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Semi-compensatory Probabilistic Model for Residential Location Choices

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Dissertation: Endogeneity and choice-set issues in residential location choice models

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PhD
Imperial College London, 2023

Masters
University of Texas at Austin, USA; 2018

Undergraduate
Indian Institute of Technology Bombay, India; 2016

Origin
Born in Lucknow, U.P., India

This research is supported by Our Planet, Our Health scheme, funded by the Wellcome Trust

Collaborators

Dr. Aruna Sivakumar

Dr. Rolf Moeckel

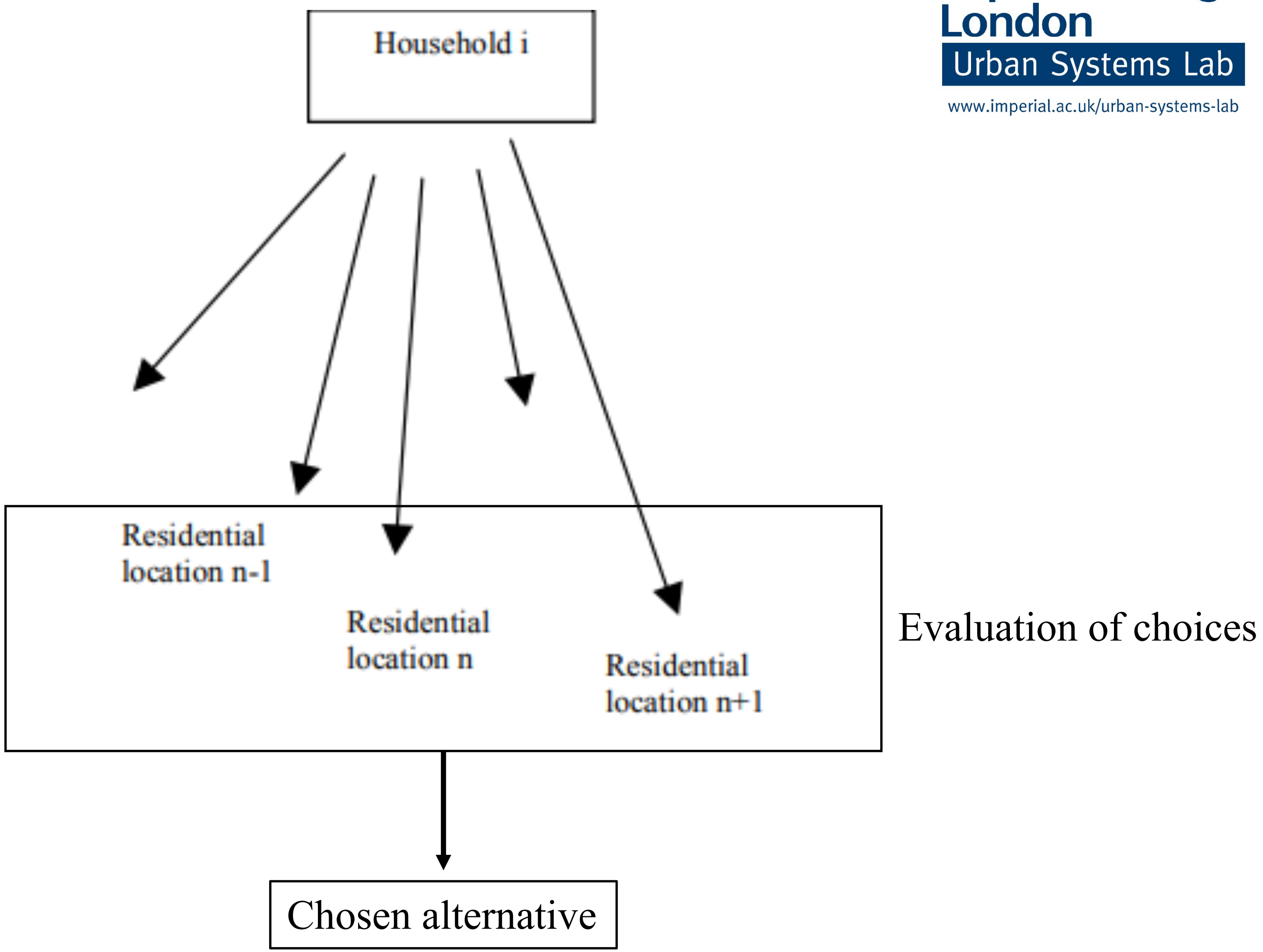
Introduction

What exactly are **residential location models?**

Where are these models employed?

Why are they significant?

……so what?

