INSTITUTO SUPERIOR TÉCNICO



Phd Program in Transportation

Transport Demand Modeling

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Session 2

Discrete Choice Models An Application of Multinomial Logit and Nested Logits

(Aknowledgements are given to Gonçalo Correia who prepared the previous version of this slides)







Application of a Multinomial Logit

Revealed Preference Experiments





- □ When calibrating discrete choice models we may recur to two different types of data: **Revealed Preference (RP)** or **Stated Preference (SP)**.
- Revealed Preference: We survey the population to what they are doing now, with the choice set they <u>perceive</u> to have available now. In mode choice (our most important choice in Transportation) this means having the attributes of the respondents, the attributes of the modes they have available (this is not straightforward) and the choices they make everyday.

A Modal Choice Revealed Preference Survey in Australia – Lab (I)

- This survey is part of the Book "Applied Choice Analysis: A Primer" by David Hensher, et al (2005). They have a Revealed and a Stated Preference Survey.
- We start just with the Revealed Preference (RP) survey for understanding how to estimate MNL models in NLOGIT (Econometric Software Inc.).
- Each respondent in the sample answered a questionnaire about the trip they had the day before of the survey.
- □ For this Lab we have filtered the data, selecting just some of the available explanatory variables.





A Modal Choice Revealed Preference Survey in Australia – Lab (II)



Variable	Meaning	IJT
ALTIJ	Alternative Number: 1 = DRIVE ALONE, 2 = RIDE SHARE, 3 = BUS, 4 = TRAIN, 5 = WALK, 6 = BICYCLE;	INSTITUTO SUPERIOR TÉCNICO
CHOICE	1, chosen, 0 not chosen	
CSET	Number of alternatives in each comparison. In this case there are always 2.	FFIID
MPTRFARE	Cost of public transport (\$AUS)	
MPTRTIME	Time on public transport (min)	
WAITTIME	Time waiting for public transport (min)	
AUTOTIME	Time inside the automobile (min)	
VEHPRKCT	Cost of parking in destination (\$AUS)	
VEHTOLCT	Paid toll (\$AUS)	
NUMBVEHS (SDC)	Number of vehicles in household	
WKROCCUP (SDC)	Occupation category:1 = Managers and Admin, 2 = Professionals, 3 = Para-professional, 4 = Tradespersons, 5 = Clerks, 6 = Sales, 7 = Plant operators, 8 = Laborers, 9 = Other	
PERAGE (SDC)	Age	5

A Modal Choice Revealed Preference Survey in Australia – Lab (III)

ISUI TITA	8	Manual Manual
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Variable (continue)	Meaning
DISDWCBD (like an SDC)	Distance to the Central Business District (CBD) (km)
TRIPTIME	Trip time in Bicycle or walking (min)

- Variables ALTIJ, CHOICE and CSET, allow building the dependent variable of the DCM.
- ALTIJ will identify the mode of transportation that each line of data represents, CHOICE will tell which of the lines (modes) has been chosen from the Choice set, and finally CSET will tell how many lines (alternatives) are in each choice which respondents have answered.
- □ In this RP survey each choice is made between the mode of transportation that the user has selected the day before and in the questionnaire they were also asked to give attribute levels of a single alternative means of traveling to work as perceived by that respondent. This second mode was deemed the alternative mode.



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Data Sample





ALTIJ	CHOICE	CSET	MPTRFARF	MPTRTIME	WAITTIME	AUTOTIME	VEHPRKCT	VEHTOI CT	NUMBVEH	WKROCCUP	PERAGE	DISDWCBD	TRIPTIME
1	1	2	0	0	0	20	0	0	2	3	39	25	0
4	0	2	4,98	20	20	0	0	0	2	3	39	25	0
1	1	2	0	0	0	15	0	0	2	1	36	20	0
2	0	2	0	0	0	15	0	0	2	1	36	20	0
1	1	2	0	0	0	30	0	0	2	1	41	23	0
2	0	2	0	0	0	30	0	0	2	1	41	23	0
1	1	2	0	0	0	20	0	0	1	1	44	16	0
4	0	2	2,5	30	10	0	0	0	1	1	44	16	0
1	0	2	0	0	0	20	0	0	4	5	45	16	0
2	1	2	0	0	0	25	0	0	4	5	45	16	0
2	1	2	0	0	0	25	0	0	1	2	30	16	0
4	0	2	2,6	30	5	0	0	0	1	2	30	16	0
2	1	2	0	0	0	15	0	0	4	5	22	13	0
4	0	2	2	40	10	0	0	0	4	5	22	13	0
2	1	2	0	0	0	20	0,5	0	1	2	32	12	0
6	0	2	0	0	0	0	0	0	1	2	32	12	50
2	0	2	0	0	0	20	0	0	1	1	39	13	0
4	1	2	2,1	35	10	0	0	0	1	1	39	13	0
1	1	2	0	0	0	15	0	0	2	5	26	15	0
4	0	2	6	40	35	0	0	0	2	5	26	15	0
1	1	2	0	0	0	20	0	0	2	5	28	14	0
4	0	2	2	30	5	0	0	0	2	5	28	14	0
2	1	2	0	0	0	15	0	0	2	5	45	15	0
4	0	2	4	15	5	0	0	0	2	5	45	15	0
1	1	2	0	0	0	15	0	0	1	2	32	14	0
4	0	2	4,98	20	10	0	0	0	1	2	32	14	0
1	1	2	0	0	0	10	0	0	4	0	35	22	0
2	0	2	0	0	0	10	0	0	4	0	35	22	0
2	0	2	0	0	0	20	0	0	0	5	39	18	0
4	1	2	2,5	40	10	0	0	0	0	5	39	18	0

(...)

