# Results, application and reweighting

Key concepts & study plan

Experimental design

Data collection & processing

Model specification & estimation

**Interpretation & application**

# Results, application and reweighting

## Introduction

- Three related topics
  - different ways of analysing outputs from random utility models
  - use of choice models in demand prediction
  - dealing with unrepresentative samples

# Interpreting outputs

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## Overview

- Many different ways of analysing outputs
  - directionality
  - marginal rates of substitution and willingness to pay
  - relative attribute importance
  - odds ratios
  - elasticities
  - marginal effects
- This session gives an overview, with more in-depth discussions later in the course

# Interpreting outputs

## Directionality

- Models use parameters to capture impacts of attributes on utilities, and hence on probabilities
- Can gain initial insights by looking at individual parameter estimates:
  - which attributes have a positive/negative impact?
  - are there attributes where the impact is not different from zero?

# Interpreting outputs

## MRS and WTP

- Key behavioural output from random utility models for continuous attributes
- Relates to trade-off behaviour
  - what change in attribute $x_1$ cancels out a change in attribute $x_2$
  - if one attribute is monetary, then MRS becomes WTP or WTA
  - if one attribute is risk, MRS becomes MAR
- Take care in interpretation
  - MRS relate to points of indifference in **utility**
  - Could tell us e.g. that one unit of $x_1$ is twice as impactful on **utility** as one unit of $x_2$
  - **BUT:** Utility $\neq$ probability
  - Does not mean that impact of $x_1$ on **probability** is twice that of $x_2$

# Interpreting outputs

## Relative attribute importance (RAI)

- With categorical attributes, cannot look at **unit** changes
- Instead focus on relative impact of changes across levels
  - e.g. impact of going from level $L_1$ to $L_2$ for $x_1$ relative to going from $L_1$ to $L_2$ for $x_2$
  - or within a given attribute (e.g. $L_1$ to $L_2$ for $x_1$ relative to $L_2$ to $L_3$ for $x_1$)
- Can also use to compare maximum possible impact on utility of different attributes
  - impact of going from worst to best for $x_1$ compared to doing same for other attributes
- Take care in interpretation
  - Just as with MRS, this relates to **utility**, not **probability**
  - RAI on probability has same order, but magnitudes may differ a lot

# Interpreting outputs

## Odds ratios

- Odds in choice modelling: probability of choosing an alternative *vs* not choosing it
  - $O_j = \frac{P_j}{1-P_j}$
- Odds ratios: odds in different conditions, e.g. at two different levels of an attribute
  - $OR_{j,x_{\mathbf{1},L_\mathbf{1}}\,vs\,x_{\mathbf{1},L_\mathbf{2}}} = \frac{O_{j,x_{\mathbf{1}},L_{\mathbf{1}}}}{O_{j,x_{\mathbf{1}},L_{\mathbf{2}}}}$
- Relates to probabilities, rather than utilities
- Can be used with continuous and categorical attributes

# Interpreting outputs

## Elasticities

- Percent change in demand in response to a percent change in an attribute
- Key output for policy in many areas
- Can be used for continuous attributes
- Only really makes sense for labelled choice settings

# Interpreting outputs

## Marginal effects

- Categorical equivalent to elasticities
- Impact on demand of a change from one level to another for an attribute
- Can also use this to look at changes of a specified size for continuous attributes
  - specific number of units
  - from worst to best value
- Again only really makes sense for labelled choice settings

# Demand prediction

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# Demand prediction

## Estimation *vs* prediction

### Estimation

- represents step of *understanding* current behaviour
- find best model parameters

### Prediction

- what is the predicted demand for each product?
- how will behaviour change under given scenario?
- e.g. some products are added/removed/changed
- involves applying estimated model, not reestimating it on changed data

# Demand prediction

## The basics of forecasting

- Apply estimated model to:
  - predict choices in **new** settings
  - predict choices for a **new** population
  - predict impact of **changes** in products
  - predict impact of **changes** in population
- Mainly relevant in labelled settings

# Demand prediction

## Forecasting matters

- Many studies are primarily interested in willingness-to-pay
- Even then, useful diagnostic check to look at forecasts
- For example, does estimated model give reasonable implied elasticities?
- Well fitting models do not necessarily lead to good forecasts!
- Substantial risk of over-fitting to estimation data

# Demand prediction

## Forecasting in practice

- Real world forecasting would likely also require adjusting the sample of respondents
- Often estimate models on small samples, and then apply them to very large samples in sample enumeration

# Demand prediction

## Sample enumeration

- Assemble a population to use in forecasting
  - either based on real data (e.g., census), or synthetic population
- Apply the model to this data, i.e., make a prediction for each person in that data
- Potentially incorporate weights in that process to make the sample representative
- Then aggregate demand
- If the model incorporates interactions with person characteristics, then the forecasts in sample enumeration will be different depending on those
  - this is one of the key benefits of using deterministic heterogeneity as much as possible

# Reweighting

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# Reweighting

## Heterogeneity and non-representative samples

- Vast majority of datasets not representative of the population
- Variety of reasons
  - Some segments are difficult to reach
  - Some segments may be oversampled on purpose
  - Increasing reliance on internet-based panels
- If behaviour in a population is homogeneous, then this is not a problem
  - definitely not the case
- ... or if heterogeneity unrelated to characteristics for which sample not representative
  - ... is this likely? Are women and men the same?
- Many studies just ignore this

# Reweighting

## Is weighting the solution?

- Some work uses weights in estimation
- Imagine a sample where distribution of women and men is 60%-40%
- Could express log-likelihood as:

$$LL = \sum_{n=1} \left(\frac{0.5}{0.6} female_n + \frac{0.5}{0.4} male_n\right) LL_n$$

- *Innocent* view is that this addresses imbalance in the sample
- What it actually implies is that each choice made by a man is more important than each choice made by a woman…
- Quite easy to show that this does not actually fix any bias

# Reweighting

## What's the solution?

- Weighting should be carried out post-estimation, through sample enumeration
- Calculate the value of interest (whether WTP or forecasts) for each individual, then average or sum over individuals
  - weighted average is nearly always different from the measure for a *representative* individual
- Two possibilities
  - apply model to the estimation sample, but with weights to correct for the sampling
  - apply model to an external sample that is larger/more representative
- Can apply model to different future scenarios, with different weights
  - unlike with weighting in estimation, these do not need to be known at the estimation stage

# Reweighting

## How does this work?

- Calculate value of interest for each person, say $WTP_n$ or predicted demand $P_{car,n}$
- Produce average WTP as $\frac{\sum_n w_n WTP_n}{\sum_n w_n}$ or total predicted demand as $\sum_n w_n P_{car,n}$
- If the prediction sample is an exogeneous representative sample, then $w_n = 1 \, \forall n$
- Works only if model captures heterogeneity along dimensions for which sample might be adjusted in application
  - e.g. to correct for gender imbalance in application, need to capture role of gender in model

# Reweighting

## How about with random heterogeneity

- Mixed Logit alone cannot do this, need deterministic heterogeneity too
- Conditionals/posteriors are not the solution either
  - Issue 1: conditionals are available for estimation sample only, not application sample
  - Issue 2: distribution of conditionals is driven by sample level heterogeneity assumptions