

# 3. Stated choice analyses

## 3.1 Stated and revealed preference data

Revealed preference (RP) data:

- These data are based on actual decisions and choices in real-world situations, i.e. individuals reveal their tastes or preferences through their decisions in the world
- Examples: Actual voting behavior in referenda, actual purchases (e.g. from scanner panel data), actual financial investments, actual purchases of cars

Stated preference (SP) data:

- These data are collected in experiments or surveys and refer to situations where a decision or choice is made by considering hypothetical scenarios
  - Example: Stated WTP for environmental policies, stated financial investments when several products with different returns and other attributes are presented, stated purchases of a car when several cars with different prices and other attributes are presented
- RP data are often considered generally superior to SP data by economists since they refer to observations of real individual behavior and thus have a high reliability and validity

However, SP data have several advantages compared with RP data:

- In contrast to RP data, SP data are not limited to situations, products, and attributes of alternatives that currently exist or have existed in the past, but can also refer to new products (e.g. new energy sources in vehicles or new financial products), new attributes of products, or products with a low market penetration
- Even for already existing situations and products, it is possible that some relevant factors and thus explanatory variables have little variability (e.g. prices of products or interest rates in financial products) so that an econometric analysis is hardly possible with RP data. Instead, SP experiments can be designed to contain as much variation in attributes as desired.
- Explanatory variables for real-world decisions can be strongly correlated (e.g. fuel efficiency and motor power of cars are mostly strongly negatively correlated, price and quality of cars can be strongly positively correlated), which makes the econometric analysis with RP data problematic
- The collection of RP data can be very time consuming, very expensive, or even impossible for specific topics
- In particular, RP data are not or only indirectly available for valuations of public goods such as environmental goods (e.g. climate protection) since they are not traded in real economic markets so that e.g. the analysis of WTP for climate protection is problematic or impossible with RP data

## Contingent valuation methods (CVM):

- In this SP approach mostly non-market resources (e.g. natural resources), which typically give some utility, are valued by respondents in a survey
- Typically, respondents are directly asked for the WTP for public goods such as for a new local recreation area or an improvement in environmental quality (e.g. an increase in biodiversity)
- The WTP questions in CVM can be based on classical open-ended formats or several types of (e.g. single or double bounded) binary choice formats
- A problem of CVM is that it strongly relies on the accuracy of the description of the resources (e.g. local recreation area) that are valued. Furthermore, CVM cannot value separate components or attributes of the resources.

## Conjoint analyses:

- In this non-choice SP approach respondents rank or rate each combination of components or attributes of several alternatives such as products
  - However, such ranking tasks are problematic with respect to utility theory, which do not necessarily reveal the WTP for some attributes. In particular, in real-world situations decision makers have to make specific choices (e.g. between several vehicles).
- As a consequence, data from stated choice experiments (SCE), where respondents are asked to indicate their preference among two or more multi-attribute alternatives, are in many situations the most attractive SP data

## 3.2 Design of stated choice experiments

Overview of main components of SCE:

- Problem definition and development, i.e. analysis of the research questions (e.g. analysis of possible preferences and WTP for electric vehicles or for sustainable investments)
- Identification and selection of choice alternatives (e.g. different energy sources and propulsion technologies in vehicles, different investment products) including the decision for labeled or unlabeled alternatives
- Selection of attributes, attribute levels, and attribute-level labels
- Selection of experimental design, i.e. specification of how attribute levels are combined to form different alternatives
- Generation of choice sets, i.e. decision on how the attribute level combinations are blocked for the presentation to the respondents

Challenges in the survey and questionnaire construction (which does not only comprise an SCE, but also other questions) for reliable econometric analyses:

- Generally, the survey design should strongly conform to the problem definition and not vice versa, i.e. the research question should not be adjusted to the survey design
- The questions must correspond to the type of data that are necessary for the econometric models (e.g. linear or nonlinear) in the empirical analysis

- The questions must be appropriate for the study, i.e. questions that are not used in the econometric analysis unnecessarily extend the length of the survey (and thus the costs and the efforts for the respondents)
- The questions must be understandable, realistic, and unambiguous for the respondents and should not be based on specific technical expertise (e.g. with respect to different energy sources and propulsion technologies in vehicles)
- Biased and leading questions as well as non-mutually exclusive categories in the SCE should be avoided
- The decision context in the SCE should be clear, i.e. a descriptive story should be provided that explains the context in which to consider the choice of the different alternatives (e.g. it should be clarified whether holiday or business trips are considered for the choice among different travel modes)
- The survey delivery method must be appropriate, e.g. phone surveys generally make no sense for SCE since the questions are too complex. While (computer-assisted) personal interviews are attractive, they can be very expensive so that recently often online surveys are conducted instead of written surveys, which were very attractive in the past.
- Finally, the whole questionnaire should be thoroughly tested before data collection, e.g. on the basis of expert talks, focus groups, and especially pre-tests with a small sample from the interesting population

## Hypothetical bias:

In order to circumvent or at least reduce problems through the hypothetical character of SCE or general SP data (especially the overestimation of WTP), several ex ante procedures are often included to increase the validity of SCE data such as cheap talk scripts (e.g. the advice that the income and wealth situation should be strongly considered in the SCE) or honesty oaths

## Labeled and unlabeled SCE:

- Labeled SCE assign specific labels to each alternative (e.g. air, train, bus, car in travel mode choices or electric, gasoline, diesel cars in the choice among different energy sources and propulsion technologies in vehicles)
- Unlabeled SCE use generic or uninformative titles or headings for the alternatives (e.g. alternative 1, alternative 2, etc.) and thus do not give additional information to the respondent
- A label for an alternative can be considered like an attribute, which is specifically obvious in quasi-labeled SCE, where each alternative refers to exactly one specification (e.g. when electric, gasoline, and diesel are included as attribute levels for the attribute energy sources and propulsion technologies)
- One advantage of unlabeled SCE is that they do not require the identification and use of all alternatives among the universal set of alternatives
- However, labeled SCE can sometimes be more realistic and also be useful for the estimation of alternative-specific constants

## Experimental designs:

- Full factorial design
  - Design in which all possible attribute level combinations (which can be differently coded) are considered
  - Example: For two attributes (e.g. purchase price and CO<sub>2</sub> emissions) with three levels, respectively (e.g. 5000, 10000, 15000 Euro and 0, 100, 200 gram per kilometer) in the case of a vehicle choice, nine (i.e. 3·3) attribute level combinations for one alternative are possible
  - In general, the number of possible attribute level combinations depends on the number  $L$  of attribute levels, the number  $k_2$  of attributes, and the number  $J$  of alternatives and thus is  $L^{k_2 J}$  in labeled SCE and  $L^{k_2}$  in unlabeled SCE
  - It is important to note that the alternatives in labeled SCE often have different attributes and especially different attribute levels (e.g. 0, 100, 200 gram CO<sub>2</sub> emissions per kilometer for electric vehicles, but only 100 and 200 gram for gasoline vehicles)
  - Full factorial designs have very attractive statistical properties for parameter estimation and statistical testing, but the number of attribute level combinations is mostly too large in practice so that commonly only a fraction of them is used

- Fractional factorial design
  - Design in which only a fraction of all possible attribute level combinations is used
  - While it is possible to randomly select a specific number of combinations, this can lead to inefficient or sub-optimal designs
  - Instead, several scientific methods can be used to select more sophisticated optimal attribute level combinations
  - One popular approach is the orthogonal fractional factorial design, which is generated such that the attributes of the design are uncorrelated. However, the minimization of the correlations in this design generally does not lead to the statistically most efficient design.
- Optimal or statistically efficient designs
  - Optimal designs often allow for correlations across the attributes, but are statistically efficient
  - A popular criterion is the determinant of the variance-covariance matrix of the parameter vector that is estimated with ML in a model. The maximization of this determinant leads to D-optimal designs.
  - The value of this determinant (i.e. of the determinant of the inverse of the variance-covariance matrix) is the basis for the calculation of the level of D-efficiency

## Generation and selection of choice sets:

- Each attribute level combination from the experimental design is a separate potential choice set and thus provides the relevant information about the alternatives, attributes, and attribute levels in the hypothetical scenario
- In each choice set it is important that the attribute levels are well defined and clear for the respondents so that a mechanism of describing unambiguously each attribute level is required. One common approach is the inclusion of pictures (e.g. for the description of colors as attribute for cars).
- It is important to ensure that the decision in each choice set is independent to the decisions in all other choice sets, i.e. that the hypothetical scenarios in the choice sets cannot be compared
- Finally, a specific number (e.g. six or 12) of the possible choice sets from the experimental design must be randomly assigned to the respondents

## No choice option:

The decision whether to include the option to not choose an alternative should be based on the objective of the study. For example, if the demand for different alternatives in a market is considered, the inclusion of the no choice alternative is mostly useful, whereas the inclusion of the no choice option can be hindering in an analysis of the effect of different attribute levels. Without the no choice alternative, the analyzed decision is a conditional choice, i.e. conditional on choosing any alternative.

It is often (especially in the case of the valuation of public goods) useful to include the status quo (i.e. baseline) alternative besides other alternatives:


- In some cases, the inclusion of the status quo alternative as additional alternative represents an inclusion of RP data in SCE (e.g. in the choice among different electricity tariffs, the current electricity tariff can be included)
- The information of the current status quo alternative must be collected before the SCE in the survey so that it can be included in the experiment
- In contrast to the other alternatives, the status quo alternative and its attribute levels remain constant across all choice sets for the same respondent
- The individual attribute levels are often coordinated with the levels in the status quo to make the hypothetical scenarios more realistic for the respondent (e.g. the electricity costs as an attribute in the choice among different electricity tariffs can be very different across households)
- These customized attribute levels (which need not refer to the inclusion of the status quo alternative) are mostly based on percentage changes from the status quo levels (e.g. -10%, 0%, +10% of the current electricity costs)
- Commonly, not the percentage changes, but the respective values that are linked with the percentage changes are presented in the choice sets (e.g. 550 Euro instead of +10%, when 500 Euro is the cost value in the status quo), which can lead to very different values across the respondents

### 3.3 Examples

Choice set of a labeled SCE, i.e. choice among the six fresh fish and seafood alternatives saithe, pangasius, monkfish, oyster, mussel, and shrimp including a no choice option (see Nguyen et al., 2015, *Food Quality and Preference*, 225-236):

If this were the only “basket” of **fresh fish and seafood** available, please choose one product for your **household consumption for one normal dinner**. *You may choose one product or “None of these products”.*

<b>Saithe</b> Fillet Imported Wild catch 14.2 €/kg	<b>Pangasius</b> Steak Imported Farmed 10.3 €/kg	<b>Monkfish</b> Fillet Imported Wild catch 19.9 €/kg	
<b>Oyster</b> Chilled French Farmed 7.9 €/kg	<b>Mussel</b> Chilled French Farmed 3.9 €/kg	<b>Shrimp</b> Raw French Farmed 20.3 €/kg	
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>