Variable Coefficient SUPERIOR **Drive alone Utility:** U(DA) =ASDR+TDRDA*AUTOTIME+COST*VEHPRKCT+COST*VEHTOLCT+VEHD*NUMBVEHS+AGE *PERAGE+MANAGE*MANAGERS/ FEUP **Ride Share Utility: New Variable!** U(RS) = ASRS +COST*VEHPRKCT+COST*VEHTOLCT/ **Bus Utility:** U(BUS) = ASBU + COST*MPTRFARE + TPTBUS*MPTRTIME+TW*WAITTIME/ Train Utility: U(TRAIN) = ASTR + COST*MPTRFARE/ +TPTTRA*MPTRTIME+TW*WAITTIME+DISTAN*DISDWCBD Walk Utility: U(WALK) = ASWA+TRPEDBI*TRIPTIME/ **Cycle Utility:** Reference U(CYCLE) = TRPEDBI*TRIPTIME Alternative



The first step on running an MNL is thinking of an initial structure for the Utility functions. My proposal is the following:

MNL's in Nlogit



□ The command in Nlogit to create MNL models is the DISCRETECHOICE (or NLOGIT) command. Go to Model->Discrete Choice->Discrete Choice.





Instead of	Main Options Output Choice variable Choice variable: CHOICE		F
having the choice we could have a frequency of choices, which Nlogit transforms in probabilities.	Data type: Individual choice Choice set Fixed number of choices: Choice based sampling weights: Data coded on one line. Code: Variable number of choices: Count variable: Use universal choice set indicator: CSET Luse universal choice set indicator: Data, RS, BUS, TRAIN, W	If we want to give a higher weigh to some choices, for instance, due to sample	
	Perform IIA test on choices: Use data scaling: ? Run Cancel	stratification	

It does not allow to specify different weighs for the same alternative attribute like travel time of BUS and travel time of Car.

	т
DISCRETE CHOICE	<u>A</u>
Main Options Output	F
Model type: Discrete Choice	
Sequential estimation Conditional model	
Use one line setup. Attribute labels:	
Utility functions Attributes V CC V CCC V CC V CCC V CCCC V CCCC V CCCC V CCCC V CCCCC V CCCCCC V CCCCCCCCCC	
Specify utility functions: Box Cox: Society Cox: Ride Share Utility	Best Option!
Tree Specification Optimization Hypothesis Tests	We have all
? Run Cancel	the freedom we want



MNL's in Nlogit





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The code in Nlogit

But the best to do is really to write the code it self:

 \rightarrow Considers all the data for estimating the model SAMPLE : all\$? Create new variable CREATE \rightarrow Creates the new variable according to an existing one. We ; if (WKROCCUP<2)MANAGERS=1 should not introduce a categorical variable directly in the if(WKROCCUP>1)MANAGERS=0\$ model because we are implicitly considering a linear effect ? Multinomial Logit DISCRETECHOICE of the categories on the utility which is most of the times ;lhs=CHOICE, CSET, ALTIJ ;choices=DA, RS, BUS, TRAIN, WALK, CYCLE false. : MODEL : FEUP ? Drive alone Utility U(DA) =ASDR+TDRDA*AUTOTIME+COST*VEHPRKCT+COST*VEHTOLCT+VEHD*NUMBVEHS+AGE*PERAGE+MANAGE*MANAGERS/ ? Ride Share Utility U(RS) = ASRS +COST * VEHPRKCT+COST * VEHTOLCT/ ? Bus Utility U(BUS) = ASBU +COST*MPTRFARE + TPTBUS*MPTRTIME+TW*WAITTIME/ ? Train Utility U(TRAIN) = ASTR + COST*MPTRFARE + TPTTRA*MPTRTIME+TW*WAITTIME+DISTAN*DISDWCBD/ ? Walk Utility U(WALK) = ASWA+TRPEDBI*TRIPTIME/ ? Cycle Utility U(CYCLE) = TRPEDBI*TRIPTIME \rightarrow Cross tabulation of true versus predicted choices :Crosstab :Describe ; Prob=Prob ~ Describes all utility functions and their coefficients estimates : CHECKDATAS →Will produce a new variable called "Prob" with the Verifies the data probability of the alternative being chosen in its choice set before estimation **Q**Run the model by selecting all text with your cursor and pressing go!

The output







It is the Log Likelihood

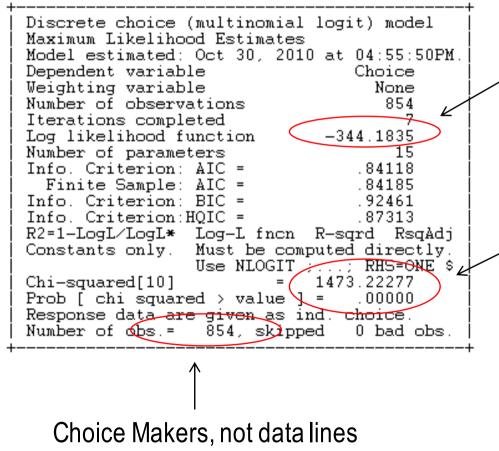
Be careful this Chi-squared is not computed correctly. It is supposed to be the test comparing LL(c) and LL(*) that is why it has 10 degrees of freedom: 15-5. However what is doing is wrong! He is applying the following: 2*(LL(c)+LL(*))=2*(392,51+34 4,18)=1473

Discrete choice and multinomial logit models

Inspecting the data set before estimation. These errors mark observations which will be skipped. Row Individual = 1st row then group number of data block

No bad observations were found in the sample

Normal exit from iterations. Exit status=0.