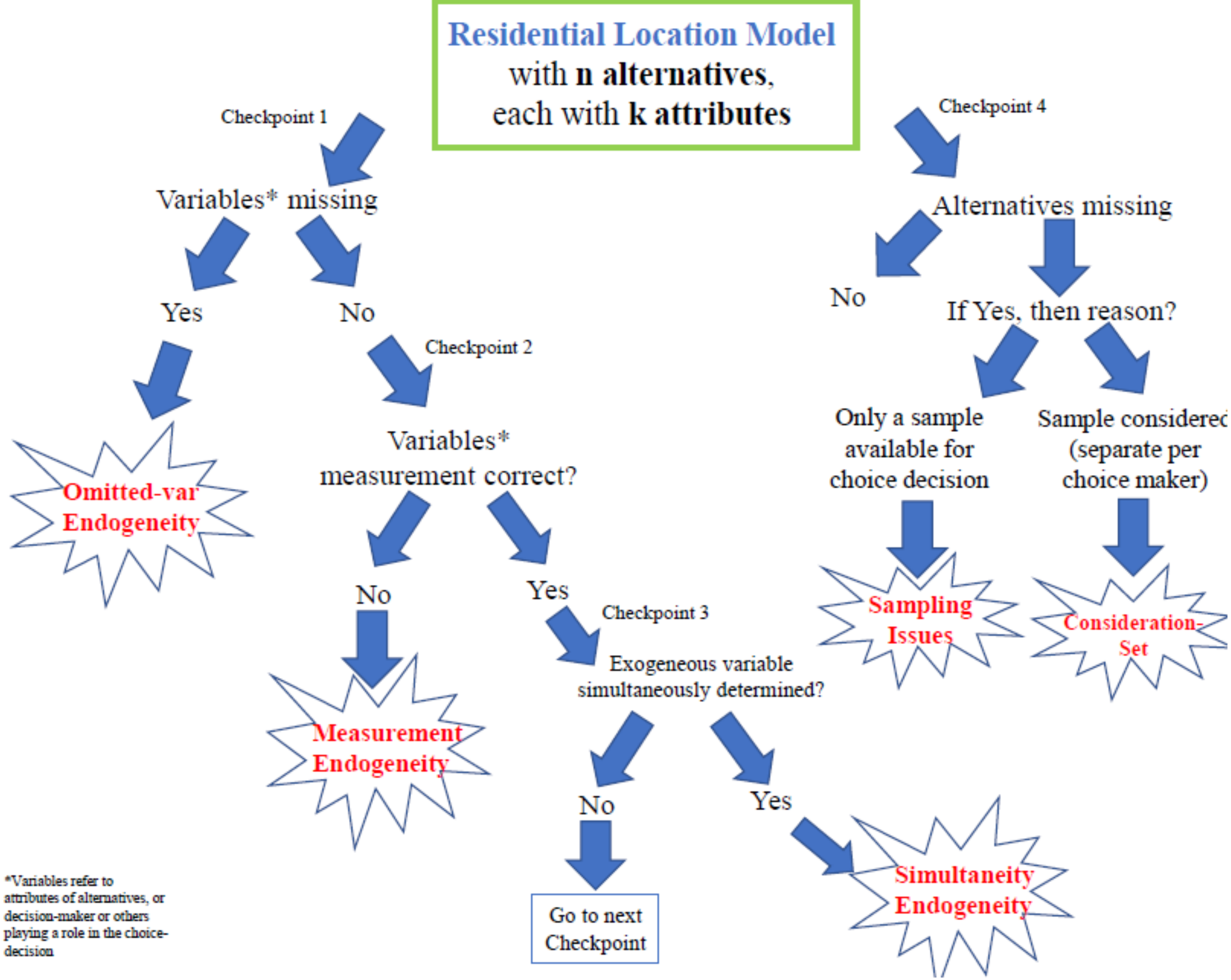


Behavioural model underlying a standard residential location choice model

Motivation

- Issues with alternatives availability or consideration (**sampling/consideration issues**), attributes' availability (**omitted-var endogeneity**), measurement error (**measurement endogeneity**) & simultaneous determination (**simultaneity endogeneity**)

- Sampling of alternatives for models other than MEV family
- *Actual* consideration set
- Realistic error structures



*Variables refer to attributes of alternatives, or decision-maker or others playing a role in the choice-decision

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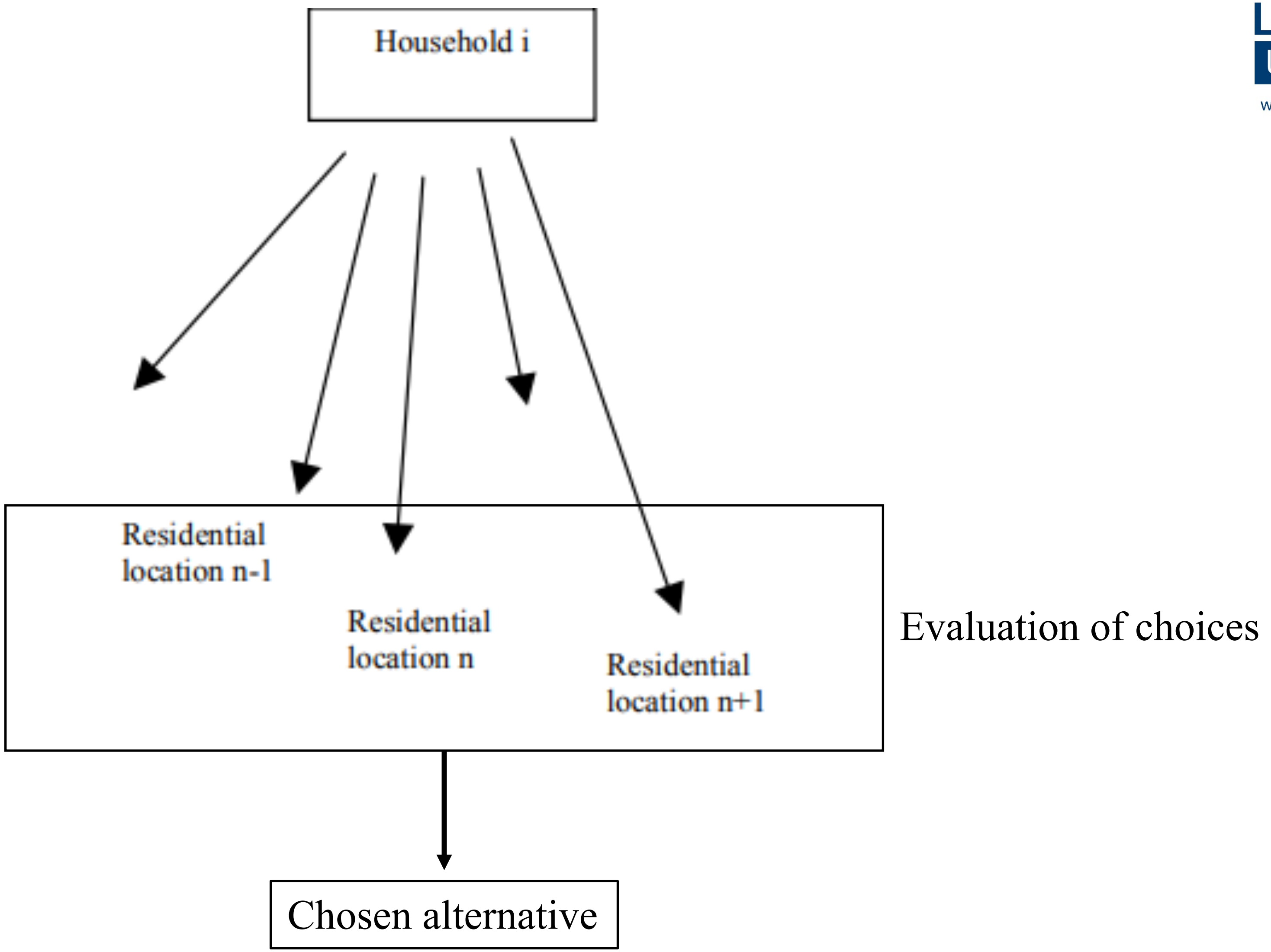
2. Current Scenario
3. Proposed framework and data
4. Results
5. Implications