None of these products

Choice set of a labeled SCE, i.e. choice among a conventional vehicle and three electric vehicles, i.e. a pure electric vehicle, an electric vehicle with range extender, and a plug-in hybrid vehicle (see Kanberger and Ziegler, 2024, *Transportation Research Part D* 126, 104031):

Let us start with the first set of choices. Which of the following four cars would you most likely choose?				
	Vehicle 1: Pure electric vehicle [Mouse click: Car powered exclusively by one or more electric motors]	Vehicle 2: Electric vehicle with range extender [Mouse click: Car powered by a combination of one or more electric motors plus a small gasoline or diesel engine for range extension]	Vehicle 3: Gasoline or diesel vehicle [Mouse click: Car powered exclusively by a gasoline or diesel engine]	Vehicle 4: Plug-in hybrid vehicle [Mouse click: Car powered by a combination of one or more small electric motors and a gasoline or diesel engine]
CO <sub>2</sub> emissions in use per 100 km	10.1 kg	11.2 kg	22.9 kg	21.2 kg
CO <sub>2</sub> emissions in the production	5,000 kg	5,800 kg	6,000 kg	8,600 kg
Range with a fully charged battery	300 km	400 km	-	150 km
Range with a full tank	-	50 km	900 km	400 km
Time to recharge the battery	180 minutes	60 minutes	-	120 minutes
Time to refuel the tank	-	2 minutes	3 minutes	5 minutes
Fuel costs per 100 km	3.50 Euro	7.20 Euro	5.50 Euro	7.50 Euro
Purchase price	8,400 Euro	15,600 Euro	14,400 Euro	12,000 Euro
My choice	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Would you rather not choose any of the cars shown above and prefer another car instead?				
<input type="checkbox"/> Yes <input type="checkbox"/> No				

Choice set of an unlabeled SCE, i.e. choice among three electricity tariffs including the five attributes location of electricity provider, electricity mix, guaranteed share of regionally generated electricity, customized electricity costs per year, type of electricity provider:

Please indicate the contract that you would most likely make among the following three contracts:			
	Contract 1	Contract 2	Contract 3
Location of the electricity provider	Within the own region	Outside the own region	Outside the own region
Energy mix in the chosen tariff	100% renewable energies (electricity provider sells both electricity from renewable energy sources and electricity produced from nuclear energy or fossil energy sources)	100% renewable energies (electricity provider only sells electricity from renewable energy sources)	Mix of renewable energies, fossil energy sources, and nuclear energy
Guaranteed share of electricity in the mix of the chosen contract that is produced within the own region	100%	0%	50%
Annual electricity costs	792 € / year	504 € / year	648 € / year
Type of the electricity provider	German national electricity provider	Foreign electricity supplier	Municipal or regional utility
	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>
Would you rather choose none of the previous electricity contracts and instead remain your current electricity contract? <input type="checkbox"/> Yes <input type="checkbox"/> No			

Choice set of an unlabeled SCE, i.e. choice among two wind energy policy options including a no choice option (see Dimitropoulos and Kontoleon, 2009, *Energy Policy*, 1842-1854):

	<b>Policy Option A</b>	<b>Policy Option B</b>	<b>None of them</b>
Wind Farm Size	<b>7-13 Wind turbines</b>	<b>21-40 Wind turbines</b>	
Wind Turbine Height	<b>90 meters</b>	<b>90 meters</b>	
Sited in a Special Protection/Conservation Area	<b>Yes</b>	<b>No</b>	<b>No new wind turbine</b>
Cooperation/Deliberation during the Planning Procedure	<b>No cooperation with the municipal authorities and local representatives</b>	<b>No cooperation with the municipal authorities and local representatives</b>	
Annual Subsidy per Household	<b>€ 100</b>	<b>€ 300</b>	<b>No Subsidy</b>
<b>Choose your most preferred option →</b>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

Choice set of an unlabeled SCE, i.e. choice among three new policy packages for the German energy transition and the status quo option with the five attributes targeted share of renewable energies until 2025, nuclear phase-out until 2022, burden sharing of the costs of the energy transition, financial support for low-income households, additional or reduced costs compared to the status quo (see Kanberger and Ziegler, 2023, *Energy Policy* 182, 113730):

Criteria	Policy package 1	Policy package 2	Policy package 3	None of the three policy packages (i. e. currently planned measures of the energy transition)
Targeted share of renewable energies in the power generation by 2025	40–45%	30–35%	55–60%	40–45%
Phase-out of all nuclear power plants by 2022	No	No	Yes	Yes
Participation of households in the costs of the energy transition	Each person should bear the same cost burden	Each household should bear costs in relation to its income	Each household should bear costs in relation to its energy consumption	Each household should bear costs in relation to its energy consumption
Financial support for low-income households	Financial support for the 10% poorest households	Financial support for the 30% poorest households	No financial support	No financial support
Additional or reduced monthly costs for your household compared to the currently planned measures of the energy transition	100 Euro more	50 Euro more	20 Euro more	The same costs
Your choice (please select your preferred policy package)	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

### 3.4 Econometric analysis

Due to the additional dimension of several choice sets for each respondent, the utility function in SCE has to be extended, i.e. the general utility (allowing for a random parameter specification) of respondent  $i$  ( $i = 1, \dots, n$ ) for alternative  $j$  ( $j = 1, \dots, J$ ) in choice set  $c$  ( $c = 1, \dots, C$ ) has a panel structure and thus is in the most general case:

$$u_{ijc} = \beta'_{ij} x_i + \gamma'_i z_{ijc} + \varepsilon_{ijc}$$

The realizations of the following dummy variables can be observed:

$$y_{ijc} = \begin{cases} 1 & \text{if } i \text{ chooses } j \text{ in choice set } c \\ 0 & \text{otherwise} \end{cases}$$

It is assumed that individual  $i$  chooses category  $j$  in choice set  $c$  if the utility of alternative  $j$  is the largest of all utilities, i.e.  $u_{ijc} > u_{ij'c}$  ( $i = 1, \dots, n$ ;  $c = 1, \dots, C$ ;  $j, j' = 1, \dots, J, j \neq j'$ )

The parameter vectors  $\beta_{ij}$  and  $\gamma_i$  are again summarized in  $\delta_i$ . Furthermore, by summarizing the  $k_2$ -dimensional vectors  $z_{ijc}$  in the  $J \cdot C \cdot k_2$ -dimensional vector  $z_i$  and then the  $k_1$ -dimensional vector  $x_i$  and  $z_i$  in the  $(k_1 + J \cdot C \cdot k_2)$ -dimensional vector  $X_i$ , the probabilities that  $i$  chooses  $j$  in  $c$  are:

$$p_{ijc}(X_i, \delta_i) = P(y_{ijc} = 1 | X_i, \delta_i) = P(u_{ijc} > u_{ij'c}; \forall j \neq j' | X_i, \delta_i)$$

## Multinomial logit models:

- In this case, the parameter vectors  $\beta_{ij}$  and  $\gamma_i$  are fixed so that it follows for the utility function:

$$u_{ijc} = \beta_j' x_i + \gamma' z_{ijc} + \varepsilon_{ijc}$$

- The  $\beta_j$  are again summarized in the  $J \cdot k_2$ -dimensional vector  $\beta$ . The assumption that the error terms  $\varepsilon_{ijc}$  are independently and identically standard extreme value distributed across all  $j = 1, \dots, J$  and all  $c = 1, \dots, C$  (and naturally also across all  $i = 1, \dots, n$ ) leads to the following choice probabilities:

$$p_{ijc}(X_i, \beta, \gamma) = P(y_{ijc} = 1 | X_i, \beta, \gamma) = \frac{e^{\beta_j' x_i + \gamma' z_{ijc}}}{\sum_{m=1}^J e^{\beta_m' x_i + \gamma' z_{imc}}}$$

- It follows for the log-likelihood function and the ML estimator:

$$\log L(\theta) = \sum_{i=1}^n \sum_{j=1}^J \sum_{c=1}^C y_{ijc} \log p_{ijc}(X_i, \beta, \gamma)$$

$$\hat{\theta}_{ML} = \arg \max_{\theta} \left[ \sum_{i=1}^n \sum_{j=1}^J \sum_{c=1}^C y_{ijc} \log p_{ijc}(X_i, \beta, \gamma) \right]$$

- However, the use of multinomial logit models on the basis of SCE data is even more restrictive since they do not only assume independence of the error terms over the  $J$  alternatives, but also over the  $C$  choice sets

## Multinomial probit models:

- As in the case of multinomial logit models the utility function is:

$$u_{ijc} = \beta_j' x_i + \gamma' z_{ijc} + \varepsilon_{ijc}$$

- By assuming that the error terms  $\varepsilon_{ijc}$  are jointly normally distributed with expectation zero and a  $J \cdot C$ -dimensional variance covariance matrix  $\Sigma$ , the choice probabilities for a specific choice set  $c$  are characterized by a  $(J-1)$ -dimensional integral:

$$\begin{aligned} p_{ijc}(X_i, \beta, \gamma, \Sigma) &= P\left(\varepsilon_{i1c} - \varepsilon_{ijc} < (\beta_j' x_i + \gamma' z_{ijc}) - (\beta_1' x_i + \gamma' z_{i1c}); \dots; \right. \\ &\quad \varepsilon_{i,j-1,c} - \varepsilon_{ijc} < (\beta_j' x_i + \gamma' z_{ijc}) - (\beta_{j-1}' x_i + \gamma' z_{i,j-1,c}); \\ &\quad \varepsilon_{i,j+1,c} - \varepsilon_{ijc} < (\beta_j' x_i + \gamma' z_{ijc}) - (\beta_{j+1}' x_i + \gamma' z_{i,j+1,c}); \dots; \\ &\quad \left. \varepsilon_{iJc} - \varepsilon_{ijc} < (\beta_j' x_i + \gamma' z_{ijc}) - (\beta_J' x_i + \gamma' z_{iJc})\right) \\ &= \int_{-\infty}^{(\beta_j' x_i + \gamma' z_{ijc}) - (\beta_1' x_i + \gamma' z_{i1c})} \dots \int_{-\infty}^{(\beta_j' x_i + \gamma' z_{ijc}) - (\beta_{j-1}' x_i + \gamma' z_{i,j-1,c})} \int_{-\infty}^{(\beta_j' x_i + \gamma' z_{ijc}) - (\beta_{j+1}' x_i + \gamma' z_{i,j+1,c})} \dots \int_{-\infty}^{(\beta_j' x_i + \gamma' z_{ijc}) - (\beta_J' x_i + \gamma' z_{iJc})} \\ &\quad \varphi_j(\omega_{1c}, \dots, \omega_{j-1,c}, \omega_{j+1,c}, \dots, \omega_{Jc}) d\omega_{1c} \dots d\omega_{j-1,c} d\omega_{j+1,c} \dots d\omega_{Jc} \end{aligned}$$

- If these choice probabilities are included in the likelihood or log-likelihood functions as in the case of multinomial logit models, it is assumed that the error terms are independent across all choice sets