Comparing to a model with equal shares

- □ Due to the error in Nlogit we must compute ourselves, the Log Likelihood ratio and the pseudo-R2 for a base model with equal shares.
- □ Each respondent chooses one of two alternatives, thus equal shares means 0.5 probability of choice in each choice set for each of the alternatives, thus we have:
 LL(0) = (1 * ln(0.5) + 0 * ln(0.5)) * 854=-591,94
- □ The Log Likelihood ratio will then be:

-2(L(0) - L(*)) = -2(-591.94 - (-344.1845)) = 495,511With degrees of freedom=15-0=15

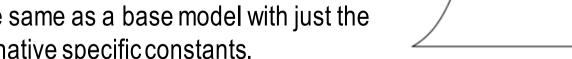
In Excel: =INV.CHI(0.05,15)=24,99

5% Rejection region 24.99 (...) 495,511

We reject the hypothesis that our model is the same as a base model with equal shares.

Pseudo R² (McFadden)= 1-(-344.1845/-591,94)=0.419





Comparing to a model with ASCs

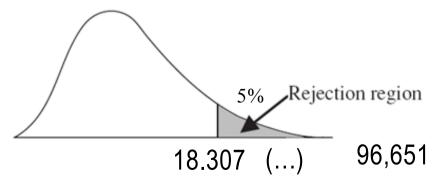
□ NLOGIT;Lhs=CHOICE,CSET,ALTIJ;Choices=DA,RS,BUS,TRAIN,WALK ,CYCLE;Rh2=ONE\$

Discrete choice (multinomial logit) model Maximum Likelihood Estimates Model estimated: Oct 30, 2010 at 05:53:26PM. Dependent variable Choice Weighting variable None Number of observations 854 Iterations completed -392.5100 Log likelihood function Number of parameters Info. Criterion: AIC = .93094 Finite Sample: AIC = .93102 Info. Criterion: BIC = .95875 Info. Criterion:HOIC = .94159 R2=1-LogL/LogL* Log-L fnon R-sard RsgAdj Constants only. Must be computed directly. Use NLOGIT :...: RHS=ONE \$ Response data are given as ind. choice. Number of obs. = 854, skipped 0 bad obs

We reject the hypothesis that our model is the same as a base model with just the alternative specific constants.

-2(L(c) - L(*)) =-2(-392.51 - (-344.1845)) == 96.651degrees of freedom=15-5=10

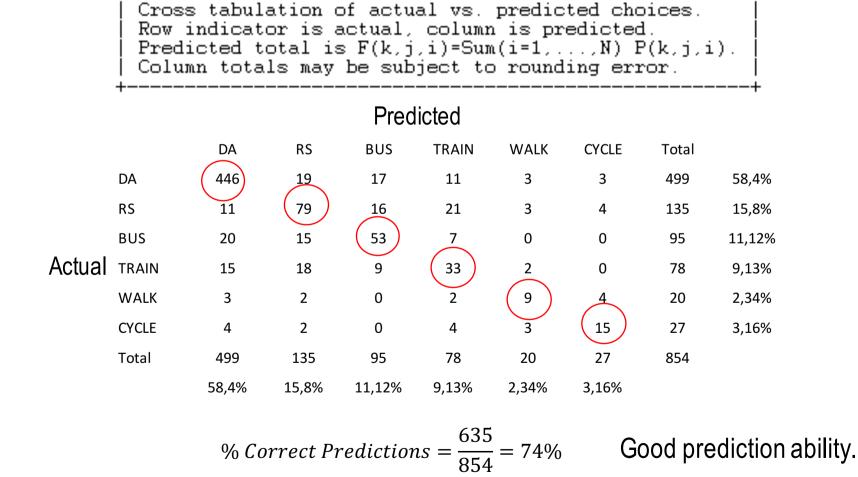
In Excel: =INV.CHI(0.05,10)=18.307





Crosstab of Actual vs Predicted

The predicted choices are obtained by computing the probabilities and if $P(i) > P(j) \forall j \in J$ we say that alternative *i* is chosen.