Residential location choice model considering all alternatives

Unrealistic assumptions

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1. Fully informed decision-maker → **Either unavailable or filtered alternatives**
2. Utility-maximizing decision-maker
3. Hundreds (or even thousands) of potential locations evaluated consistently
4. Homogeneity in choice behaviour
5. No cut-off criteria based on
   a. Housing costs and budget
   b. Transportation costs
   c. Desirable characteristics

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Potentially unaware and cognitively restricted decision-maker

Unrealistic assumptions

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1. Fully informed decision-maker
2. Utility-maximizing decision-maker
3. Hundreds (or even thousands) of potential locations evaluated consistently
4. Homogeneity in choice behaviour → **Violation of disjunctive and conjunctive rules**
5. No cut-off criteria based on
    a. Housing costs and budget
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Compensatory vs Non-compensatory decisions

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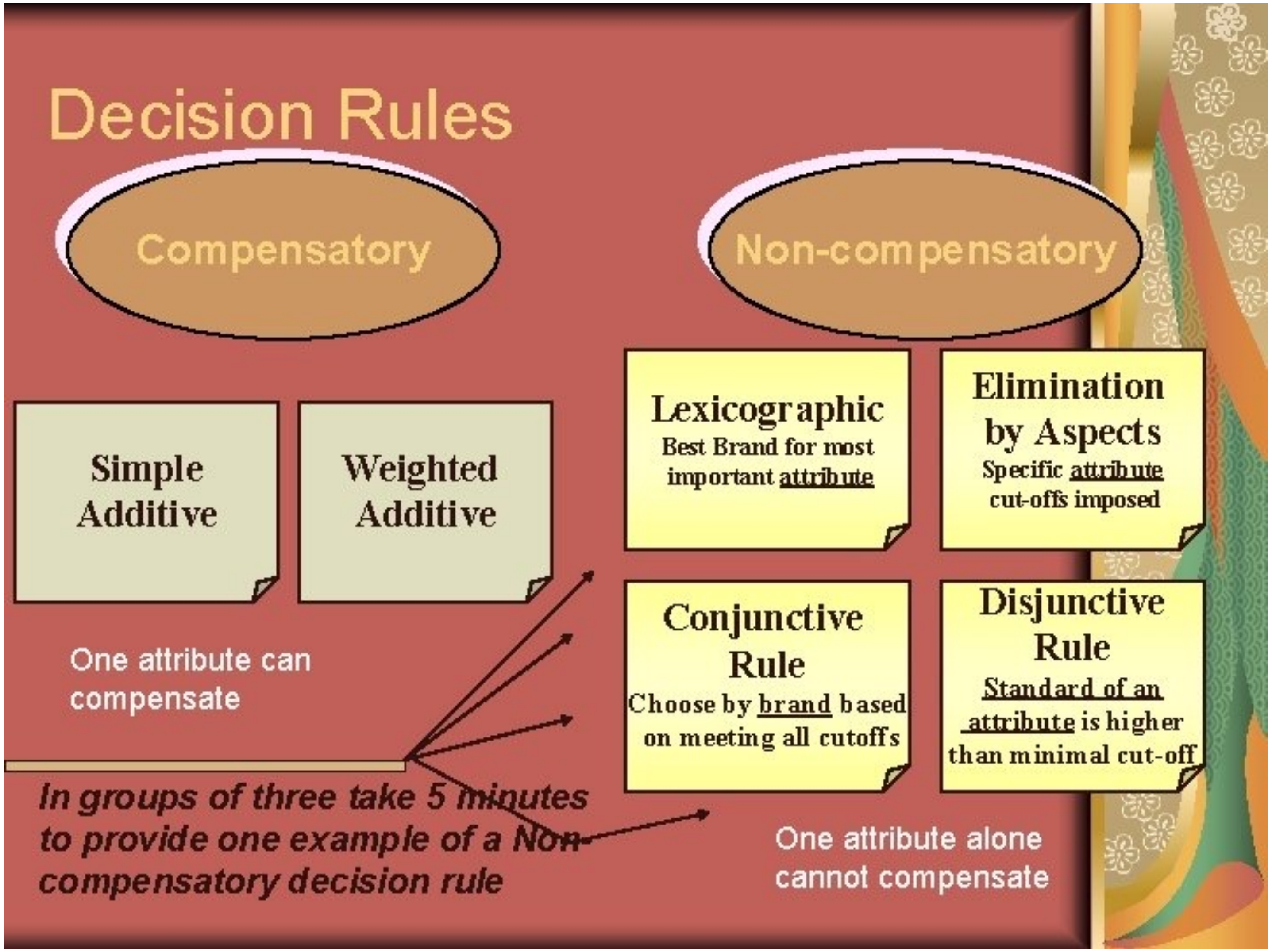