- Generally, each individual has to decide among  $J^C$  alternative sequences across all  $C$  choice sets, i.e. in each choice set  $c$  a respondent has to choose one alternative  $j_{ic}$  (with  $j_{ic} = 1, \dots, J$ ). For flexible correlations across  $\varepsilon_{ijc}$  it follows for the probability that individual  $i$  chooses a specific category sequence  $s$  across all  $C$  choice sets:

$$p_{is}(\mathbf{X}_i, \beta, \gamma, \Sigma) = P(u_{ij_{ic}} > u_{ikc}; k, j_{ic} = 1, \dots, J; k \neq j_{ic}; \forall c; \mathbf{X}_i, \beta, \gamma)$$

$$\begin{aligned}
&= P(\varepsilon_{i11} - \varepsilon_{ij_{i1}} < (\beta'_{j_{i1}} - \beta'_1)\mathbf{x}_{i1} + \gamma'(z_{ij_{i1}1} - z_{i11}); \dots; \\
&\quad \varepsilon_{i,j_{i1}-1,1} - \varepsilon_{ij_{i1}} < (\beta'_{j_{i1}} - \beta'_{j_{i1}-1})\mathbf{x}_{i1} + \gamma'(z_{ij_{i1}1} - z_{i,j_{i1}-1,1}); \\
&\quad \varepsilon_{i,j_{i1}+1,1} - \varepsilon_{ij_{i1}} < (\beta'_{j_{i1}} - \beta'_{j_{i1}+1})\mathbf{x}_{i1} + \gamma'(z_{ij_{i1}1} - z_{i,j_{i1}+1,1}); \dots; \\
&\quad \varepsilon_{iJ1} - \varepsilon_{ij_{i1}} < (\beta'_{j_{i1}} - \beta'_J)\mathbf{x}_{i1} + \gamma'(z_{ij_{i1}1} - z_{iJ1}); \dots; \\
&\quad \varepsilon_{i1C} - \varepsilon_{ij_{iC}} < (\beta'_{j_{iC}} - \beta'_1)\mathbf{x}_{iC} + \gamma'(z_{ij_{iC}1} - z_{i1C}); \dots \\
&\quad \varepsilon_{i,j_{iC}-1,C} - \varepsilon_{ij_{iC}} < (\beta'_{j_{iC}} - \beta'_{j_{iC}-1})\mathbf{x}_{iC} + \gamma'(z_{ij_{iC}1} - z_{i,j_{iC}-1,C}); \\
&\quad \varepsilon_{i,j_{iC}+1,C} - \varepsilon_{ij_{iC}} < (\beta'_{j_{iC}} - \beta'_{j_{iC}+1})\mathbf{x}_{iC} + \gamma'(z_{ij_{iC}1} - z_{i,j_{iC}+1,C}); \dots; \\
&\quad \varepsilon_{iJC} - \varepsilon_{ij_{iC}} < (\beta'_{j_{iC}} - \beta'_J)\mathbf{x}_{iC} + \gamma'(z_{ij_{iC}1} - z_{iJC})) \\
&= \int_{-\infty}^{(\beta'_{j_{i1}}\mathbf{x}_{i1} + \gamma'z_{ij_{i1}1}) - (\beta'_1\mathbf{x}_{i1} + \gamma'z_{i11})} \dots \int_{-\infty}^{(\beta'_{j_{iC}}\mathbf{x}_{iC} + \gamma'z_{ij_{iC}1}) - (\beta'_J\mathbf{x}_{iC} + \gamma'z_{iJC})} \\
&\varphi_s(\omega_{11}, \dots, \omega_{j_{i1}-1,1}, \omega_{j_{i1}+1,1}, \dots, \omega_{J1}, \dots, \omega_{1C}, \dots, \omega_{j_{iC}-1,C}, \omega_{j_{iC}+1,C}, \dots, \omega_{JC}) \\
&d\omega_{11} \cdots d\omega_{j_{i1}-1,1} d\omega_{j_{i1}+1,1} \cdots d\omega_{J1} \cdots d\omega_{1C} \cdots d\omega_{j_{iC}-1,C} d\omega_{j_{iC}+1,C} \cdots d\omega_{JC}
\end{aligned}$$

- Dependent on the category sequence  $s$ ,  $\varphi_s(\cdot)$  is the joint density function of the normally distributed differences of  $\varepsilon_{ijc}$ . The choice probabilities are now characterized by  $(J-1) \cdot C$ -dimensional integrals in the most flexible approaches.
- However, the huge number of variance covariance parameters even for moderate values of  $J$  and  $C$  can hardly be identified in practice, i.e. in the estimation procedure
- Against this background, some panel data approaches (i.e. multiperiod multinomial probit models) include some structure in the variance covariance parameters (besides the relationships between the alternatives) which refer to unobserved heterogeneity and intertemporal autoregressive correlations. In the case of SCE these correlations refer to taste persistence and memory effects across the choice sets, i.e.:

$$\varepsilon_{ijc} = \alpha_{ij} + v_{ijc} \quad \text{with} \quad v_{ijc} = \rho_j v_{i,j,c-1} + \sqrt{1-\rho_j^2} \eta_{ijc}$$

- The normally distributed  $\eta_{ijc}$  comprise correlations between the alternatives, the  $\rho_j$  denote autocorrelation coefficients and thus possible memory effects, and the normally distributed  $\alpha_{ij}$  represent stochastic effects that are invariant across the choice sets and thus refer to taste persistence
- Such approaches strongly decrease the number of model parameters compared to the case without variance covariance structure

- In the general case, the choice probabilities have again to be simulated (e.g. by the GHK simulator) with  $\tilde{p}_{is}(X_i, \beta, \gamma, \Sigma)$
- For the SML estimation, the following observable dummy variables are defined:

$$y_{is} = \begin{cases} 1 & \text{if } i \text{ chooses alternative sequence } s \\ 0 & \text{otherwise} \end{cases}$$

- It follows for the specific simulated log-likelihood function and the SML estimator:

$$\log \tilde{L}(\beta, \gamma, \Sigma) = \sum_{i=1}^n \sum_s y_{is} \log \tilde{p}_{is}(X_i, \beta, \gamma, \Sigma)$$

$$\hat{\theta}_{\text{SML}} = \arg \max_{\theta} \left[ \sum_{i=1}^n \sum_s y_{is} \log \tilde{p}_{is}(X_i, \beta, \gamma, \Sigma) \right]$$

- While the simplifying approaches as discussed above strongly decrease the number of model parameters in the SML estimation, they are mostly not included in common econometric software packages such as Stata (only correlations across the alternatives are considered), which makes the use of multinomial probit models for SCE data less attractive than the use of mixed logit models

## Mixed logit models:

- By assuming that the  $\varepsilon_{ijc}$  are independently and identically standard extreme value distributed and the parameter vectors  $\beta_{ij}$  and  $\gamma_i$  (summarized in  $\delta_i$ ) are random, it follows for the conditional choice probabilities:

$$p_{ijc}(\mathbf{X}_i | \delta_i) = P(y_{ijc} = 1 | \mathbf{X}_i, \delta_i) = \frac{e^{\beta'_{ij}\mathbf{X}_i + \gamma'_i Z_{ijc}}}{\sum_{m=1}^J e^{\beta'_{im}\mathbf{X}_i + \gamma'_i Z_{imc}}}$$

- Especially with respect to unlabeled SCE, however, it is more common to only consider choice probabilities with alternative specific attributes:

$$p_{ijc}(\mathbf{X}_i | \gamma_i) = \frac{e^{\gamma'_i Z_{ijc}}}{\sum_{m=1}^J e^{\gamma'_i Z_{imc}}}$$

- If  $p_{ijc}(\mathbf{X}_i | \gamma_i)$  symbolizes the conditional probability that a specific alternative  $j_{ic}$  (with  $j_{ic} = 1, \dots, J$ ) is chosen by respondent  $i$  in choice set  $c$ , the joint conditional probabilities of the observed sequence  $s$  of choices across all  $C$  choice sets are:

$$p_{is}(\mathbf{X}_i | \gamma_i) = \prod_{c=1}^C p_{ij_{ic}}(\mathbf{X}_i | \gamma_i) = \prod_{c=1}^C \frac{e^{\gamma'_i Z_{ij_{ic}c}}}{\sum_{m=1}^J e^{\gamma'_i Z_{imc}}}$$

- It follows for the unconditional choice probabilities:

$$p_{is}(X_i) = \int \prod_{c=1}^C \frac{e^{\gamma'z_{ijic}}}{\sum_{m=1}^J e^{\gamma'z_{imc}}} f(\gamma) d\gamma$$

- If  $f(\gamma|b, W)$  is the density function of normally distributed vectors with expectation  $b$  and variance covariance matrix  $W$ , it specifically follows:

$$p_{is}(X_i, b, W) = \int \prod_{c=1}^C \frac{e^{\gamma'z_{ijic}}}{\sum_{m=1}^J e^{\gamma'z_{imc}}} \phi(\gamma|b, W) d\gamma$$

- These probabilities can again be approximated by the mixed logit model simulator:

$$\tilde{p}_{is}(X_i, b, W) = \frac{1}{R} \sum_{r=1}^R \prod_{c=1}^C \frac{e^{\gamma_r'z_{ijic}}}{\sum_{m=1}^J e^{\gamma_r'z_{imc}}}$$

- It follows for the specific SML estimator:

$$\hat{\theta}_{SML} = \arg \max_{\theta} \left[ \sum_{i=1}^n \log \left( \frac{1}{R} \sum_{r=1}^R \prod_{c=1}^C \frac{e^{\gamma_r'z_{ijic}}}{\sum_{m=1}^J e^{\gamma_r'z_{imc}}} \right) \right]$$

## Latent class logit models:

- The basis is the following utility function of respondent  $i$  for alternative  $j$  in choice set  $c$  with only alternative specific attributes:

$$u_{ijc} = \gamma_q' z_{ijc} + \varepsilon_{ijc}$$

- By assuming that the  $\varepsilon_{ijc}$  are independently and identically standard extreme value distributed, it follows for the probabilities that  $i$  chooses  $j$  in choice set  $c$  under the condition that  $i$  belongs to class  $q$ :

$$p_{ijcq}(z_i | \gamma_q) = \frac{e^{\gamma_q' z_{ijc}}}{\sum_{m=1}^J e^{\gamma_q' z_{imc}}}$$

- If  $p_{ijcq}(X_i | Y_i)$  symbolizes the conditional probability that a specific alternative  $j_{ic}$  (with  $j_{ic} = 1, \dots, J$ ) is chosen by respondent  $i$  in class  $q$  in choice set  $c$ , the joint conditional probabilities of the observed sequence  $s$  of choices across all  $C$  choice sets are:

$$p_{iqs}(z_i | \gamma_q) = \prod_{c=1}^C p_{ijcq}(z_i | \gamma_q) = \prod_{c=1}^C \frac{e^{\gamma_q' z_{ijcc}}}{\sum_{m=1}^J e^{\gamma_q' z_{imc}}}$$