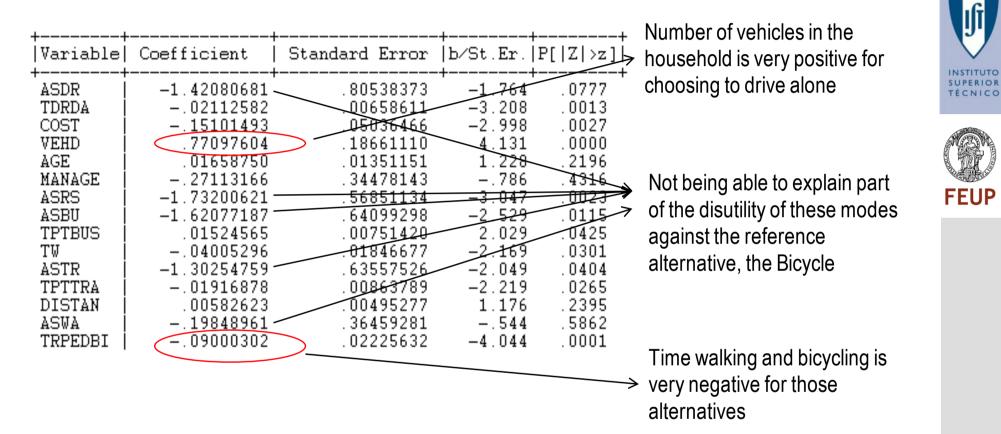






MNL Coefficients results

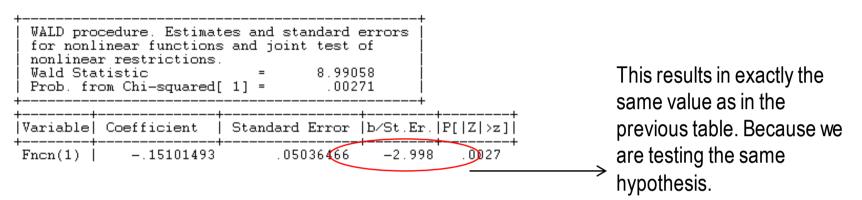




Experiment at home: Try considering one alternative specific coefficient for the travel time in bicycle and another for the time walking ... see what happens. Determine the value of driving time alone.

Wald Statistic

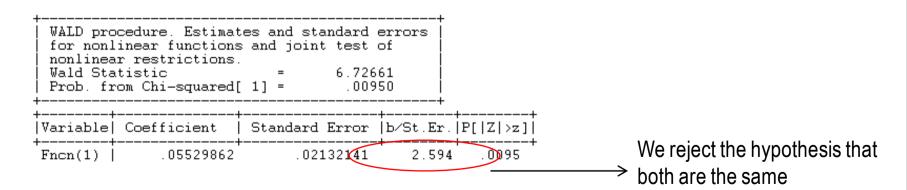
Test if we can reject the hypothesis of the cost parameter being zero: WALD;FN1:COST-0\$





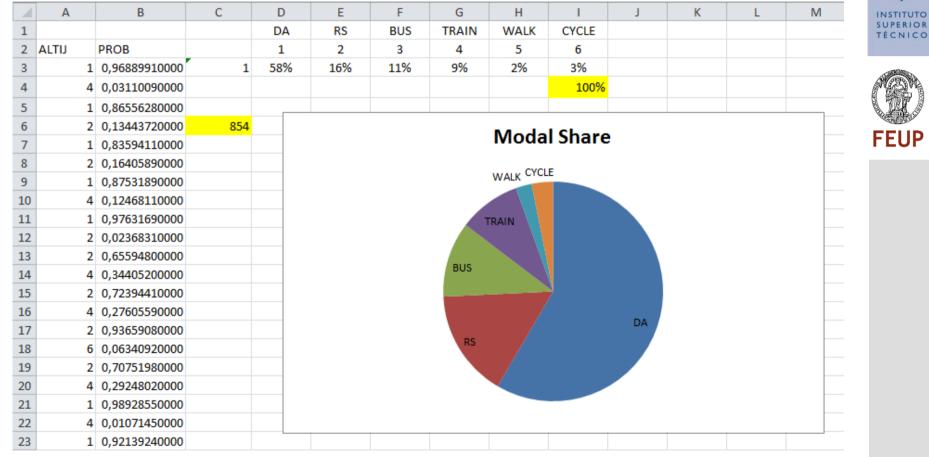
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Test if we can reject the hypothesis of the travel time inside the bus and the time waiting for the bus have the same weight in the Utility function: WALD;FN1:TPTBUS-TW\$



Aggregating across Individuals

With the Prob variable we may aggregate across individuals and obtain the modal shares using Excel:



□ See that the model is reproducing the shares in the sample. This must always happen because it is a direct result of the estimation process.







Application of a Nested Logit

Walk Car/Bus closest stop 5 min. 5 min. 4 min. 4 min. Time to your destination from Walk Walk Bus Bus

Every 5 min.

\$1.00

4 min.

1. car, toll road

\$1.00

Free

3. bus Total time in the vehicle 10 min. (one way) Time from home to your Walk Car/Bus

5 min.

(Hensher et al, 2005)

SA101

Travel time to work

(otherwise free)

Parking cost (per day)

the closest stop

Frequency of service

Return fare

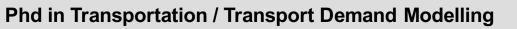
Fuel cost (per day)

Time variability

Toll (one way)

15 min. 10 min. None None \$1.00 Free Pay toll if you leave at this time 6-10 am

- The experiment showed 4 transportation alternatives to the respondents in several cities in Australia.
- However the choice set was between: Car with toll; Car with no toll; bus; train; busway and light rail (these last two, were non-existent at that time).



A mode choice SP experiment Australia (I)

2. car. non-toll road

\$3.00

Free

4. train

10 min.

Every 5 min.

\$1.00

4 min.

5 min.







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A mode choice SP experiment Australia (II)

- □ To initiate this experiment the trip length in terms of travel time relevant for each respondent's current commuting trip was first established so that the travel choices could be given in a context that had some reality for the respondent. The travel choice sets were divided into trip lengths of:
 - Less than 30 minutes: Short trip
 - 30–45 minutes: Medium trip
 - Over 45 minutes: Long trip

In participating in the choice experiments, each respondent was asked to consider a context in which the offered set of attributes and levels represented the only available means of undertaking a commuter trip from the current residential location to the current workplace location. It was made clear that the purpose was to establish each respondent's coping strategies under these circumstances.