Reference: https://slidetodoc.com/buyer-behaviour-individual-decision-making-chp-9-with/

Unrealistic assumptions

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→ **Heterogenous non-compensatory criteria corresponding to costs and budget cut-offs**

Literature evidence

- Manski's two-step choice model (1977):
    - **non-compensatory decision rules to derive a consideration set**
    - followed by a compensatory choice model

1. Manski, C.F., 1977. The structure of random utility models. Theory and decision, 8(3), p.229.
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5. Swait, J., 2009. Choice models based on mixed discrete/continuous PDFs. Transportation Research Part B: Methodological, 43(7), pp.766-783.
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- Probabilistic Independent Availability Logit (PIAL) model (Swait, 1984, 2009):
  - **without allowing for dependence in consideration**
  - non-compensatory rules in an individual's decision making

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  - **without allowing for dependence in consideration**
  - non-compensatory rules in an individual's decision making
- The **decision trees resolve the ambiguity in deriving exact conditions for each observation by using disjunctions-of-conjunctions** decision rules (Brathwaite et al., 2017).

1. Manski, C.F., 1977. The structure of random utility models. Theory and decision, 8(3), p.229.
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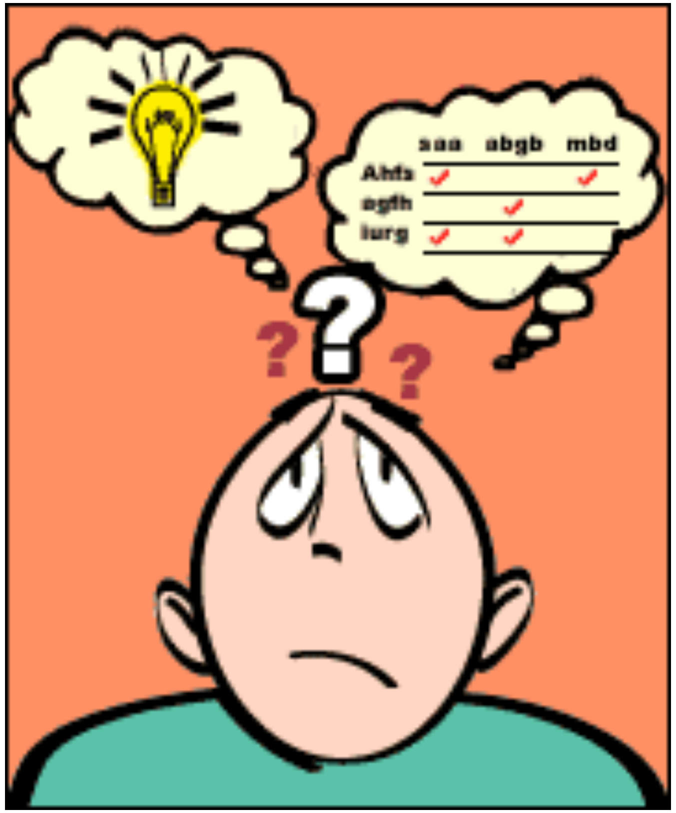
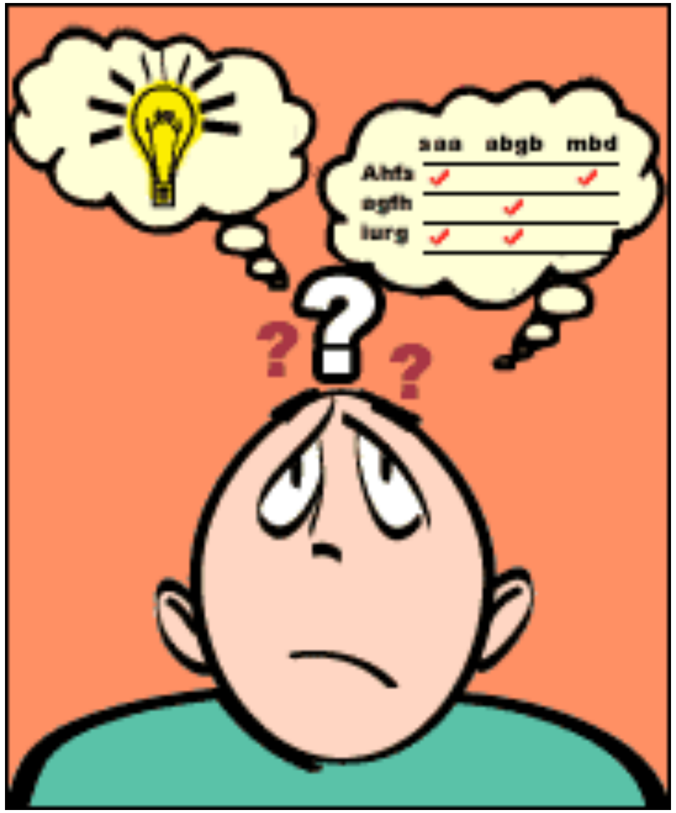
Objective of research:

