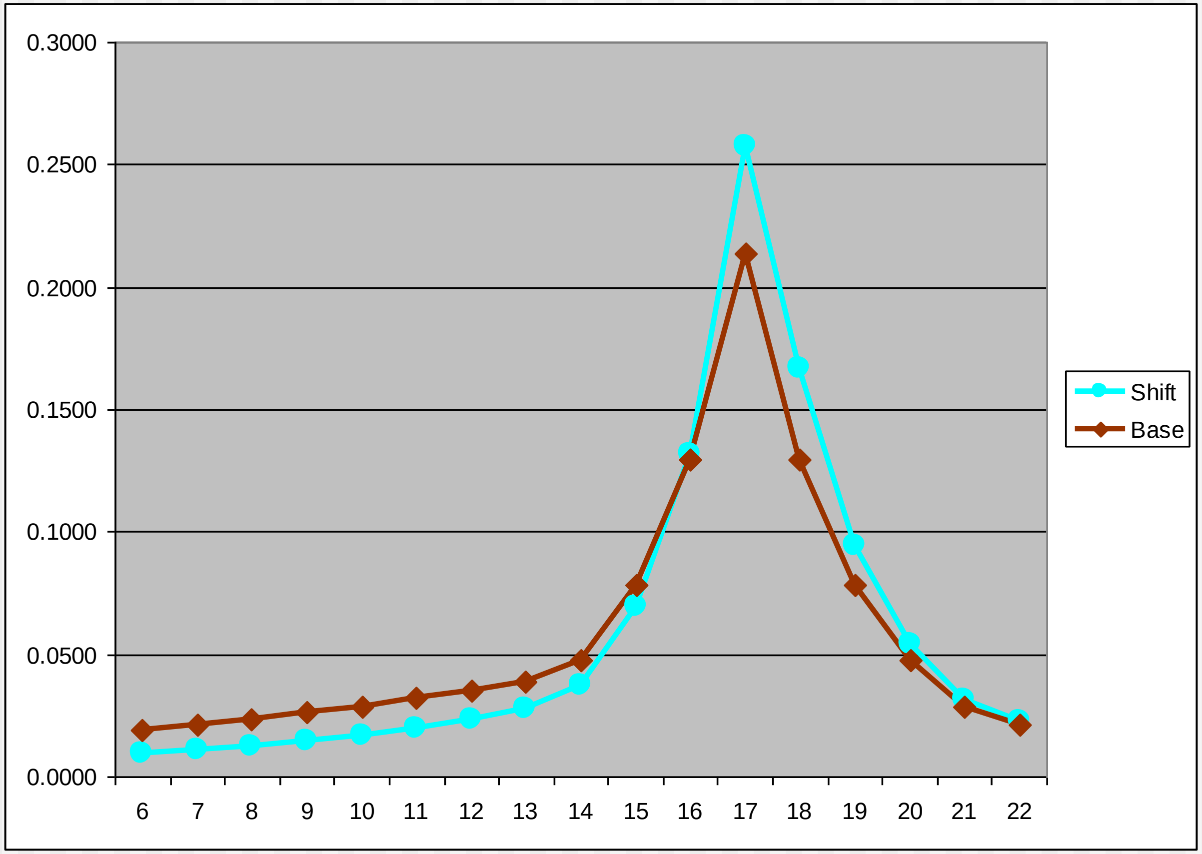
Core Utility Structure

- Consider one-dimensional choice-of-duration model in discrete time categories:
  - 0 hours
  - 1 hour
  - 2 hours
  - …
- Consider a utility structure with a single “shift” variable *X* and coefficient *C* :
  - U(0)=A(0)+0*X*C
  - U(1)=A(1)+1*X*C
  - U(2)=A(2)+2*X*C
  - ….