The set of attributes and their levels







FEUP

short (<30 mins.)	car no toll	car toll rd	public transport	bus	train	busway	light rail
Travel time to work	15, 20, 25	10, 12, 15	Total time in the vehicle (one-way)	10, 15, 20	10, 15, 20	10, 15, 20	10, 15, 20
Pay toll if you leave at this time (otherwise free)	None	6–10, 6:30–8:30, 6:30–9	Frequency of service	Every 5, 15, 25			
Toll (one-way)	None	1, 1.5, 2	Time from home to closest stop	Walk 5, 15, 25			
Fuel cost (per day)	3, 4, 5	1, 2, 3	Time to destination from closest stop	Walk 5, 15, 25			
Parking cost (per day)	Free, \$10, 20	Free, \$10, 20	Return fare	1, 3, 5	1, 3, 5	1, 3, 5	1, 3, 5
Time variability	$0, \pm 4, \pm 6$	0,±1,±2					
medium (30–45 mins.)	car no toll	car toll rd	public transport	bus	train	busway	light rail
Travel time to work	30, 37, 45	20, 25, 30	Total time in the vehicle (one-way)	20, 25, 30	20, 25, 30	20, 25, 30	20, 25, 30
Pay toll if you leave at this time (otherwise free)	None	6–10, 6:30–8:30, 6:30–9	Frequency of service	Walk 5, 15, 25			
Toll (one-way)	None	2, 3, 4	Time from home to closest stop	Walk 5, 15, 25			
Fuel cost (per day)	6, 8, 10	2, 4, 6	Time to destination from closest stop	Walk 5, 15, 25 Bus 4, 6, 8			
Parking cost (per day) Time variability	Free, \$10, 20 0, ±7, ±11	Free, \$10, 20 0, ±2, ±4	Return fare	2, 4, 6	2, 4, 6	2, 4, 6	2, 4, 6
long (>45 mins.)	car no toll	car toll rd	public transport	bus	train	busway	light rail
Travel time to work Pay toll if you leave at this time (otherwise free)	45, 55, 70 None	30, 37, 45 6–10, 6:30–8:30, 6:30–9	Total time in the vehicle (one-way) Frequency of service	30, 35, 40 Walk 5, 15, 25			
Toll (one-way)	None	3, 4.5, 6	Time from home to closest stop	Walk 5, 15, 25			
Fuel cost (per day)	9, 12, 15	3, 6, 9	Time to destination from closest stop	Walk 5, 15, 25			
(r · · · · · ·) /	- , , -	1 1-	r and a second r	Bus 4, 6, 8			
Parking cost (per day) Time variability	Free, \$10, 20 0, ±11, ±17	Free, \$10, 20 0, ±7, ±11	Return fare	3, 5, 7	3, 5, 7	3, 5, 7	3, 5, 7

(Hensher et al, 2005)

Stated preference database

□ We will use this data in the next session to use Nested Logit models.

						\mathbf{i}							
ID	CITY	SPRP	SPEXP	ALTISPRP	ALTIJ	SPCHOICE	CHOICE	CSET	PCART	SPCARNT	SPBUS	SPTN	SPBW
1000	1	2	1	7	1	2	0	4	0	1	0	0	0
1000	1	2	1	8	2	2	1	4	0	1	0	0	0
1000	1	2	1	10	4	2	0	4	0	1	0	0	0
1000	1	2	1	12	6	2	0	4	0	1	0	0	0
1000	1	2	2	7	1	6	0	4	0	0	0	0	0
1000	1	2	2	8	2	6	0	4	0	0	0	0	0
1000	1	2	2	11	5	6	0	4	0	0	0	0	0
1000	1	2	2	12	6	6	1	4	0	0	0	0	0
1000	1	2	3	7	1	4	0	4	0	0	0	1	0
1000	1	2	3	8	2	4	0	4	0	0	0	1	0
1000	1	2	3	9	3	4	0	4	0	0	0	1	0
1000	1	2	3	10	4	4	1	4	0	0	0	1	0
1001	1	2	1	7	1	2	0	4	0	1	0	0	0
1001	1	2	1	8	2	2	1	4	0	1	0	0	0
1001	1	2	1	10	4	2	0	4	0	1	0	0	0
1001	1	2	1	12	6	2	0	4	0	1	0	0	0
1001	1	2	2	7	1	1	1	4	1	0	0	0	0
1001	1	2	2	8	2	1	0	4	1	0	0	0	0
1001	1	2	2	9	3	1	0	4	1	0	0	0	0
1001	1	2	2	10	4	1	0	4	1	0	0	0	0
1001	1	2	3	7	1	6	0	4	0	0	0	0	0
1001	1	2	3	8	2	6	0	4	0	0	0	0	0
1001	1	2	3	11	5	6	0	4	0	0	0	0	0
1001	1	2	3	12	6	6	1	4	0	0	0	0	0





(...)

The Hausman IIA Test of the IIA hypothesis (I)

- As we have seen Logit is built under the hypothesis that the error terms on the utility functions are IID which has the important behavioral imposition of the IIA hypothesis for multinomial Logit models.
- The main test for verifying if this is acceptable or not, is the Hausman-test. This encompasses two main steps:
 - > First step Run an unrestricted model with all the alternatives included
 - Second step Run a model with only a restricted number of alternatives and compute the statistic q (shown in next slide). Compare the statistic with a Chi-Squared distribution.
- □ What the test does is to see if extracting one alternative from the choice set changes the relation between the remaining alternatives. If it changes we reject the IIA.