- explicitly accounting for *non-compensatory consideration* of choice alternatives



Objective of research:

- explicitly accounting for *non-compensatory consideration* of choice alternatives
- allowing for heterogeneity across HHs in their consideration behaviour



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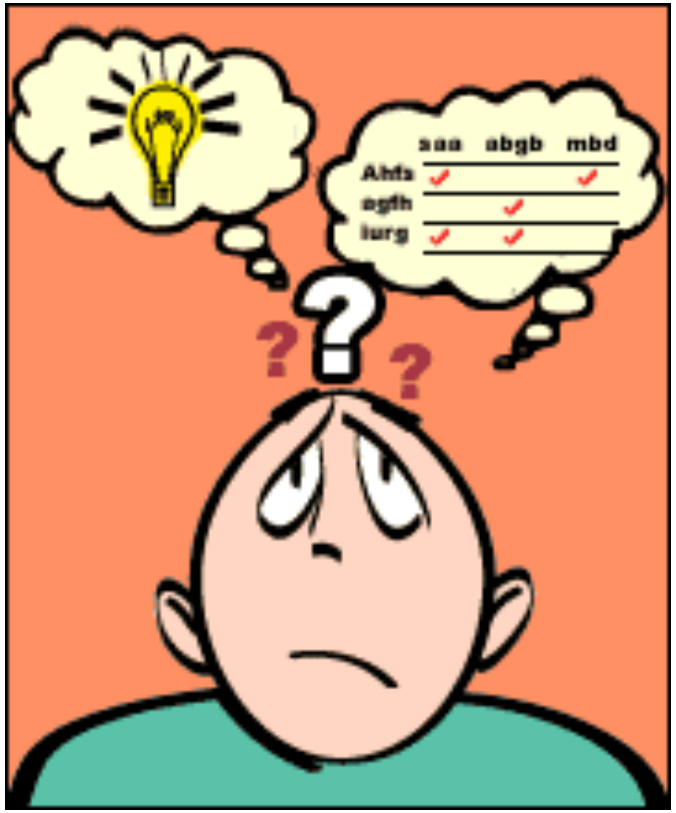

- explicitly accounting for *non-compensatory consideration* of choice alternatives
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- *compensatory choice* decision for a *residential location* model

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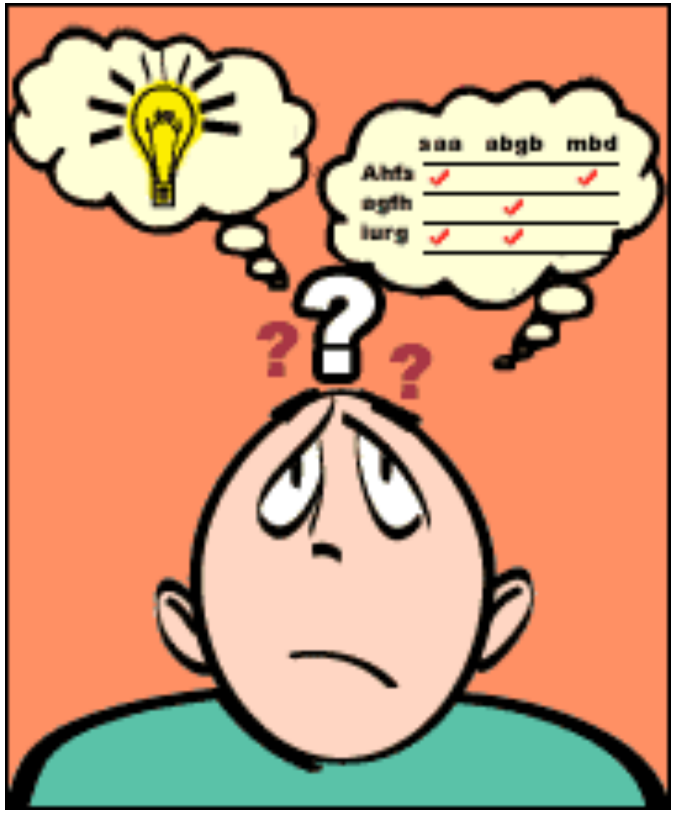
Objective of research:

- explicitly accounting for *non-compensatory consideration* of choice alternatives
- allowing for heterogeneity across HHs in their consideration behaviour
- *compensatory choice* decision for a *residential location* model
- ensuring that no observation is ever described by more than one conjunctive condition