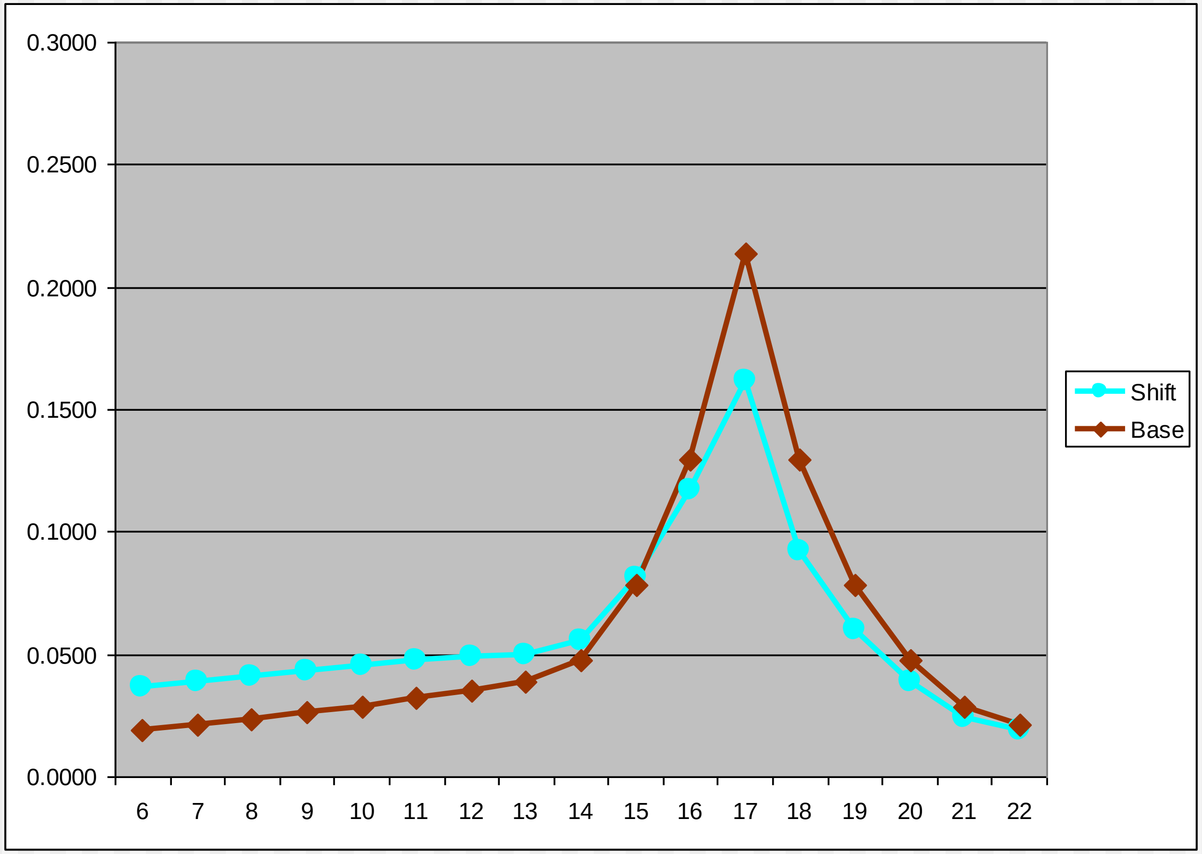
Shift Effect Example - Base



Shift Effect Example – Positive Shift Coefficient (C > 0)



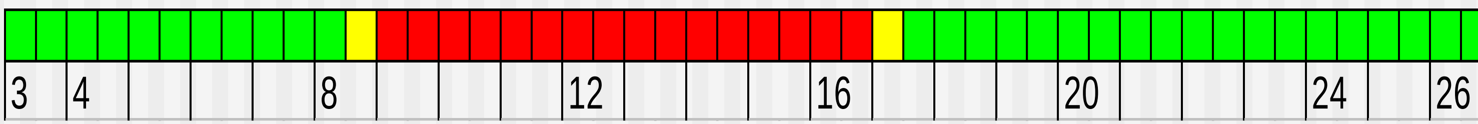
Shift Effect Example – Negative Shift Coefficient (C < 0)



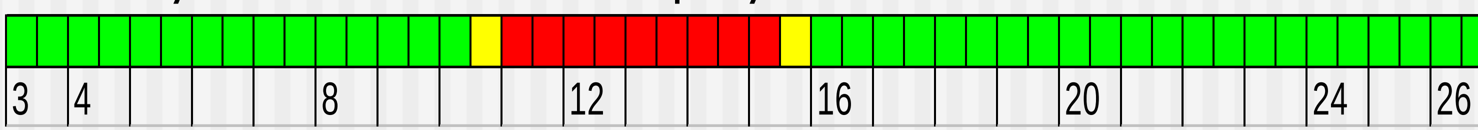
Example effects of shift variables

- part time employees more likely to arrive at work later and have shorter work day