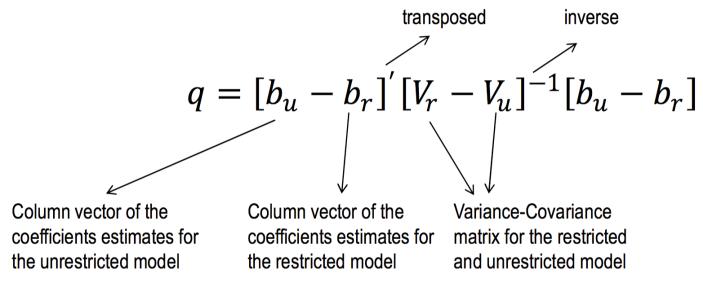


The Hausman IIA Test of the IIA hypothesis (II)



FEIID

The test statistic:



(not including alternative specific coefficients)

 \Box The test statistic q, is given as a Chi-Squared statistic with the number of degrees of freedom equal to the number of estimated parameters.

The Hausman IIA Test of the IIA hypothesis (III)

- Nlogit has an option which allows to use this test in the MNL menu, but is very limited and fails a lot of times because it is not prepared for all ways of representing survey information in Nlogit. The best option is to specify the test itself.
- Let's consider the following model applied to the SP Lab data (Australia's SP experiment):

NLOGIT	ASCCART
;lhs= choice, cset, altij	FUEL
;Choices = cart, carnt, bus, train, busway, LR	
;Model:	ASCCARNT
U(cart) = asccart + fuel*fuel /	ASCBUS
U(carnt) = asccarnt + fuel*fuel /	FARE
U(bus) = ascbus + fare*fare /	
U(train) = asctn + fare*fare /	ASCTN
U(busway) = ascbusw + fare*fare /	ASCBUSW
U(LR) = fare*fare \$	

□ This is the unconstrained model because it has all the alternatives







The Hausman IIA Test of the IIA hypothesis (IV)



FFUP

- For each estimated model, NLOGIT saves the parameters in a column vector named B (this matrix is overwritten each time a new model is estimated).
- □ The *B* column vector may be accessed via the project dialog box under the Matrices folder.
- □ Remember that the Hausman-test of the IIA assumption is performed using only those parameters which are not constant terms. As such, not all of the parameters of the *B* column vector are required (i.e. b_u and b_r do not include any parameters that are constant terms).
- □ For the above example, b_u will have only two parameters, those being for the fuel and fare attributes.

The Hausman IIA Test of the IIA hypothesis (V)

- FEUP
- □ To construct b_u , we must first create a permutation matrix, *J1*, which is used to extract the relevant parameters from the *B* column vector. The number of rows of the *J1* matrix will be equal to the number of parameters required for the b_u column vector, and the number of columns will equal the number of parameters present within the *B* column vector. This is because each column of the *J1* matrix is associated with each row of the *B* matrix (e.g. column one of the *J1* matrix is related to the *asccart* parameter, column two to the fuel parameter etc.).
- In the construction of the J1 matrix, a zero is placed in each column associated with a row in the B column vector for which the parameter in B is to be discarded. A "1" means that the related parameter located in the B column vector is to be retained. For the above example, the J1 matrix is shown below. The command MATRIX; is used to either create or manipulate matrices in NLOGIT.

MATRIX; J1 = [0,1,0,0,0,0,0 / 0,0,0,0,1,0,0] \$

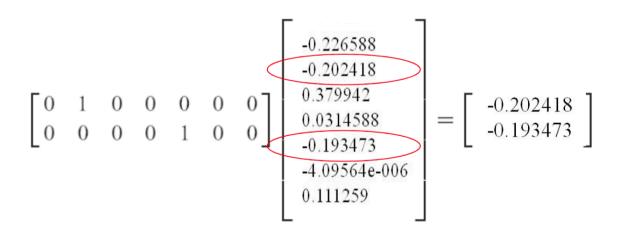
The Hausman IIA Test of the IIA hypothesis (VI)





□ Once *J1* is created, b_u and V_u (as with b_u , the elements of the variance– covariance matrix for the test, V_u , are not inclusive of elements related to constant terms) are created using the **MATRIX** command:

MATRIX; Bu = J1*B \$



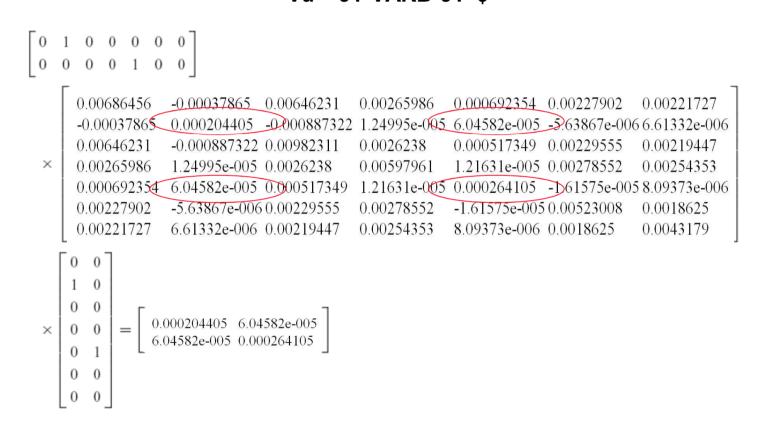
The Hausman IIA Test of the IIA hypothesis (VII)







□The variance-covariance matrix is stored in VARB, under Matrices, thus: Vu = J1*VARB*J1' \$