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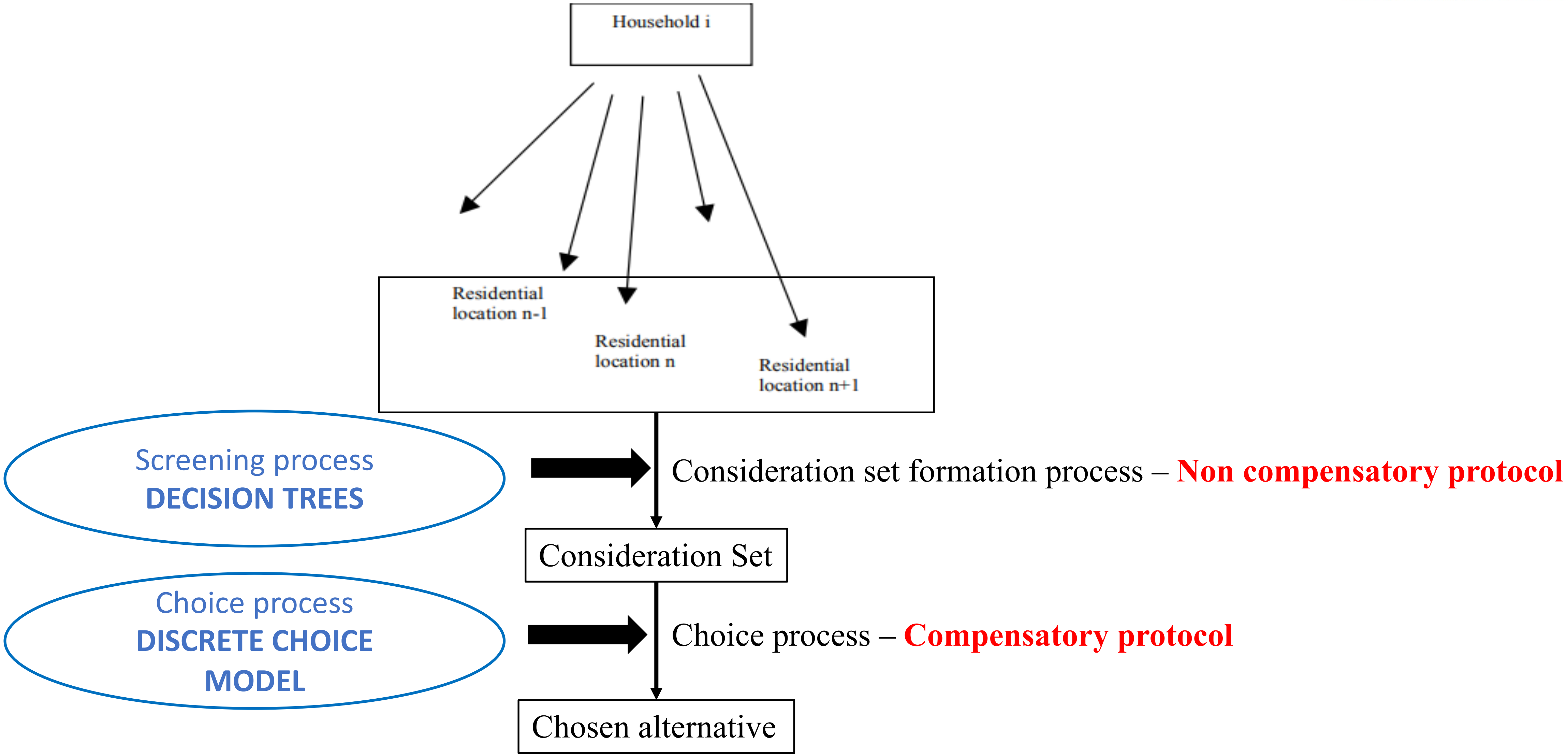
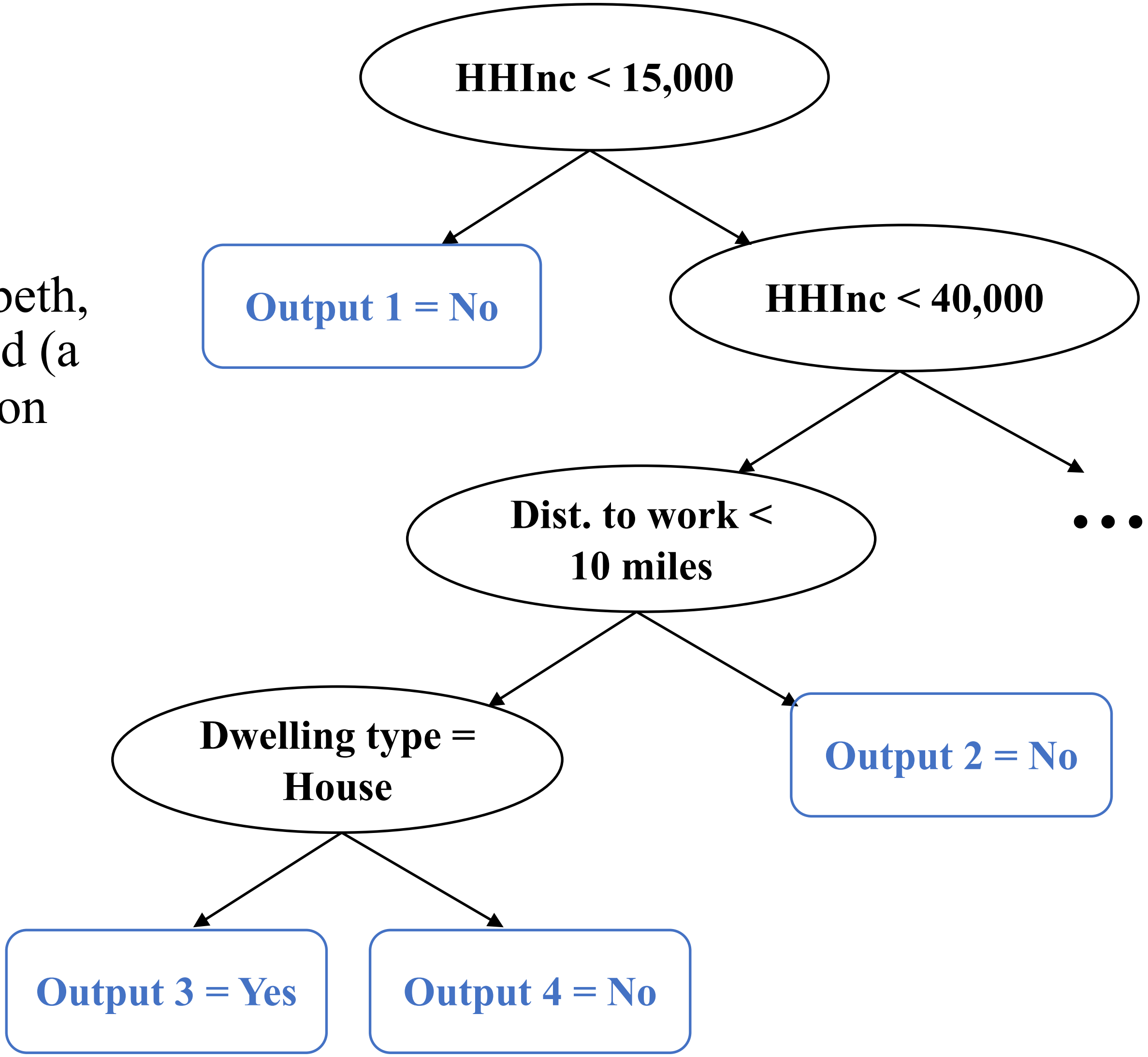
Proposed behavioural model