Likely outcome for FT employee:



Likely outcome for PT employee:

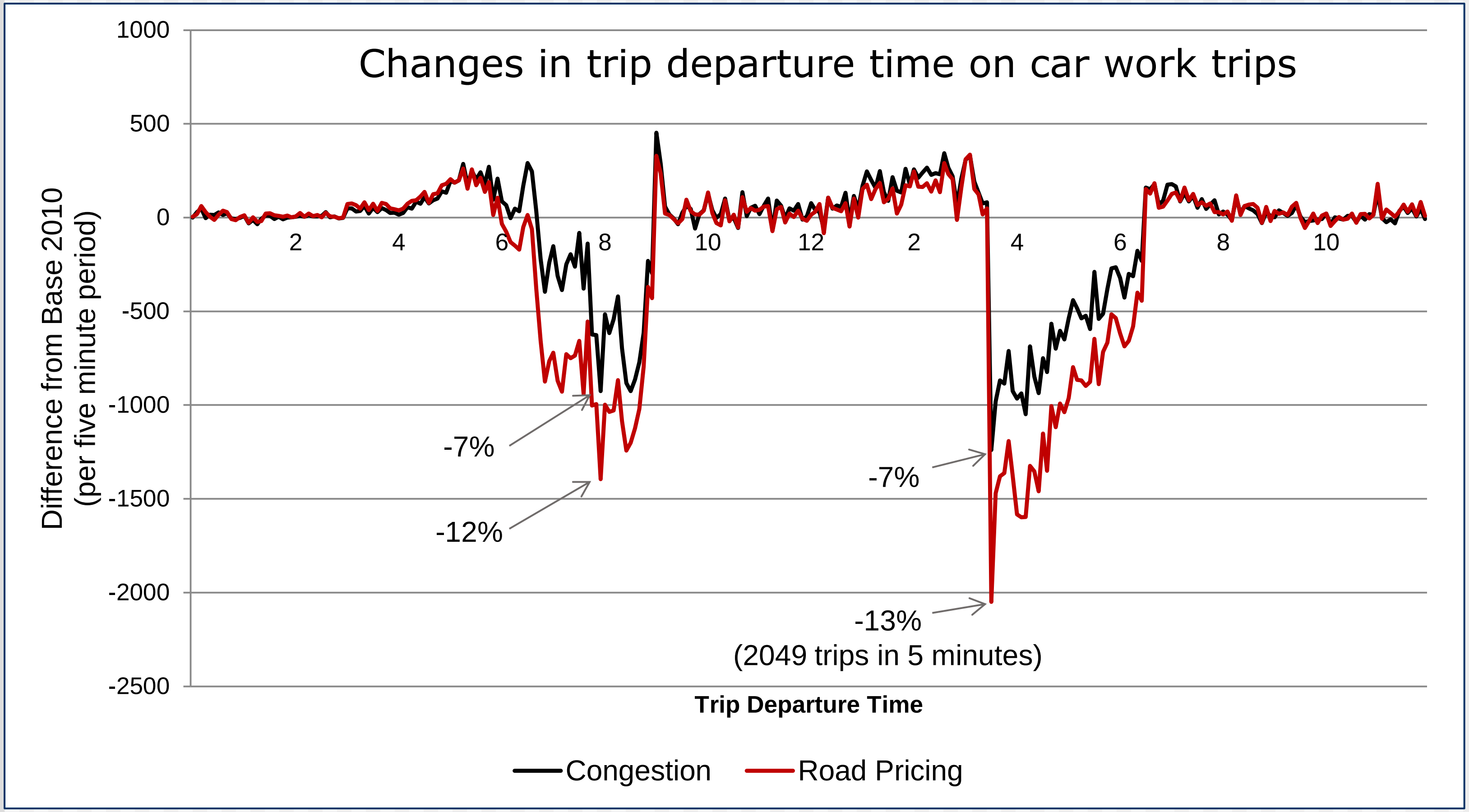


- People shift travel to periods with lower travel time and cost

COMPAS Scenario analysis: Congestion and Road Pricing

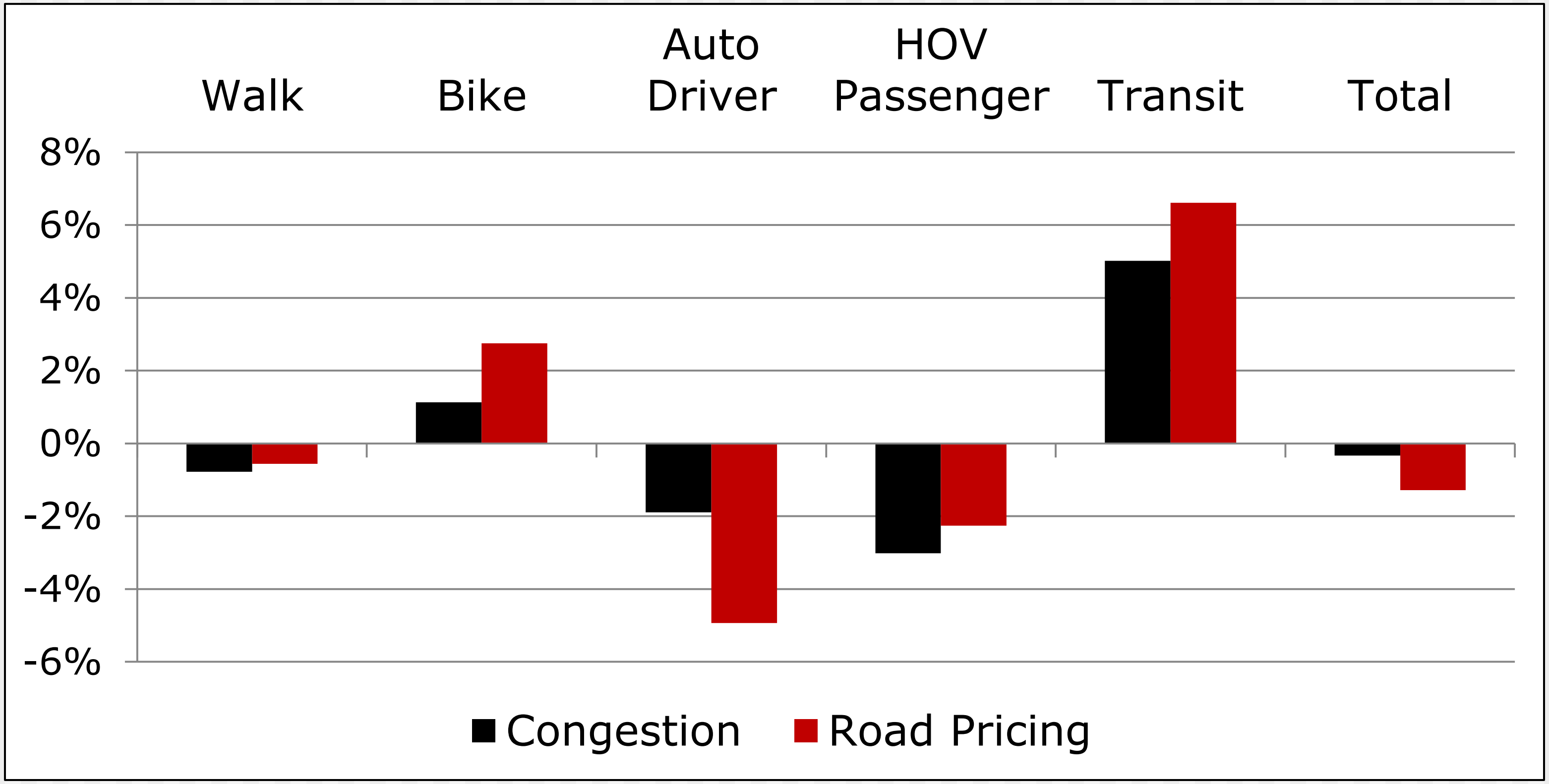
- Two scenarios:
  - Increased road **congestion** (2040 levels)
  - Increased road congestion AND per km **road prices**
    - 2 DKK/km (US$ 0.36) during peak periods
    - 1 DKK between peaks
    - 0.5 DKK night time

COMPAS Scenario analysis: Congestion and Road Pricing



COMPAS Scenario analysis: Congestion and Road Pricing

Percent change in trips on work tours



Sensitivity to pricing via auto path type choice

(uses findings of SHRP 2 C04 and C10)

In some cases, a driver has the choice between a faster tolled path and a slower untolled path.