The Hausman IIA Test of the IIA hypothesis (VIII)



- FEUP
- □ Now we have to do the same for a **restricted model**. To estimate the restricted model we must take out all observations (i.e. choices) from the sample for which the alternative(s) which are to be removed were chosen.
- Fortunately the data base has a series of dummy variables which are equal to one for choice sets in which specific alternatives where chosen (or zero otherwise) we have decided to take out the **Bus** alternative (arbitrary). For the bus alternative, this variable is called **spbus**. But be careful you can't take out an <u>alternative which leaves the remaining model undetermined!</u>
- □ As well as removing choice sets in which the alternative(s) to be removed (in this case is the Bus) were chosen, we are also required to remove any rows of data related to the alternative(s) to be removed from choice sets in which those alternatives were not chosen.
- ☐ Assuming that we are to remove the bus alternative (altij equal to three), the following **REJECT** commands will remove all reference to the bus alternative from the sample to be used:

The Hausman IIA Test of the IIA hypothesis (IX)

are erased

Rejects the lines of the

survey where the respondent

all 4 lines of the experiment

answered bus. In this case





Rejects the lines of the survey where the bus option appeared but was not chosen

REJECT; spbus=1 \$ <

REJECT; altij=3 \$

□The rejection of an alternative such as the bus alternative means that for observations where that alternative was once present, the choice set size will be smaller by the number of alternatives removed;

 \Box (e.g. if bus was one of four alternatives, removing this alternative will leave three remaining alternatives and hence the choice set size decreases from four to three). This has implications for both altij and cset in the model commands, neither of which can be used without modification.

The Hausman IIA Test of the IIA hypothesis (X)





CREATE Alternatives are renumbered ;if(altij<3)altijn=altij ;if(altij>3)altijn=altij-1 ;if(cn<3)csetn=3 ;if(cn>2)csetn=cset \$ If the experiment had Bus, cn<3 then the choice set should be reduced to three. The restricted model should now be: NI OGIT ;lhs= choice, csetn, altijn ;Choices = cart, carnt, train, busway, LR < Bus has disappeared :Model: U(cart) = asccart + fuel*fuel / This utility disapears U(carnt) = asccarnt + fuel*fuel / ?U(bus) = ascbus + fare*fare / U(train) = asctn + fare*fare / U(busway) = ascbusw + fare*fare / U(LR) = fare*fare \$



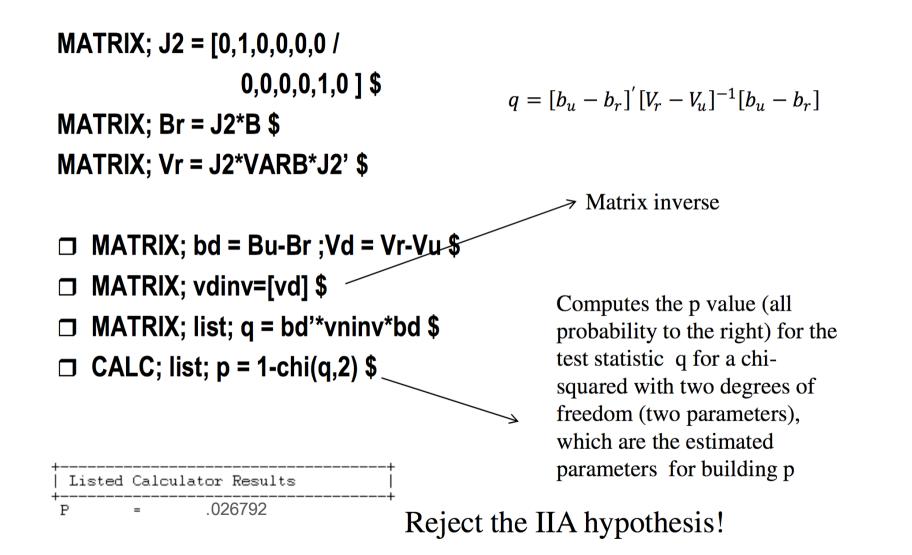
The Hausman IIA Test of the IIA hypothesis (XI)

The resulting coeficients are:

ASCCART FUEL ASCCARNT ASCTN FARE ASCBUSW 

To obtain the required b_r and V_r matrices we may use the same method we employed to obtain b_u and V_u. The number of parameters for the restricted model is smaller by the number of alternative specific parameters related to alternatives included in the unrestricted model. As such, the number of columns in the permutation matrix will also be fewer by this number.

The Hausman IIA Test of the IIA hypothesis (XII)



35

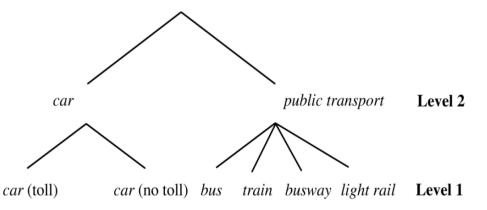
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Applying the Nested Logit Structure to the SP data experiment

The decision regarding the shape of the nested structure is the analyst choice. We first start with a structure which has proved many times to be significant:

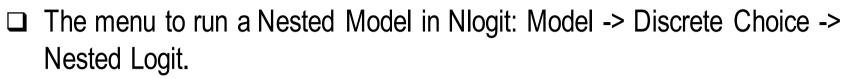


- In this perspective we are saying that both car options are correlated in their error components, that is, all the attributes that we are forgetting in the systematic part of utility may be correlated in that branch.
- □ We are proposing the same for the public transport branch.