- By including the multinomial logit model formula in the class membership model, the probability that  $i$  belongs to class  $q$  is again:

$$H_{iq} = \frac{e^{\beta'_q x_i}}{\sum_{q'=1}^Q e^{\beta'_{q'} x_i}}$$

- It follows for the unconditional probabilities of the observed sequence  $s$  of choices across all  $M$  choice sets:

$$p_{is}(z_i) = \sum_{q=1}^Q H_{iq} p_{iqs}(z_i | \gamma_q) = \sum_{q=1}^Q \left[ \frac{e^{\beta'_q x_i}}{\sum_{q'=1}^Q e^{\beta'_{q'} x_i}} \prod_{c=1}^C \frac{e^{\gamma'_q z_{ijc} c}}{\sum_{m=1}^J e^{\gamma'_q z_{imc}}} \right]$$

- Finally, it follows for the ML estimator:

$$\hat{\theta}_{ML} = \arg \max_{\theta} \left[ \sum_{i=1}^n \log \left( \sum_{q=1}^Q \left[ \frac{e^{\beta'_q x_i}}{\sum_{q'=1}^Q e^{\beta'_{q'} x_i}} \prod_{c=1}^C \frac{e^{\gamma'_q z_{ijc} c}}{\sum_{m=1}^J e^{\gamma'_q z_{imc}}} \right] \right) \right]$$

## 3.5 Applications

---

Example 1: Energy sources and propulsion technologies in vehicles (I)

In Ziegler (2012, *Transportation Research Part A* 46, 1372-1385), an SCE (that is based on a computer-randomized fractional factorial design) with respect to the preferences for alternative energy sources or propulsion technologies in vehicles is examined:

- The data stem from Computer Assisted Personal Interviews (CAPI), conducted in selected car dealerships and technical inspection agencies (TÜV) between August 2007 and March 2008
- 598 persons from the population of German residents with valid drivers' licenses, who intend or at least could imagine to purchase a vehicle in the near future, participated in the survey
- The people were asked for details (e.g. size, motor power) of the currently used and future vehicle as well as for socio-demographic variables (e.g. age, gender, education)
- The SCE comprises six choice sets with seven hypothetical vehicles types
- It is a quasi-labeled experiment, i.e. each of the seven vehicles refers to exactly one energy source or propulsion technology
- The vehicles were additionally characterized by five attributes

---

## Example 1: Energy sources and propulsion technologies in vehicles (II)

### Alternatives:

- Gasoline
- Diesel
- Hybrid
- Gas (i.e. natural gas, liquid petroleum gas)
- Biofuel
- Hydrogen
- Electric

### Further attributes:

- Purchase price (in Euro)
  - Motor power (in horsepower)
  - Fuel costs (in Euro per 100 kilometers)
  - CO<sub>2</sub> emissions (in gram per kilometer)
  - Service station availability (in % of stations with respective fuel)
-

---

## Example 1: Energy sources and propulsion technologies in vehicles (III)

### Attribute levels:

- Customized purchase price: 75%, 100%, 125% of stated values for all vehicle types
- Customized motor power: 75%, 100%, 125% of stated values for all vehicle types
- Fuel costs: 5 Euro, 10 Euro, 20 Euro for all vehicle types
- CO<sub>2</sub> emissions: 90 gram, 170 gram, 250 gram for gasoline, diesel, hybrid, and gas vehicles, „no emissions“, 90 gram, 170 gram, 250 gram for biofuel, hydrogen, and electric vehicles
- Service station availability: 60%, 100% for gasoline and diesel vehicles, 20%, 60%, 100% for hybrid, gas, biofuel, hydrogen, and electric vehicles

### Dependent variable:

Choice between gasoline, diesel, hybrid, gas, biofuel, hydrogen, and electric vehicles, whereby gasoline vehicles is chosen as base category

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---

## Example 1: Energy sources and propulsion technologies in vehicles (IV)

### Alternative specific attributes:

- Purchase price in two variants
  - Divided by 100000 (price\_100000)
  - In decimals with respect to the customization (price\_decimal)
- Motor power in two variants
  - Divided by 1000 (motorpower\_1000)
  - In decimals with respect to the customization (motorpower\_decimal)
- Fuel costs divided by 100 (fuelcosts\_100)
- CO<sub>2</sub> emissions divided by 1000 (CO2emissions\_1000)
- Service station availability divided by 100 (servicestation\_100)

### Individual characteristics:

- Age in years divided by 100 (age\_100)
  - Gender dummy (male)
  - Dummy for environmental-friendly purchases (environment\_friendly)
-

---

## Example 1: Energy sources and propulsion technologies in vehicles (V)

The following estimations are considered:

- ML estimation of the conditional logit model and SML estimation (with  $R = 50$ ) of the independent multinomial probit model (with robustly estimated variances) with all alternative specific attributes (two different variants, respectively) and alternative specific constants
- ML estimation of the full multinomial logit model (without robustly estimated variances and with `price_decimal` and `motorpower_decimal`)
- A Hausman-McFadden test (but SML estimations of more flexible full multinomial probit model mostly do not converge to a maximum)
- SML estimation of a mixed logit model (with  $R = 100$  Halton draws and robustly estimated variances) with all alternative specific attributes and alternative specific constants, whereby the parameters of the alternative specific attributes (except `price_decimal`) are assumed to be normally distributed
- SML estimation of a full mixed logit model (with  $R = 5$  Halton draws), whereby the parameters of the alternative specific attributes are normally distributed (except for `price_decimal`)
- Simulated likelihood ratio test for the validity of a multinomial logit model
- Estimation of several WTP

# Example 1: Energy sources and propulsion technologies in vehicles (VI)

```
asclogit choice price_100000 motorpower_1000 fuelcosts_100 CO2emissions_1000 servicestation_100, case(choiceaset)
alternatives(alternatives) base(gasoline) robust
```

```
Alternative-specific conditional logit      Number of obs      =      25116
Case variable: choiceaset                 Number of cases     =      3588
Alternative variable: alternatives         Alts per case: min =      7
                                           avg =      7.0
                                           max =      7
                                           Wald chi2(5)       =     1092.67
Log pseudolikelihood = -6115.6117         Prob > chi2         =      0.0000
```

(Std. Err. adjusted for clustering on choiceaset)

choice	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
alternatives						
price_100000	-3.689678	.3617452	-10.20	0.000	-4.398685	-2.98067
motorpower_1000	5.942402	.6453878	9.21	0.000	4.677466	7.207339
fuelcosts_100	-7.528909	.3306354	-22.77	0.000	-8.176943	-6.880876
CO2emissions_1000	-4.124038	.2818152	-14.63	0.000	-4.676386	-3.571691
servicestation_100	1.232526	.0607206	20.30	0.000	1.113516	1.351537
biofuel						
_cons	-.6258317	.0707213	-8.85	0.000	-.7644428	-.4872205
diesel						
_cons	.0869089	.0549912	1.58	0.114	-.0208719	.1946896
electric						
_cons	-.9183785	.0760347	-12.08	0.000	-1.067404	-.7693532
gas						
_cons	-.2106324	.0645314	-3.26	0.001	-.3371116	-.0841532
gasoline (base alternative)						
hybrid						
_cons	-.1594116	.0633919	-2.51	0.012	-.2836575	-.0351658
hydrogen						
_cons	-.321559	.0658271	-4.88	0.000	-.4505778	-.1925402

# Example 1: Energy sources and propulsion technologies in vehicles (VII)

```
asmprobit choice price_100000 motorpower_1000 fuelcosts_100 CO2emissions_1000 servicestation_100, case(choicest)
alternatives(alternatives) correlation(independent) stddev(homoskedastic) base(gasoline) intpoints(50) robust
```

```
Alternative-specific multinomial probit      Number of obs      =      25116
Case variable: choicest                     Number of cases    =      3588
Alternative variable: alternatives          Alts per case: min =      7
                                              avg =      7.0
                                              max =      7
```

```
Integration sequence:      Hammersley
Integration points:        50      Wald chi2(5)      =      1049.43
Log simulated-pseudolikelihood = -6127.711      Prob > chi2      =      0.0000
```

(Std. Err. adjusted for clustering on choicest)

choice	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
-----						
alternatives						
price_100000	-2.278243	.2494233	-9.13	0.000	-2.767104	-1.789383
motorpower_1000	3.793377	.4130764	9.18	0.000	2.983762	4.602991
fuelcosts_100	-4.659235	.2046631	-22.77	0.000	-5.060367	-4.258103
CO2emissions_1000	-2.51397	.1756331	-14.31	0.000	-2.858204	-2.169735
servicestation_100	.7763197	.0389192	19.95	0.000	.7000395	.8525998
-----						
biofuel						
_cons	-.3960761	.0453435	-8.74	0.000	-.4849479	-.3072044
-----						
diesel						
_cons	.0601152	.0374664	1.60	0.109	-.0133175	.1335479
-----						
electric						
_cons	-.5842113	.0476469	-12.26	0.000	-.6775975	-.4908252
-----						
gas						
_cons	-.1360489	.0421063	-3.23	0.001	-.2185757	-.0535221
-----						
gasoline						
	(base alternative)					
-----						
hybrid						
_cons	-.1103021	.0416094	-2.65	0.008	-.1918551	-.0287492
-----						
hydrogen						
_cons	-.2024039	.0430118	-4.71	0.000	-.2867055	-.1181023
-----						

# Example 1: Energy sources and propulsion technologies in vehicles (VIII)

```
asclogit choice price_decimal motorpower_decimal fuelcosts_100 CO2emissions_1000 servicestation_100, case(choicest)
alternatives(alternatives) base(gasoline) robust
```

```
Alternative-specific conditional logit      Number of obs      =      25116
Case variable: id                        Number of cases     =      3588
Alternative variable: alternatives        Alts per case: min =      7
                                           avg =      7.0
                                           max =      7
                                           Wald chi2(5)       =     1063.69
Log pseudolikelihood = -6141.756          Prob > chi2         =      0.0000
```

(Std. Err. adjusted for clustering on id)

choice	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
alternatives						
price_decimal	-.9513986	.088458	-10.76	0.000	-1.124773	-.7780242
motorpower_decimal	.4919794	.1085127	4.53	0.000	.2792985	.7046603
fuelcosts_100	-7.571348	.3293427	-22.99	0.000	-8.216848	-6.925848
CO2emissions_1000	-4.115056	.2810027	-14.64	0.000	-4.665811	-3.564301
servicestation_100	1.223275	.060173	20.33	0.000	1.105338	1.341212
biofuel						
_cons	-.6287628	.0705405	-8.91	0.000	-.7670196	-.490506
diesel						
_cons	.089125	.0548691	1.62	0.104	-.0184165	.1966664
electric						
_cons	-.9209775	.07597	-12.12	0.000	-1.069876	-.7720791
gas						
_cons	-.2060089	.06458	-3.19	0.001	-.3325834	-.0794344
gasoline (base alternative)						
hybrid						
_cons	-.1581784	.0633614	-2.50	0.013	-.2823643	-.0339924
hydrogen						
_cons	-.3186239	.06567	-4.85	0.000	-.4473347	-.1899131