Step 1: Non-compensatory probabilistic consideration set formation

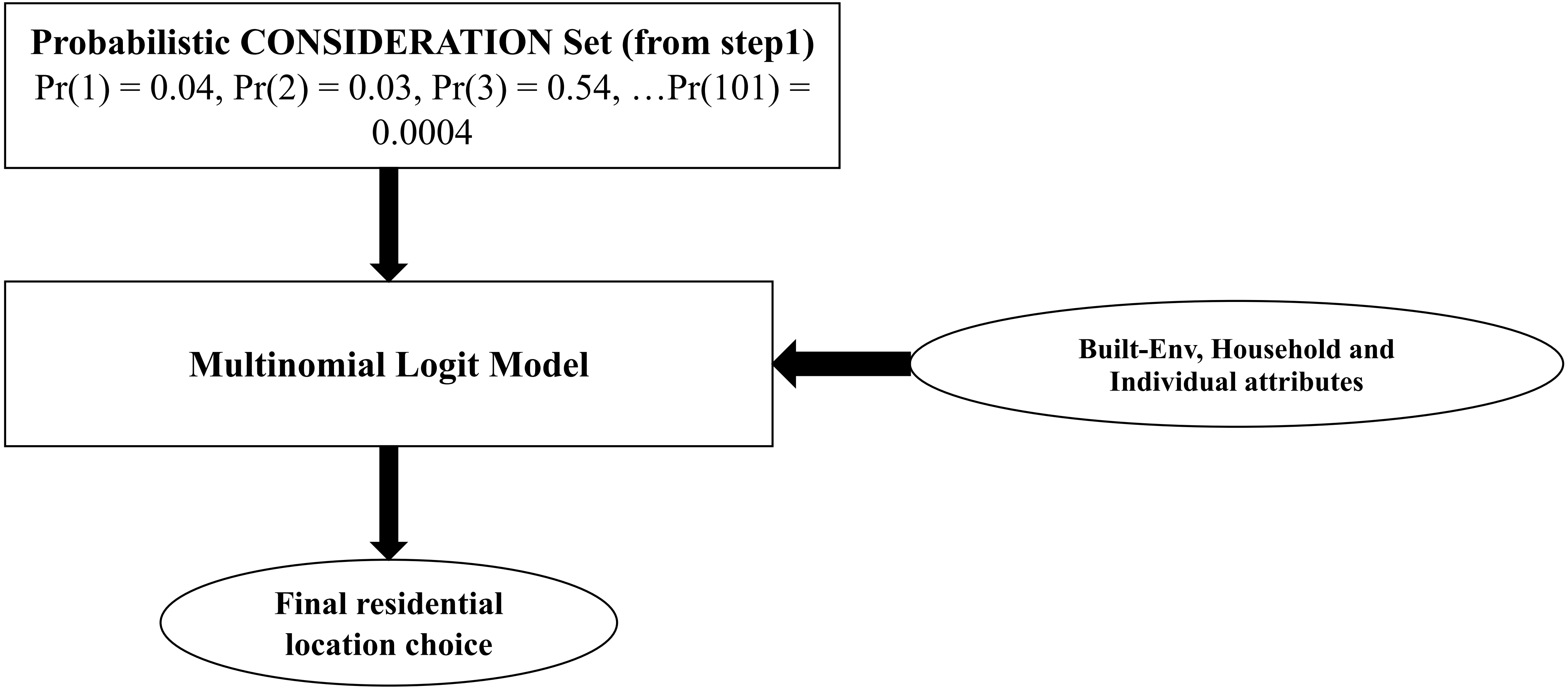
Example case: Will a neighbourhood (Lambeth, London) be considered (a snapshot of the decision tree)?