In AB model, for each auto trip simulate VOT-dependent binary choice between path with toll and path without toll.

Binary path type (toll/no toll) choice model

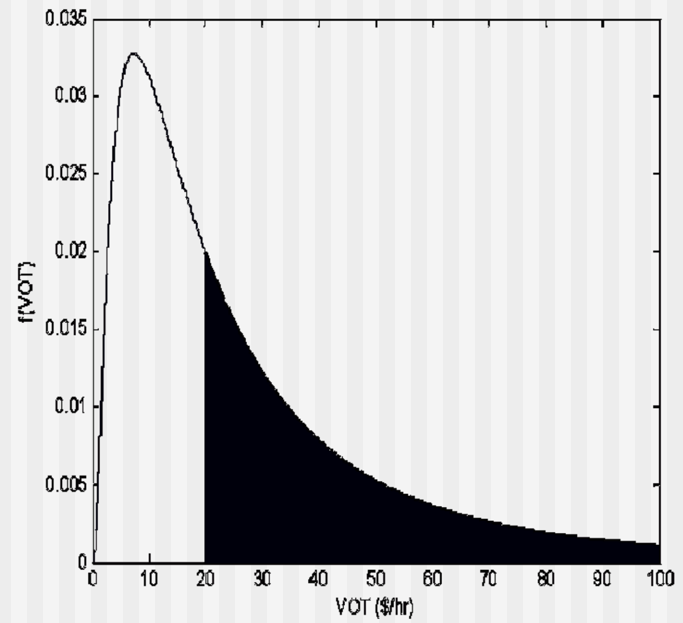
Utilities for the best tolled (*t*) and non-tolled (*n*) paths of individual *i* :

$$V_{ni} = \beta_i time_{ni} + \gamma_i (distance_{ni} \cdot oc_i)$$
$$V_{ti} = \alpha_i + \beta_i time_{ti} + \gamma_i (toll_{ti} + distance_{ti} \cdot oc_i)$$

- *oc* is operating cost per distance unit
- *time*, *toll* and *distance* depend on *i*'s origin, destination, time-of-day, vehicle occupancy, and value-of-time class

Assigning VOT class to a tour

- A function of
  - Income
  - Purpose
  - Random component
- Lognormal approximates observed distribution of VOT



Details

- Synthetic population and long term models
- Day models
- Tour models
- Fine-grained spatial scale

Why use a fine-grained representation of space?

- measure attractiveness better for location choice
- capture neighborhood effects on location choices
- include the impact of true walk distances in travel choices
- model short intra-zonal travel choices better
- represent transit alternatives more accurately in mode choice
- Handle bicycle and walk modes as effectively as cars and transit

Why use a fine-grained representation of space?

- measure attractiveness better for location choice
- capture neighborhood effects on location choices
- include the impact of true walk distances in travel choices
- model short intra-zonal travel choices better
- represent transit alternatives more accurately in mode choice
- Handle bicycle and walk modes as effectively as cars and transit

Use parcels or microzones for destination choice.