# Example 1: Energy sources and propulsion technologies in vehicles (IX)

```
asmprobit choice price_decimal motorpower_decimal fuelcosts_100 CO2emissions_1000 servicestation_100, case(choiceset)
alternatives(alternatives) correlation(independent) stddev(homoskedastic) base(gasoline) intpoints(50) robust
```

```
Alternative-specific multinomial probit      Number of obs      =      25116
Case variable: id                          Number of cases     =      3588
Alternative variable: alternatives           Alts per case: min =      7
                                              avg =      7.0
                                              max =      7
Integration sequence:                      Hammersley
Integration points:                        50                Wald chi2(5)       =      1028.44
Log simulated-pseudolikelihood = -6154.4005        Prob > chi2        =      0.0000
```

(Std. Err. adjusted for clustering on id)

choice	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
alternatives						
price_decimal	-.5823166	.0557268	-10.45	0.000	-.6915392	-.4730941
motorpower_decimal	.3102772	.07013	4.42	0.000	.172825	.4477295
fuelcosts_100	-4.68001	.1982548	-23.61	0.000	-5.068583	-4.291438
CO2emissions_1000	-2.503315	.1684615	-14.86	0.000	-2.833494	-2.173137
servicestation_100	.7718634	.0383062	20.15	0.000	.6967846	.8469422
biofuel						
_cons	-.3974431	.0454821	-8.74	0.000	-.4865863	-.3082999
diesel						
_cons	.0598091	.0374048	1.60	0.110	-.0135029	.1331211
electric						
_cons	-.5847496	.0474987	-12.31	0.000	-.6778453	-.4916539
gas						
_cons	-.1328942	.0422736	-3.14	0.002	-.215749	-.0500394
gasoline (base alternative)						
hybrid						
_cons	-.109475	.0417199	-2.62	0.009	-.1912445	-.0277056
hydrogen						
_cons	-.2019579	.0408415	-4.94	0.000	-.2820058	-.12191

## Example 1: Energy sources and propulsion technologies in vehicles (X)

```
asclogit choice price_decimal motorpower_decimal fuelcosts_100 CO2emissions_1000 servicestation_100,
case(choiceset) alternatives(alternatives) casevars(age_100 male environment_friendly) base(gasoline)
```

```
Alternative-specific conditional logit      Number of obs      =      25116
Case variable: id                        Number of cases    =      3588
Alternative variable: alternatives        Alts per case: min =      7
                                           avg =      7.0
                                           max =      7
                                           Wald chi2(23)     =      1304.16
Log likelihood = -6060.8399                Prob > chi2        =      0.0000
```

choice	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
alternatives						
price_decimal	-.9487371	.088781	-10.69	0.000	-1.122745	-.7747296
motorpower_decimal	.4837028	.1107786	4.37	0.000	.2665806	.7008249
fuelcosts_100	-7.631049	.3260682	-23.40	0.000	-8.270131	-6.991967
CO2emissions_1000	-4.175772	.2779365	-15.02	0.000	-4.720518	-3.631027
servicestation_100	1.234832	.0610008	20.24	0.000	1.115273	1.354392
biofuel						
age_100	-2.562941	.4518629	-5.67	0.000	-3.448576	-1.677306
male	.1996596	.1465551	1.36	0.173	-.0875832	.4869024
environment_friendly	.6928068	.1451092	4.77	0.000	.4083979	.9772156
_cons	.1747254	.2188197	0.80	0.425	-.2541534	.6036041
diesel						
age_100	-1.59606	.3667013	-4.35	0.000	-2.314781	-.8773383
male	.5861857	.1290669	4.54	0.000	.3332191	.8391523
environment_friendly	-.0562276	.1284784	-0.44	0.662	-.3080407	.1955854
_cons	.4156353	.1861066	2.23	0.026	.0508731	.7803974

## Example 1: Energy sources and propulsion technologies in vehicles (XI)

-----							
electric							
	age_100	-3.748376	.4972008	-7.54	0.000	-4.722872	-2.773881
	male	.3511305	.1605061	2.19	0.029	.0365443	.6657167
environment_friendly		.6176549	.159052	3.88	0.000	.3059188	.9293911
	_cons	.3139058	.2351709	1.33	0.182	-.1470208	.7748323
-----							
gas							
	age_100	-3.133422	.4372221	-7.17	0.000	-3.990361	-2.276482
	male	.5779072	.1487424	3.89	0.000	.2863774	.8694371
environment_friendly		.2334947	.1478441	1.58	0.114	-.0562743	.5232637
	_cons	.7257773	.2116237	3.43	0.001	.3110025	1.140552
-----							
gasoline		(base alternative)					
-----							
hybrid							
	age_100	-1.882713	.4233082	-4.45	0.000	-2.712382	-1.053044
	male	.4848538	.1462962	3.31	0.001	.1981186	.771589
environment_friendly		.3669965	.1419393	2.59	0.010	.0888005	.6451925
	_cons	.2569248	.2099813	1.22	0.221	-.1546309	.6684805
-----							
hydrogen							
	age_100	-2.868189	.4129016	-6.95	0.000	-3.677461	-2.058917
	male	.6137354	.1410775	4.35	0.000	.3372286	.8902422
environment_friendly		.6222545	.1352587	4.60	0.000	.3571524	.8873567
	_cons	.343097	.2041127	1.68	0.093	-.0569565	.7431505
-----							

estimates store allalt

## Example 1: Energy sources and propulsion technologies in vehicles (XII)

```
asclogit choice price_decimal motorpower_decimal fuelcosts_100 CO2emissions_1000 servicestation_100 if
energysource != 3 & energysource != 4, case(choiceset) alternatives(alternatives) casevars(age_100 male
environment_friendly) base(gasoline)
```

```
Alternative-specific conditional logit      Number of obs      =      13785
Case variable: id                        Number of cases    =      2757

Alternative variable: alternatives        Alts per case: min =      5
                                           avg =      5.0
                                           max =      5

                                           Wald chi2(17)     =      880.49
                                           Prob > chi2       =      0.0000

Log likelihood = -3785.0231
```

choice	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
-----						
alternatives						
price_decimal	-.9736709	.1064197	-9.15	0.000	-1.18225	-.7650922
motorpower_decimal	.4152834	.1334683	3.11	0.002	.1536904	.6768764
fuelcosts_100	-7.54238	.3851393	-19.58	0.000	-8.297239	-6.787521
CO2emissions_1000	-4.167421	.3342439	-12.47	0.000	-4.822527	-3.512315
servicestation_100	1.233177	.0779781	15.81	0.000	1.080343	1.386011
-----						
diesel						
age_100	-1.477723	.3628389	-4.07	0.000	-2.188874	-.7665715
male	.5868516	.1302823	4.50	0.000	.331503	.8422001
environment_friendly	-.0537079	.130038	-0.41	0.680	-.3085778	.2011619
_cons	.3530199	.1860886	1.90	0.058	-.011707	.7177468
-----						
electric						
age_100	-3.555125	.4921031	-7.22	0.000	-4.519629	-2.590621
male	.3199779	.1621268	1.97	0.048	.0022152	.6377405
environment_friendly	.5792934	.1611062	3.60	0.000	.263531	.8950558
_cons	.2431727	.2361371	1.03	0.303	-.2196475	.7059929
-----						
gasoline						
	(base alternative)					
-----						
hybrid						
age_100	-1.672995	.4181398	-4.00	0.000	-2.492534	-.8534563
male	.4580474	.1477446	3.10	0.002	.1684732	.7476216
environment_friendly	.3534737	.1434089	2.46	0.014	.0723975	.6345499
_cons	.1762681	.2101444	0.84	0.402	-.2356075	.5881436
-----						
hydrogen						
age_100	-2.662978	.4078856	-6.53	0.000	-3.462419	-1.863536
male	.5663865	.1427493	3.97	0.000	.2866029	.84617
environment_friendly	.5759117	.1369431	4.21	0.000	.307508	.8443153
_cons	.2943916	.2056368	1.43	0.152	-.1086491	.6974322
-----						

# Example 1: Energy sources and propulsion technologies in vehicles (XIII)

hausman allalt, alleqs

	---- Coefficients ----			
	(b)	(B)	(b-B)	sqrt(diag(V_b-V_B))
	allalt	.	Difference	S.E.
-----				
alternatives				
price_deci~1	-.9487371	-.9736709	.0249337	.
motorpower~1	.4837028	.4152834	.0684193	.
fuelcost~100	-7.631049	-7.54238	-.0886684	.
CO2emis~1000	-4.175772	-4.167421	-.0083514	.
services~100	1.234832	1.233177	.0016556	.
-----				
diesel				
age_100	-1.59606	-1.477723	-.1183369	.0530827
male	.5861857	.5868516	-.0006659	.
environmen~y	-.0562276	-.0537079	-.0025197	.
-----				
electric				
age_100	-3.748376	-3.555125	-.1932514	.0710159
male	.3511305	.3199779	.0311526	.
environmen~y	.6176549	.5792934	.0383615	.
-----				
hybrid				
age_100	-1.882713	-1.672995	-.209718	.0659466
male	.4848538	.4580474	.0268064	.
environmen~y	.3669965	.3534737	.0135228	.
-----				
hydrogen				
age_100	-2.868189	-2.662978	-.2052112	.0641641
male	.6137354	.5663865	.0473489	.
environmen~y	.6222545	.5759117	.0463429	.

b = consistent under Ho and Ha; obtained from asclogit

B = inconsistent under Ha, efficient under Ho; obtained from asclogit

Test: Ho: difference in coefficients not systematic

chi2(17) = (b-B)' [(V\_b-V\_B)^(-1)] (b-B)  
 = 61.10  
 Prob>chi2 = 0.0000  
 (V\_b-V\_B is not positive definite)

## Example 1: Energy sources and propulsion technologies in vehicles (XIV)

```

mixlogit choice price_decimal diesel gas biofuel hydrogen hybrid electric,
group(choiceset) id(individuals) rand(motorpower_decimal fuelcosts_100
CO2emissions_1000 servicestation_100) nrep(100) robust

```

```

Mixed logit model                               Number of obs   =       25116
                                                Wald chi2(11)   =       704.67
Log likelihood = -5893.353                       Prob > chi2     =       0.0000

```

choice	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
Mean						
price_decimal	-1.152931	.1197803	-9.63	0.000	-1.387696	-.918166
diesel	.114394	.0970001	1.18	0.238	-.0757227	.3045108
gas	-.2601992	.109164	-2.38	0.017	-.4741566	-.0462417
biofuel	-.8163822	.1087872	-7.50	0.000	-1.029601	-.6031632
hydrogen	-.4452178	.1117935	-3.98	0.000	-.664329	-.2261066
hybrid	-.2064548	.1038973	-1.99	0.047	-.4100897	-.0028198
electric	-1.149051	.1149146	-10.00	0.000	-1.374279	-.9238223
motorpower_decimal	.5606585	.1533231	3.66	0.000	.2601507	.8611664
fuelcosts_100	-10.38913	.6569293	-15.81	0.000	-11.67669	-9.10157
CO2emissions_1000	-5.072652	.407195	-12.46	0.000	-5.870739	-4.274564
servicestation_100	1.515371	.1045673	14.49	0.000	1.310423	1.720319
SD						
motorpower_decimal	1.657275	.2688995	6.16	0.000	1.130241	2.184308
fuelcosts_100	9.506411	.7197837	13.21	0.000	8.095661	10.91716
CO2emissions_1000	6.318972	.4597666	13.74	0.000	5.417846	7.220098
servicestation_100	1.683082	.1190606	14.14	0.000	1.449728	1.916437