Other variable checks involving:

1. No. of vehicles
2. No of working adults
3. Transit pass ownership
4. Mode share
5. Housing cost/rent

Step 2: Compensatory choice decision



Data: London Travel Demand Survey

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London Travel Demand Survey (LTDS, 2005-2019):

- continuous household survey of the London area,
- covering the London boroughs as well as a limited area outside Greater London,
- comprising the 32 London boroughs and the City of London,
- available data includes yearly cycle 2018-19 as well as every year before this back till 2005,
- has person, household, trips and vehicle data

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Consideration results

Consideration of alternatives	**Zone 1**	**Zone 2**	**Zone 3**	**Zone 4**
Ratio of HH income to HH size	0.6360	0.8248	0.9947	0.9633
Distance from CBD	-0.7141	-1.0640	-2.6507	-1.9756
Consideration of Zone 1	---	-0.5925	0.1251	-0.1246
Consideration of Zone 2	---	---	---	---
Consideration of Zone 3	---	---	---	---
Consideration of Zone 4	---	---	---	---
Consideration of Zone 5	---	---	---	---

'---' shows insignificant

Reduced variables in consideration step
may lead to lessened impact and insignificance!

Choice results

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	Zone 1	Zone 2	Zone 3	Zone 4
Const.	-0.8175	-0.3660	-0.8384	-1.0460
No of HH trips	0.0440	0.0279	0.0920	---
No of persons	0.4431	0.5187	0.4320	0.4895
No of adults	-0.1394	0.1473	-0.0867	-0.1031
No. of workers	0.0908	-0.0699	-0.2497	---
No of vehicles	0.1944	0.6138	0.4594	0.3824
Transit pass ownership	0.0684	---	-0.0904	---
No of licensed drivers	-0.2500	-0.4276	-0.1944	-0.3282
Dwelling type house	---	---	---	---
Dwelling type townhouse	0.4898	0.5544	-0.6733	0.9211
Inc 100,000 to125,000	-0.5802	-1.4562	---	-0.8622
Inc 15,000 to 40,000	-0.3386	-0.4289	-0.2622	-0.4323
Inc 40,000 to 60,000	0.1113	---	0.6179	---
Inc 60,000 to 100,000	-0.3558	-0.9513	0.2169	-0.5754
Inc more than 125,000	---	---	---	---

'---' shows insignificant

RESULTS:

- Standard MNL assumes that HHs consider all neighbourhoods in London
    - **Average probability of consideration is 0.15**
- It is not surprising that model produced similar results as MNL with regard to most factors, the different choice sets implied by the conditional logit and CSF models render them with different substantive implications
- **Distance from the CBD is a statistically significant predictor of which regions are included in the choice set.**
    - This is consistent with past work finding that most moves occur over short distances (e.g., Clark and Smith 1982).
- **Turning to the coefficients describing the probability of considering neighbourhoods within a given affordability range, we see that household income is a strong predictor: higher-income households consider more expensive neighbourhoods.**

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IMPLICATIONS

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- Need to be careful about neighbourhood consideration in understanding segregation dynamics.
- Choice set formation is an important mechanism through which place stratification occurs.
- A racially and economically segregated urban landscape coupled with affordability constraints produces heterogeneous choice sets.
- Cognitively plausible choice model presented here can be straightforwardly extended to other domains in which people identify viable choice from among a larger set of alternatives.

FUTURE WORK

This research further aims to build on these initial findings by

- ❑ making probabilistic predictions with higher accuracy,
- ❑ representing heterogeneity in a population’s non-compensatory rules
- ❑ accommodating large numbers of alternatives, and
- ❑ alleviating the independence in consideration set formation.

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Thank you!
Questions?

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Dr. Aruna Sivakumar
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And Urban Systems
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Email: ***a.sivakumar@imperial.ac.uk***

Proposed application plans for summer in TUM

SILO Model enhancement

- SILO employs a logit-based household relocation module

- Goal: to eradicate limited alternative restriction in residential (re)location choice models by combining probabilistic decision trees with a traditional multinomial choice model to account for non-compensatory consideration of choice alternatives followed by a compensatory choice decision

SILO Model enhancement – Assumptions

Current assumptions*:

1. A household will evaluate a sample of 20 randomly drawn vacant dwellings inside a region (i.e. a set of zones) which has been chosen in a prior step

2. a multinomial logit choice model is used in which the probability of choosing a dwelling depends on the utility of the dwelling in comparison of the utilities of all other dwelling alternatives

3. Commute travel time constraint**: When households look for a new housing location, the job locations of all household members are taken into account

* Kuehnel N, Ziemke D, Moeckel R, Nagel K. The end of travel time matrices: Individual travel times in integrated land use/transport models. Journal of Transport Geography. 2020 Oct 1;88:102862.

** Moeckel, R., 2017. Constraints in household relocation: Modeling land-use/transport interactions that respect time and monetary budgets. Journal of Transport and Land Use, 10(1), pp.211-228.

SILO Model enhancement – Analysis proposed

Catering assumptions:

1. The two-step process of choosing a zone followed by location choice to be merged into a joint choice system

2. More behaviourally realistic and complex model type (instead of MNL) to be used to predict location choices

3. Testing other assumptions within each of the model's essential factors:
    1. Housing cost constraints
    2. Commute travel time constraint
    3. Household budget (allocation) constraint
    4. (Non-essential) desirable location factors

Thank you!
Questions?