- Parcel attributes include:
  - Location
  - Area
  - Housing units
  - Enrollment by school type
  - Employment by sector
  - Transportation network access
  - Urban form measures
  - Offstreet parking

Ex. TAZs, microzones and parcels

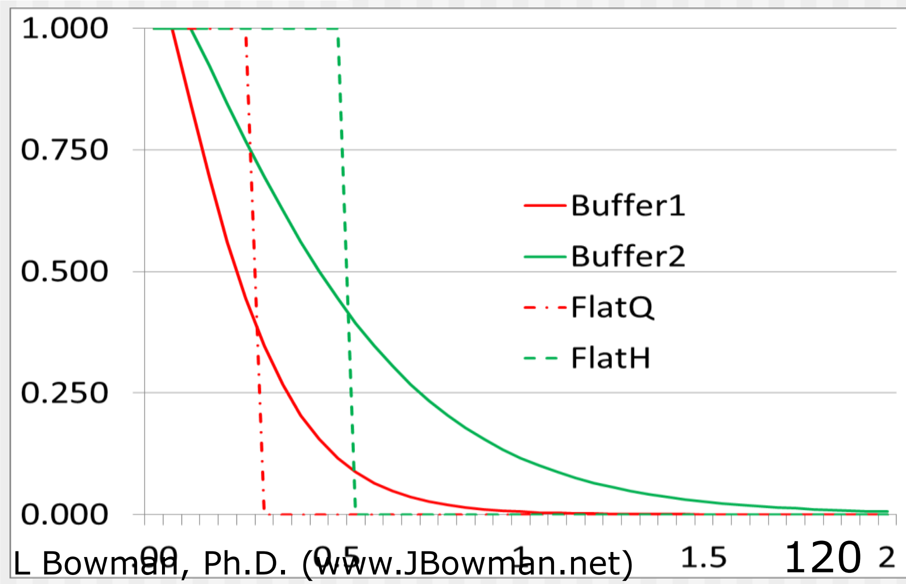
Why use a fine-grained representation of space?

- measure attractiveness better for location choice
- capture neighborhood effects on location choices
- include the impact of true walk distances in travel choices
- model short intra-zonal travel choices better
- represent transit alternatives more accurately in mode choice
- Handle bicycle and walk modes as effectively as cars and transit

Measure attributes in neighborhood of parcel or microzone centroid

- Attributes buffered
  - Housing units
  - Employment by sector
  - School enrollment
  - Street intersections by type (dead end, 3-way, 4-way)

Distance decay weighting function



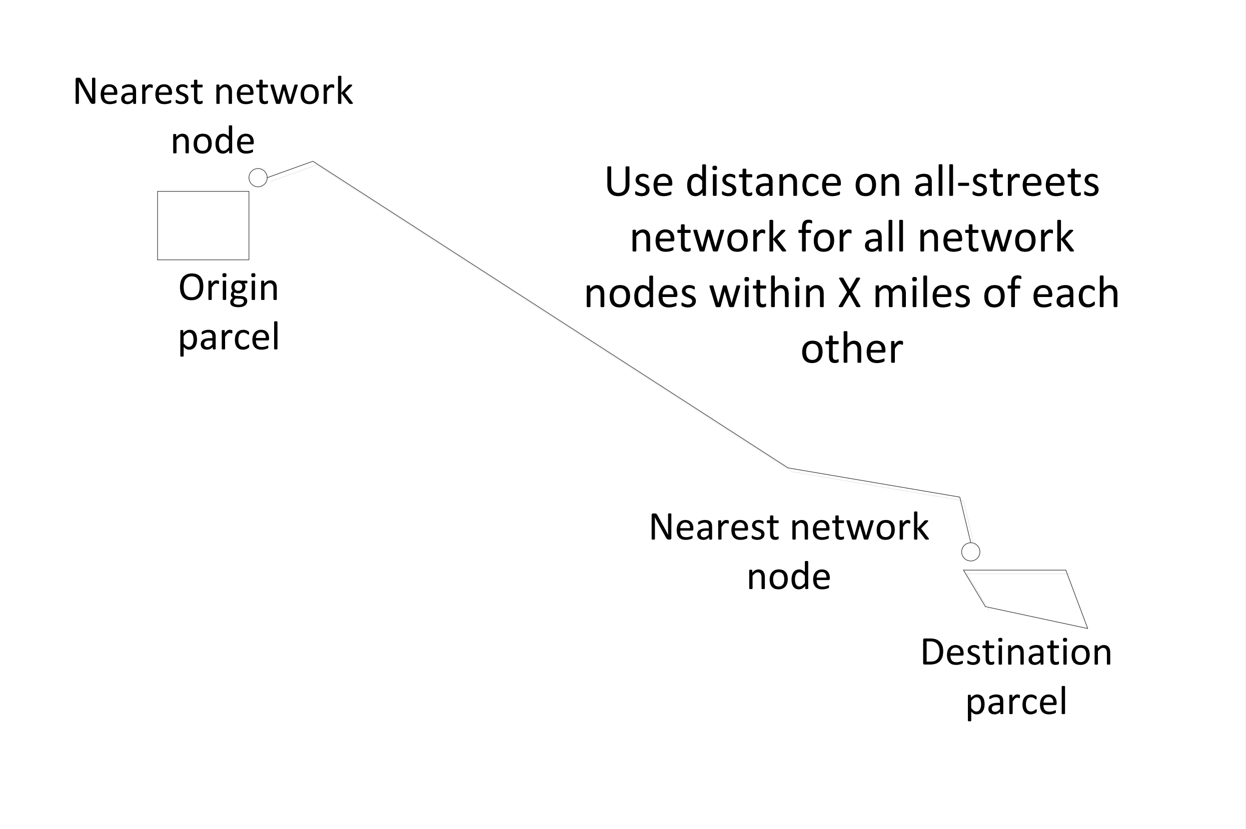
Meal Tour Destination Choice Model (PSRC)