## Example 1: Energy sources and propulsion technologies in vehicles (XV)

```

mixlogit choice price_decimal diesel gas biofuel hydrogen hybrid electric age_diesel age_gas
age_biofuel age_hydrogen age_hybrid age_electric male_diesel male_gas male_biofuel
male_hydrogen male_hybrid male_electric env_diesel env_gas env_biofuel env_hydrogen env_hybrid
env_electric, group(choiceset) id(individuals) rand(motorpower_decimal fuelcosts_100
CO2emissions_1000 servicestation_100) nrep(5)

```

Mixed logit model

Number of obs = 25116

LR chi2(4) = 252.43

Log likelihood = -5934.6262

Prob > chi2 = 0.0000

choice	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
Mean						
price_decimal	-1.032654	.0943062	-10.95	0.000	-1.217491	-.847817
diesel	.4778174	.1920106	2.49	0.013	.1014835	.8541512
gas	.861209	.2192962	3.93	0.000	.4313963	1.291022
biofuel	.2782128	.232375	1.20	0.231	-.1772337	.7336594
hydrogen	.3371377	.2186315	1.54	0.123	-.0913721	.7656476
hybrid	.3603566	.2167583	1.66	0.096	-.0644819	.785195
electric	.3766095	.2519047	1.50	0.135	-.1171147	.8703337
age_diesel	-.0174023	.0037944	-4.59	0.000	-.0248391	-.0099655
age_gas	-.0355684	.0045697	-7.78	0.000	-.0445249	-.026612
age_biofuel	-.0305214	.0048031	-6.35	0.000	-.0399353	-.0211076
age_hydrogen	-.0314858	.0044428	-7.09	0.000	-.0401934	-.0227782
age_hybrid	-.0215847	.0043804	-4.93	0.000	-.0301701	-.0129992
age_electric	-.0419787	.005316	-7.90	0.000	-.052398	-.0315595
male_diesel	.6239399	.1338339	4.66	0.000	.3616304	.8862495
male_gas	.622389	.1549903	4.02	0.000	.3186137	.9261644
male_biofuel	.2201399	.1569898	1.40	0.161	-.0875544	.5278342
male_hydrogen	.7132127	.15203	4.69	0.000	.4152394	1.011186
male_hybrid	.5021938	.1522135	3.30	0.001	.2038609	.8005267
male_electric	.3860522	.1712318	2.25	0.024	.0504441	.7216603

---

## Example 1: Energy sources and propulsion technologies in vehicles (XVI)

---

env_diesel	-.0581815	.1330155	-0.44	0.662	-.3188872	.2025241
env_gas	.2444517	.1536347	1.59	0.112	-.0566668	.5455703
env_biofuel	.7172262	.1547238	4.64	0.000	.4139732	1.020479
env_hydrogen	.6128832	.1460365	4.20	0.000	.3266569	.8991096
env_hybrid	.3709122	.1474779	2.52	0.012	.0818609	.6599636
env_electric	.6119939	.1695082	3.61	0.000	.2797639	.9442239
motorpower_decimal	.5443154	.1178504	4.62	0.000	.3133329	.7752978
fuelcosts_100	-8.656736	.4241358	-20.41	0.000	-9.488026	-7.825445
CO2emissions_1000	-4.697025	.3377086	-13.91	0.000	-5.358922	-4.035129
servicestation_100	1.316358	.0745108	17.67	0.000	1.170319	1.462396
<hr/>						
SD						
motorpower_decimal	.0233069	.3343648	0.07	0.944	-.6320361	.6786499
fuelcosts_100	-6.080686	.6500041	-9.35	0.000	-7.354671	-4.806702
CO2emissions_1000	4.922441	.4547904	10.82	0.000	4.031068	5.813814
servicestation_100	1.158471	.1103848	10.49	0.000	.942121	1.374821

---

estimates store mixlogit

```
asclogit choice price_decimal motorpower_decimal fuelcosts_100 CO2emissions_1000
servicestation_100, case(choiceset) alternatives(alternatives) casevars(age_100 male
environment_friendly) base(gasoline)
```

lrtest mixlogit, force

```
Likelihood-ratio test                    LR chi2(4) =    252.43
(Assumption: . nested in mixlogit)       Prob > chi2 =    0.0000
```

---

## Example 1: Energy sources and propulsion technologies in vehicles (XVII)

Estimated WTP (based on the customized purchase price in decimals) for reduced CO<sub>2</sub> emissions (in 1000 gram per kilometer) and for service station availability (in decimals of stations with respective fuel):

- Page 33: Multinomial logit model with only alternative specific attributes
  - $\widehat{WTP}_{CO_2} = -4.325$  [ $= -(-4.115056 / -0.9513986)$ ], i.e. the estimated average WTP is approximately 0.4325 percentage points with respect to the purchase price for a reduction of the CO<sub>2</sub> emissions by 1 gram (which is  $0.004325 \cdot 20725 = 89.64$  Euro due to the average purchase price of 20725 Euro)
  - $\widehat{WTP}_{station} = 1.286$  [ $= -(1.223275 / -0.9513986)$ ], i.e. the estimated average WTP is approximately 1.286 percentage points with respect to the purchase price for an increase of the service station availability by 1 percentage point (which is  $0.01286 \cdot 20725 = 266.52$  Euro)
- Page 34: Independent multinomial probit model with only alternative specific attributes
  - $\widehat{WTP}_{CO_2} = -4.299$  or  $0.004299 \cdot 20725 = 89.10$  Euro
  - $\widehat{WTP}_{station} = 1.326$  or  $0.01326 \cdot 20725 = 274.81$  Euro

---

## Example 1: Energy sources and propulsion technologies in vehicles (XVIII)

- Page 35: Full multinomial logit model
  - $\widehat{WTP}_{CO_2} = -4.401$  or  $0.004401 \cdot 20725 = 91.21$  Euro
  - $\widehat{WTP}_{station} = 1.302$  or  $0.01302 \cdot 20725 = 269.84$  Euro
- Page 39/40/41: Mixed logit models with only alternative specific attributes and full mixed logit model
  - $\widehat{WTP}_{CO_2} = -4.400$  (91.19 Euro) and  $-4.548$  (94.27 Euro)
  - $\widehat{WTP}_{station} = 1.314$  (272.40 Euro) and  $1.127$  (264.19 Euro)

Estimated WTP (based on the purchase price divided by 100000) for reduced CO<sub>2</sub> emissions (in 1000 gram per kilometer) and for service station availability (in decimals of stations with respective fuel):

- Page 31: Multinomial logit model with only alternative specific attributes
  - $\widehat{WTP}_{CO_2} = -1.118$  [ $= -(-4.124038 / -3.689678)$ ], i.e. the estimated average WTP is approximately 111.8 Euro for a reduction of the CO<sub>2</sub> emissions by 1 gram
  - $\widehat{WTP}_{station} = 0.334$  [ $= -(1.232526 / -3.689678)$ ], i.e. the estimated average WTP is approximately 334 Euro for an increase of the service station availability by 1 percentage point

---

## Example 1: Energy sources and propulsion technologies in vehicles (XIX)

Finally, the ML estimation of a latent class logit model with two classes and with alternative specific attributes and alternative specific constants is considered (age\_100, male, and environment\_friendly are included in the membership model):

```
lclogit choice price_decimal motorpower_decimal fuelcosts_100 CO2emissions_1000
servicestation_100 diesel gas biofuel hydrogen hybrid electric, membership(age_100 male
environment_friendly) group(choiceset) id(individuals) nclasses(2) seed(2)
```

Latent class model with 2 latent classes

Choice model parameters and average class shares

---

Variable	Class1	Class2
price_deci~1	-1.159	-0.281
motorpower~1	0.575	0.104
fuelcost~100	-9.333	-3.465
CO2emis~1000	-4.892	-1.115
services~100	1.344	0.927
diesel	0.224	-0.054
gas	0.517	-2.422
biofuel	0.025	-2.599
hydrogen	0.395	-3.551
hybrid	0.556	-2.282
electric	-0.227	-3.772
Class Share	0.780	0.220

---

---

## Example 1: Energy sources and propulsion technologies in vehicles (XX)

Class membership model parameters : Class2 = Reference class

---

Variable	Class1	Class2
age_100	-4.964	0.000
male	0.092	0.000
environmen~y	0.568	0.000
_cons	3.386	0.000

---

lclogitml

Latent class model with 2 latent classes

---

choice	Coefficient	Std. err.	z	P> z	[95% conf. interval]
choice1					
price_decimal	-1.158792	.1059631	-10.94	0.000	-1.366476 - .9511084
motorpower_decimal	.5748627	.1291412	4.45	0.000	.3217506 .8279747
fuelcosts_100	-9.333472	.4100292	-22.76	0.000	-10.13711 -8.52983
CO2emissions_1000	-4.892207	.3204516	-15.27	0.000	-5.52028 -4.264133
servicestation_100	1.344335	.0688776	19.52	0.000	1.209338 1.479333
diesel	.2236502	.085048	2.63	0.009	.0569593 .3903412
gas	.5170894	.0889466	5.81	0.000	.3427573 .6914215
biofuel	.0246264	.0932984	0.26	0.792	-.1582352 .2074879
hydrogen	.3948669	.0897299	4.40	0.000	.2189996 .5707341
hybrid	.5555942	.0877449	6.33	0.000	.3836174 .7275711
electric	-.2266319	.0985213	-2.30	0.021	-.41973 -.0335337

---

## Example 1: Energy sources and propulsion technologies in vehicles (XXI)

```

-----+-----
choice2 |
  price_decimal |  -.2806668  .2366267  -1.19  0.236  -.7444467  .1831131
  motorpower_decimal |  .1042983  .3175214   0.33  0.743  -.5180322  .7266288
  fuelcosts_100 | -3.465026  .7931911  -4.37  0.000  -5.019652  -1.9104
  CO2emissions_1000 | -1.115138  .8750632  -1.27  0.203  -2.83023  .5999548
  servicestation_100 |  .9266868  .2236876   4.14  0.000  .4882671  1.365106
  diesel |  -.0540939  .0877225  -0.62  0.537  -.2260269  .1178391
  gas |  -2.421538  .2684773  -9.02  0.000  -2.947744  -1.895332
  biofuel |  -2.598783  .2716144  -9.57  0.000  -3.131138  -2.066429
  hydrogen |  -3.551382  .480541   -7.39  0.000  -4.493225  -2.609539
  hybrid |  -2.28184   .2755736  -8.28  0.000  -2.821954  -1.741726
  electric |  -3.771694  .4938859  -7.64  0.000  -4.739692  -2.803695
-----+-----
share1 |
  age_100 |  -4.964043  .6984837  -7.11  0.000  -6.333046  -3.59504
  male |  .0923229  .2666069   0.35  0.729  -.4302169  .6148627
environment_friendly |  .5684257  .2510127   2.26  0.024  .0764499  1.060402
  _cons |  3.385687  .4091422   8.28  0.000  2.583783  4.187591
-----+-----