Attribute	Parcel size effect (relative to base)	Neighborhood effect (coefficient)
Food employment	1.000	0.261
Retail employment		0.010
Service employment		-0.190
Total employment	Tiny	
Households	Tiny	

Why use a fine-grained representation of space?

- measure attractiveness better for location choice
- capture neighborhood effects on location choices
- include the impact of true walk distances in travel choices
- model short intra-zonal travel choices better
- represent transit alternatives more accurately in mode choice
- Handle bicycle and walk modes as effectively as cars and transit

Short distance calculations



- Use for:
  - Walk access to transit
  - Distance on all short trips
  - Adjusting TAZ-based travel times by all modes

Use all-streets network to measure impedance for short trips

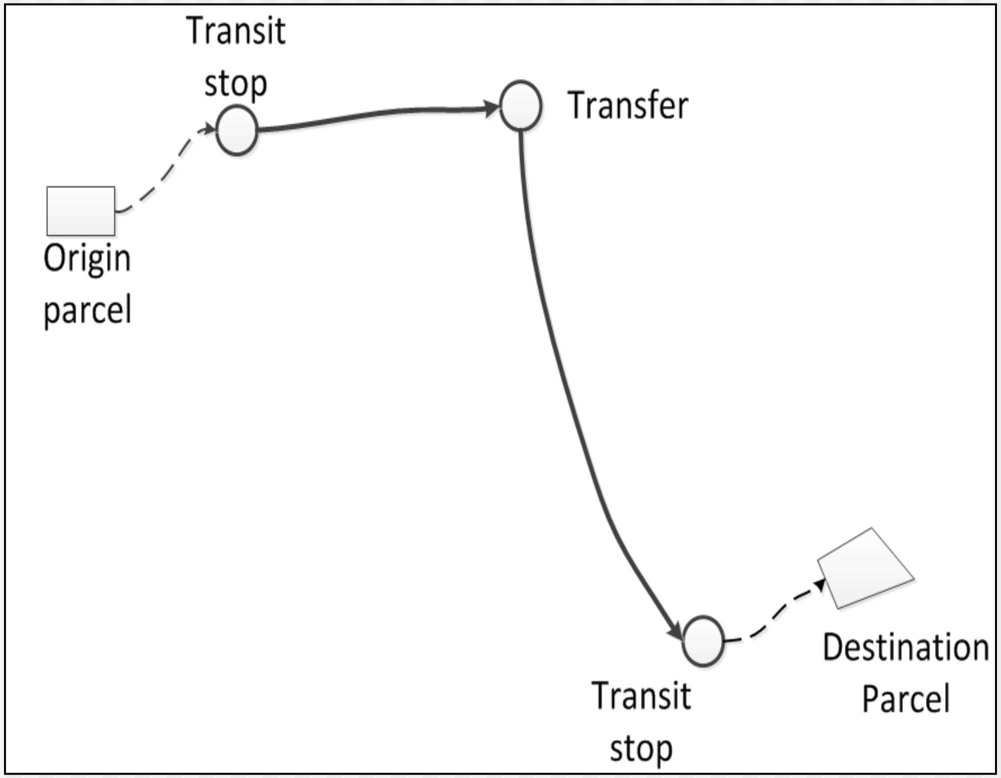
- Associate each parcel (or microzone) and transit stop with its nearest node
- Calculate shortest network paths between all node pairs less than 2-3 miles apart
- Use for impedance calculations
  - instead of zone-to-zone impedance for walk and short bike trips
  - for transit walk access and egress times
  - rescale zone-to-zone auto impedance for short trips
- Use for weighting in the parcel (or microzone) buffer calculations

Why use a fine-grained representation of space?

- measure attractiveness better for location choice
- capture neighborhood effects on location choices
- include the impact of true walk distances in travel choices
- model short intra-zonal travel choices better
- represent transit alternatives more accurately in mode choice
- Handle bicycle and walk modes as effectively as cars and transit

Measure walk access and egress more accurately (Philadelphia)

- Walk access and egress impedance: parcel-to-stop using Enhanced short distance calculation
- Transit impedance from boarding stop to alighting stop
- AB model chooses best combination of transit stops



…improves work mode choice estimation results (and prediction)

	TAZ-based		Link-based	
Log-likelihood	-4637		-4607	
Values of time	$/hr	(T)	$/hr	(T)
Car- drive alone	2.2	(1.2)	4.6	(2.5)
Transit- in vehicle	1.4	(1.4)	1.9	(1.9)
Transit- wait	5.9	(3.5)	5.3	(3.3)
Transit- walk	0.9	(0.2)	**12.2**	**(6.1)**

From Portland Metro (Bowman, et al, 2001)

Use similar techniques for other mode combinations

- Auto park and ride
- Auto park and walk
- Auto kiss and ride
- Bicycle park and ride
- Bicycle on board transit

Why use a fine-grained representation of space?

- measure attractiveness better for location choice
- capture neighborhood effects on location choices
- include the impact of true walk distances in travel choices
- model short intra-zonal travel choices better
- represent transit alternatives more accurately in mode choice
- Handle bicycle and walk modes as effectively as cars and transit

Modeling Bicycle Demand

Traditional limitations of models for bicycle mode

- Often combined with walk as "non-motorized" mode
- Many trips are intrazonal…not modeled
- Mode choice utility function includes only distance….no path attributes

Modeling Bicycle Demand
Improvements

- Fine-grained geography
  - Less intra-zonals
  - Measure impedance more accurately
- Route choice model
- Use route choice logsum in mode choice model
- Model bicycle access to transit (“bike and ride”) explicitly

Bicycle Route Choice Model

- use all-streets network
- with bicycle-specific attributes for disaggregate bike route choice model
  - Link type (wide cycle track, narrow cycle track, lane, etc)
  - Cumulative elevation gain (or loss)
  - Motorized volumes and speeds (or proxies)
  - Bicycle intersection provisions (eg: automatic signal activation; coordinated signals timed for cycles)
  - Number of stops and turns

Bicycle Route Choice Model

Hood, Jeffrey & Sall, Elizabeth & Charlton, Billy, 2011. A GPS-based bicycle route choice model for San Francisco, California, Transportation Letters: The International Journal of Transportation Research (2011) 3: (63-75).

Broach, Joseph & Dill, Jennifer & Gliebe, John, 2012. "Where do cyclists ride? A route choice model developed with revealed preference GPS data," Transportation Research Part A: Policy and Practice, Elsevier, vol. 46(10), pages 1730-1740.

Collaborators

- Moshe Ben-Akiva (1993-1998)
- Keith Lawton at Metro (1995-2000)
- Mark Bradley (since 1996)
- Gordon Garry & Bruce Griesenbeck at SACOG (since 2001)
- John Gibb & John Long at DKS (since 2005)
- Joe Castiglione (since 2007)
- Resource Systems Group (since 2008)
- Suzanne Childress & PSRC (since 2010)
- Goran Vuk at Danish Road Directorate (since 2011)
- Christian Overgård Hansen & DTU Transport (since 2011)