```

test price\_decimal

```

( 1) [choice1]price_decimal = 0
( 2) [choice2]price_decimal = 0
      chi2( 2) = 124.02
      Prob > chi2 = 0.0000

```

test environment\_friendly

```

( 1) [share1]environment_friendly = 0
      chi2( 1) = 5.13
      Prob > chi2 = 0.0235

```

---

## Example 1: Energy sources and propulsion technologies in vehicles (XXII)

### Interpretation:

- Age has a significantly negative effect and environmental awareness has a significantly positive effect on the membership in class 1, whereas gender has no significant effect on the class membership
- The members of class 2 have a strong significant preference for gasoline vehicles compared to alternative energy sources and propulsion technologies
- The estimated effects of the alternative specific attributes for the members of class 1 are similar to the previously estimated effects
- In contrast, only the effects of fuel costs and service station availability are significant for the members of class 2
- Therefore, the estimation of WTP is only useful for the members of class 1, e.g. for reduced CO<sub>2</sub> emissions (in 1000 gram per kilometer) and for service station availability (in decimals of stations with respective fuel):
  - $\widehat{WTP}_{CO_2} = -4.222$  [= -(-4.892207/-1.158792)] or 87.50 Euro
  - $\widehat{WTP}_{station} = 1.160$  [= -(1.344335/-1.158792)] or 240.43 Euro

---

## Example 2: Choice among fixed-interest investment products (I)

In Gutsche and Ziegler (2016, discussion paper), two unlabeled SCE (based on “Balanced Overlap” designs for which 50 different versions of randomized choice sets were created for each SCE and assigned to the respondents) are examined, which comprised choices among several investment products:

- While one SCE referred to the choice among four different equity funds (the data are discussed and examined in the tutorial), the other SCE referred to the choice among four alternative fixed-interest investment products with an investment horizon of three years
- All data stem from a computer-based survey during December 2013 and January 2014, carried out in cooperation with the German market research institute GfK SE, which drew a sample from its internal representative (in terms of age, gender, and place of origin) online panel
- 1001 respondents from the population of financial decision makers in Germany with a minimum of investment experiences (i.e. the respondents must have at least a savings account) participated in the survey and thus in this SCE
- The SCE was based on six choice sets and comprised four attributes, i.e. provider, annual nominal interest rate, sustainability criteria, and transparency logo

---

## Example 2: Choice among fixed-interest investment products (II)

### Attribute levels:

- Provider (dummy variables): Big bank (base variable), municipal savings bank, co-operative bank, direct bank, sustainability bank
- Annual nominal interest rate: 1.30%, 1.50%, 1.70%, 1.90%, 2.10%
- Sustainability criteria (dummy variables): No consideration (base variable), consideration without sustainability certificate, consideration with sustainability certificate (summarized in the variable sustainability)
- Transparency logo (dummy variables): No transparency logo (base variable), transparency logo issued by an NGO, transparency logo issued by the state (summarized in the variable transparency)

### Individual characteristics:

- Social values and norms (dummy variables): Warm glow, expectations from the social environment, membership to an environmental organization, affinity with left or right-wings parties
- Socio-demographic variables (dummy variables with the exception of age, which is measured in years): Female, high education, living together or married, Western Germany

---

## Example 2: Choice among fixed-interest investment products (III)

Typical choice set:

Please indicate which of the following four investment products you would most likely purchase.				
Attribute	Three-year fixed-interest investment product A	Three-year fixed-interest investment product B	Three-year fixed-interest investment product C	Three-year fixed-interest investment product D
Provider	Direct bank	Direct bank	Big bank	Municipal savings bank
Yearly nominal interest rate	1.30%	1.70%	1.50%	1.30%
Sustainability criteria	No consideration	Consideration with certificate	Consideration without certificate	No consideration
Transparency logo	No transparency logo	Transparency logo issued by an NGO	Transparency logo issued by the state	No transparency logo
	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>	<input type="checkbox"/>

---

## Example 2: Choice among fixed-interest investment products (IV)

The following estimations are considered:

- ML estimation of the conditional logit model with robustly estimated variances, but without including alternative specific constants (since it is an unlabeled SCE) and SML estimation of the corresponding mixed logit model
- Simulated likelihood ratio test for the validity of the conditional logit model
- SML estimation of the full mixed logit model including the individual characteristics as interaction terms with sustainability (based on  $n = 708$  respondents due to missing values for the individual characteristics)
- (Approximate) replications of the results in Table 10 and Table 11 of the paper (results in the paper are based on Stata 12): ML estimation of latent class logit models with two and three classes with the alternative specific attributes and the alternative specific constants and with five iterations in the additional ML estimation with the Newton-Raphson algorithm, whereby the individual characteristics are included in the membership model (also based on  $n = 708$  respondents)
- Estimation of WTP for sustainability criteria, respectively (i.e. the estimated average value of percentage points with respect to the yearly nominal interest rate, the persons are willing to sacrifice for sustainability criteria)

## Example 2: Choice among fixed-interest investment products (V)

```
asclogit choice InterestRate Sustainability Transparency MunicipalBank CooperativeBank
DirectBank SustBank, case(gid) alternatives(alternative) noconstant robust
```

```
Alternative-specific conditional logit      Number of obs      =      24024
Case variable: gid                        Number of cases    =      6006
Alternative variable: alternative          Alts per case: min =      4
                                           avg =      4.0
                                           max =      4
                                           Wald chi2(7)      =      2465.47
                                           Prob > chi2       =      0.0000
```

Log pseudolikelihood = -6471.0994

(Std. Err. adjusted for clustering on gid)

choice	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
alternative						
InterestRate	3.079548	.0682445	45.13	0.000	2.945791	3.213305
Sustainability	.5999934	.0361356	16.60	0.000	.529169	.6708178
Transparency	.6910839	.0354122	19.52	0.000	.6216772	.7604906
MunicipalBank	.5325289	.0512667	10.39	0.000	.432048	.6330098
CooperativeBank	.5008757	.0505109	9.92	0.000	.401876	.5998753
DirectBank	.1375595	.0508649	2.70	0.007	.0378662	.2372528
SustBank	.3190195	.0545459	5.85	0.000	.2121115	.4259274

estimates store condlogit

$$\rightarrow W\hat{T}P_{\text{sust}} = -0.195 [=-(0.5999934/3.079548)]$$

## Example 2: Choice among fixed-interest investment products (VI)

```

mixlogit choice InterestRate, group(gid) id(id) rand(Sustainability Transparency MunicipalBank
CooperativeBank DirectBank SustBank) nrep(10) robust

```

```

Mixed logit model                Number of obs   =       24024
                                Wald chi2(7)      =       1042.91
Log likelihood = -6266.5199      Prob > chi2    =       0.0000

```

choice	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
-----+-----						
Mean						
InterestRate	3.535709	.1235619	28.61	0.000	3.293532	3.777886
Sustainability	.7223758	.0521778	13.84	0.000	.6201091	.8246425
Transparency	.8350265	.0559949	14.91	0.000	.7252786	.9447744
MunicipalBank	.5144328	.0695416	7.40	0.000	.3781338	.6507318
CooperativeBank	.5070607	.0656249	7.73	0.000	.3784382	.6356832
DirectBank	.1352623	.0580148	2.33	0.020	.0215553	.2489693
SustBank	.251023	.0713139	3.52	0.000	.1112502	.3907957
-----+-----						
SD						
Sustainability	.8885514	.0901503	9.86	0.000	.7118601	1.065243
Transparency	.6820224	.1363723	5.00	0.000	.4147377	.9493072
MunicipalBank	1.057992	.1410059	7.50	0.000	.7816253	1.334358
CooperativeBank	.692157	.1346609	5.14	0.000	.4282265	.9560875
DirectBank	-.1793131	.1130124	-1.59	0.113	-.4008133	.0421872
SustBank	-.7008728	.1580349	-4.43	0.000	-1.010616	-.3911302

```
estimates store mixedlogit
```

$$\rightarrow W\hat{TP}_{\text{sust}} = -0.204 [=-(0.7223758/3.535709)]$$

## Example 2: Choice among fixed-interest investment products (VII)

lrtest mixedlogit condlogit, force

Likelihood-ratio test

(Assumption: condlogit nested in mixedlogit)

LR chi2(6) = 409.16

Prob > chi2 = 0.0000

## Replication of results in Table 6 of the paper (with R = 1000 Halton draws):

mixlogit choice InterestRate, group(gid) id(id) rand(Sustainability Transparency MunicipalBank  
CooperativeBank DirectBank SustBank) nrep(1000) robust

Mixed logit model

Number of obs = 24,024

Wald chi2(7) = 869.85

Prob > chi2 = 0.0000

Log likelihood = -6145.605

choice	Coefficient	Robust std. err.	z	P> z	[95% conf. interval]	
Mean						
InterestRate	3.973192	.1517999	26.17	0.000	3.67567	4.270715
Sustainability	.8328645	.0586778	14.19	0.000	.7178581	.9478709
Transparency	1.02731	.0620928	16.54	0.000	.9056102	1.149009
MunicipalBank	.4871003	.0744113	6.55	0.000	.3412569	.6329437
CooperativeBank	.5017479	.0711371	7.05	0.000	.3623218	.6411741
DirectBank	.1129445	.0629538	1.79	0.073	-.0104425	.2363316
SustBank	.2153831	.0764495	2.82	0.005	.0655449	.3652213
SD						
Sustainability	1.067187	.0738109	14.46	0.000	.9225199	1.211853
Transparency	1.052439	.0817108	12.88	0.000	.8922888	1.212589
MunicipalBank	1.288292	.1068582	12.06	0.000	1.078853	1.49773
CooperativeBank	1.069791	.1038642	10.30	0.000	.8662205	1.273361
DirectBank	.5094532	.152021	3.35	0.001	.2114976	.8074088
SustBank	1.14098	.104213	10.95	0.000	.9367259	1.345233

$$\rightarrow W\hat{T}P_{\text{sust}} = -0.210 [=-(0.8328645/3.973192)]$$

## Example 2: Choice among fixed-interest investment products (VIII)

```

mixlogit choice InterestRate SustWarmGlow SustExpectEnvironment SustEnvOrganization SustLeftWing SustAge SustFemale
SustHighEducation SustLivingTogether SustWest, group(gid) id(id) rand(Sustainability Transparency MunicipalBank
CooperativeBank DirectBank SustBank) nrep(10) robust

```

```

Mixed logit model          Number of obs   =      16992
                          Wald chi2(16)      =      783.02
Log likelihood = -4342.2057  Prob > chi2     =      0.0000

```

	choice	Coef.	Robust Std. Err.	z	P> z	[95% Conf. Interval]	
-----							
Mean							
	InterestRate	3.584653	.1500836	23.88	0.000	3.290495	3.878812
	SustWarmGlow	.7232644	.1209516	5.98	0.000	.4862035	.9603253
	SustExpectEnvironment	-.1086212	.1985252	-0.55	0.584	-.4977235	.2804811
	SustEnvOrganization	.3547227	.2034193	1.74	0.081	-.0439717	.7534172
	SustLeftWing	.493711	.1146748	4.31	0.000	.2689526	.7184694
	SustAge	-.0006806	.0046267	-0.15	0.883	-.0097487	.0083874
	SustFemale	.0994594	.1138096	0.87	0.382	-.1236034	.3225222
	SustHighEducation	.1314268	.1206158	1.09	0.276	-.1049758	.3678294
	SustLivingTogether	.2125078	.1210841	1.76	0.079	-.0248128	.4498283
	SustWest	-.3499575	.1597018	-2.19	0.028	-.6629673	-.0369477
	Sustainability	.2970432	.2980038	1.00	0.319	-.2870336	.8811199
	Transparency	.9263078	.0653271	14.18	0.000	.7982691	1.054346
	MunicipalBank	.4276778	.0798278	5.36	0.000	.2712182	.5841373
	CooperativeBank	.5166195	.0804274	6.42	0.000	.3589848	.6742542
	DirectBank	.1069876	.0692616	1.54	0.122	-.0287626	.2427379
	SustBank	.2129217	.0840255	2.53	0.011	.0482347	.3776087
-----							
SD							
	Sustainability	.7966505	.0901661	8.84	0.000	.6199282	.9733728
	Transparency	.759705	.1264612	6.01	0.000	.5118457	1.007564
	MunicipalBank	.861888	.1400705	6.15	0.000	.5873548	1.136421
	CooperativeBank	.762845	.1777057	4.29	0.000	.4145483	1.111142
	DirectBank	-.3154558	.1424412	-2.21	0.027	-.5946354	-.0362763
	SustBank	.6836249	.1400416	4.88	0.000	.4091483	.9581014
-----							

---

## Example 2: Choice among fixed-interest investment products (IX)

```
lcclogit choice InterestRate Sustainability Transparency MunicipalBank CooperativeBank DirectBank
SustBank, nclasses(2) group(gid) id(id) membership (WarmGlow ExpectEnvironment EnvOrganization LeftWing
Age Female HighEducation LivingTogether West) seed(100)
```

Latent class model with 2 latent classes

Choice model parameters and average class shares

---

Variable	Class1	Class2
InterestRate	10.734	1.705
Sustainability	0.672	0.896
Transparency	0.945	0.869
MunicipalBank	0.150	0.685
CooperativeBank	0.329	0.670
DirectBank	-0.196	0.272
SustBank	-0.531	0.488
Class Share	0.353	0.647

---

Class membership model parameters : Class2 = Reference class

---

Variable	Class1	Class2
WarmGlow	-1.049	0.000
ExpectEnvironment	-0.739	0.000
EnvOrganization	-1.314	0.000
LeftWing	-0.601	0.000
Age	-0.015	0.000
Female	-0.406	0.000
HighEducation	0.412	0.000
LivingTogether	0.037	0.000
West	0.719	0.000
_cons	0.192	0.000

---

## Example 2: Choice among fixed-interest investment products (X)

lclogitml, iterate(5)

Latent class model with 2 latent classes

choice	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
-----						
choice1						
InterestRate	10.75694	.7324159	14.69	0.000	9.321435	12.19245
Sustainability	.6722578	.1396196	4.81	0.000	.3986083	.9459072
Transparency	.9447249	.133568	7.07	0.000	.6829364	1.206514
MunicipalBank	.1504348	.1795637	0.84	0.402	-.2015036	.5023731
CooperativeBank	.3282753	.1778241	1.85	0.065	-.0202536	.6768041
DirectBank	-.1959491	.1809963	-1.08	0.279	-.5506953	.1587971
SustBank	-.5327292	.2110043	-2.52	0.012	-.9462901	-.1191684
-----						
choice2						
InterestRate	1.708049	.1109394	15.40	0.000	1.490612	1.925486
Sustainability	.8953473	.0546982	16.37	0.000	.7881407	1.002554
Transparency	.8688197	.0554445	15.67	0.000	.7601504	.977489
MunicipalBank	.6842631	.079772	8.58	0.000	.5279128	.8406134
CooperativeBank	.6695327	.0802939	8.34	0.000	.5121595	.8269059
DirectBank	.271587	.0817662	3.32	0.001	.1113282	.4318458
SustBank	.4873413	.081315	5.99	0.000	.3279669	.6467157
-----						
share1						
WarmGlow	-1.05113	.2212985	-4.75	0.000	-1.484868	-.6173932
ExpectEnvironment	-.7393002	.4323563	-1.71	0.087	-1.586703	.1081025
EnvOrganization	-1.315412	.4571276	-2.88	0.004	-2.211366	-.4194584
LeftWing	-.6005403	.1992126	-3.01	0.003	-.9909899	-.2100908
Age	-.0146788	.0080105	-1.83	0.067	-.030379	.0010214
Female	-.4071172	.2041019	-1.99	0.046	-.8071497	-.0070847
HighEducation	.4120408	.2115082	1.95	0.051	-.0025077	.8265894
LivingTogether	.0377725	.2158235	0.18	0.861	-.3852338	.4607788
West	.7193132	.2722074	2.64	0.008	.1857966	1.25283
_cons	.1900472	.5197133	0.37	0.715	-.8285722	1.208667
-----						

---

## Example 2: Choice among fixed-interest investment products (XI)

```
lcclogit choice InterestRate Sustainability Transparency MunicipalBank CooperativeBank DirectBank  
SustBank, nclasses(3) group(gid) id(id) membership (WarmGlow ExpectEnvironment EnvOrganization LeftWing  
Age Female HighEducation LivingTogether West)
```

Latent class model with 3 latent classes

Choice model parameters and average class shares

---

Variable	Class1	Class2	Class3
InterestRate	2.891	0.829	11.226
Sustainabi~y	1.646	0.197	0.641
Transparency	1.403	0.411	1.015
MunicipalB~k	0.564	0.788	0.197
Cooperativ~k	0.619	0.764	0.262
DirectBank	0.509	0.004	-0.217
SustBank	0.929	-0.311	-0.605
Class Share	0.413	0.250	0.336

---

Class membership model parameters : Class3 = Reference class

---

Variable	Class1	Class2	Class3
WarmGlow	1.723	0.186	0.000
ExpectEnvi~t	0.445	1.267	0.000
EnvOrganiz~n	1.471	1.307	0.000
LeftWing	0.989	0.179	0.000
Age	0.016	0.013	0.000
Female	0.383	0.414	0.000
HighEducat~n	-0.154	-0.691	0.000
LivingToge~r	0.089	-0.117	0.000
West	-0.720	-0.551	0.000
_cons	-1.472	-0.410	0.000

---

## Example 2: Choice among fixed-interest investment products (XII)

lcclogitml, iterate(5)

Latent class model with 3 latent classes

choice	Coefficient	Std. err.	z	P> z	[95% conf. interval]	
-----						
choice1						
InterestRate	2.888044	.2001507	14.43	0.000	2.495756	3.280332
Sustainability	1.64287	.119378	13.76	0.000	1.408893	1.876847
Transparency	1.402851	.1011061	13.88	0.000	1.204686	1.601015
MunicipalBank	.5623126	.1391263	4.04	0.000	.2896302	.8349951
CooperativeBank	.6178661	.1370431	4.51	0.000	.3492665	.8864656
DirectBank	.506818	.1384667	3.66	0.000	.2354284	.7782077
SustBank	.9257285	.1411869	6.56	0.000	.6490072	1.20245
-----						
choice2						
InterestRate	.8245511	.1869836	4.41	0.000	.45807	1.191032
Sustainability	.195132	.0977312	2.00	0.046	.0035824	.3866816
Transparency	.4081522	.110466	3.69	0.000	.1916427	.6246616
MunicipalBank	.7904712	.1353572	5.84	0.000	.525176	1.055766
CooperativeBank	.7648099	.1329771	5.75	0.000	.5041796	1.02544
DirectBank	.0043657	.1380623	0.03	0.975	-.2662314	.2749627
SustBank	-.3123663	.1782552	-1.75	0.080	-.6617401	.0370076
-----						
choice3						
InterestRate	11.22759	.8509539	13.19	0.000	9.559752	12.89543
Sustainability	.6403667	.148278	4.32	0.000	.3497471	.9309863
Transparency	1.014638	.1495712	6.78	0.000	.7214842	1.307793
MunicipalBank	.1967508	.1930677	1.02	0.308	-.1816549	.5751566
CooperativeBank	.2618062	.1877001	1.39	0.163	-.1060792	.6296917
DirectBank	-.2170513	.1917068	-1.13	0.258	-.5927897	.1586872
SustBank	-.6060597	.2181889	-2.78	0.005	-1.033702	-.1784173
-----						

## Example 2: Choice among fixed-interest investment products (XIII)

-----							
share1							
WarmGlow		1.720155	.2615109	6.58	0.000	1.207603	2.232707
ExpectEnvironment		.4472109	.4943392	0.90	0.366	-.5216761	1.416098
EnvOrganization		1.471052	.516438	2.85	0.004	.458852	2.483252
LeftWing		.9858048	.2478956	3.98	0.000	.4999383	1.471671
Age		.0156652	.0097753	1.60	0.109	-.003494	.0348244
Female		.3856622	.2513257	1.53	0.125	-.1069272	.8782516
HighEducation		-.1561053	.2601372	-0.60	0.548	-.6659648	.3537542
LivingTogether		.0877052	.2651321	0.33	0.741	-.4319441	.6073545
West		-.7191945	.316097	-2.28	0.023	-1.338733	-.0996557
_cons		-1.461182	.669632	-2.18	0.029	-2.773636	-.148727
-----							
share2							
WarmGlow		.1846444	.2883651	0.64	0.522	-.3805408	.7498295
ExpectEnvironment		1.26877	.48893	2.59	0.009	.3104845	2.227055
EnvOrganization		1.3086	.5255866	2.49	0.013	.2784688	2.33873
LeftWing		.1784874	.2461125	0.73	0.468	-.3038844	.6608591
Age		.0133733	.0097155	1.38	0.169	-.0056687	.0324153
Female		.4121972	.2456358	1.68	0.093	-.0692402	.8936345
HighEducation		-.6900033	.2497134	-2.76	0.006	-1.179433	-.200574
LivingTogether		-.1169762	.2587856	-0.45	0.651	-.6241867	.3902344
West		-.551594	.3171306	-1.74	0.082	-1.173158	.0699706
_cons		-.4158729	.6231495	-0.67	0.505	-1.637224	.8054778
-----							

→ Model with two classes:  $\widehat{WTP}_{sust} = -0.062$  [ $=-(0.6722578/10.75694)$ ] in the first and  $\widehat{WTP}_{sust} = -0.524$  [ $=-(0.8953473/1.708049)$ ] in the second class

→ Model with three classes:  $\widehat{WTP}_{sust} = -0.569$  [ $=-(1.64287/2.888044)$ ] in the first,  $\widehat{WTP}_{sust} = -0.237$  [ $=-(0.195132/0.8245511)$ ] in the second, and  $\widehat{WTP}_{sust} = -0.057$  [ $=-(0.6403667/11.22759)$ ] in the third class