First NL model (I)



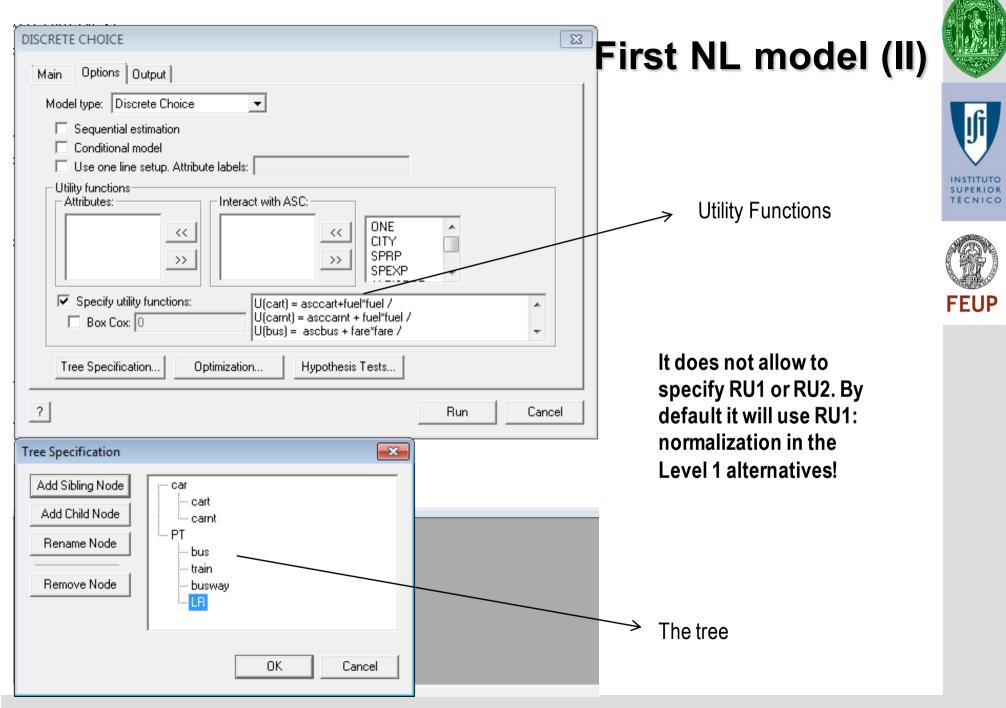
□ In the first screen you do exactly the same as you did for the MNL's.

DISCRETE CHOICE			×
Main Options Output			
Choice variable Choice variable: CHOICE Data type: Individual cho	ice 💌 🗌 Use ordinary weights:		
Choice set			
O Fixed number of choices:	Choice names:		
	Use choice based sampling weights:		
	Data coded on one line. Code:		
Variable number of choices:	Count variable:	CSET	
	Use universal choice set indicator:	ALTIJ 👻	
	Choice names:	ht, bus, train, busway, LR	
Perform IIA test on choices:	🔲 Use data scaling:		
?	[Run Cance	9



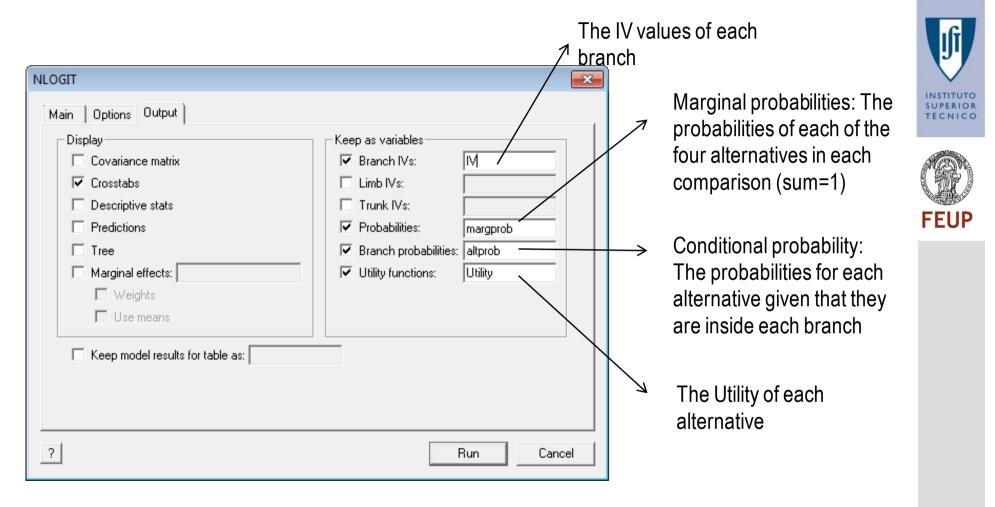
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First NL model (III)





First NL model (IV)

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NLOGIT :lhs = choice, cset, altij ;choices = cart, carnt, bus, train, busway, LR ;tree = car(cart, carnt), PT(bus, train, busway, LR) :RU1 :start = logit ;ivset: (car)=[1.0] :maxit = 100 :Prob=MARGPROB ;cprob=ALTPROB :ivb=IVBRANCH ;Utility=U1 :model: U(cart) = asccart + fuel*fuel/ U(carnt) = asccarnt + fuel*fuel / U(bus) = ascbus + fare*fare/ U(train) = asctn + fare*fare / U(busway) = ascbusw + fare*fare / U(LR) = fare*fare :Crosstab\$

Begins by running an MNL for having initial values for estimating the parameters.

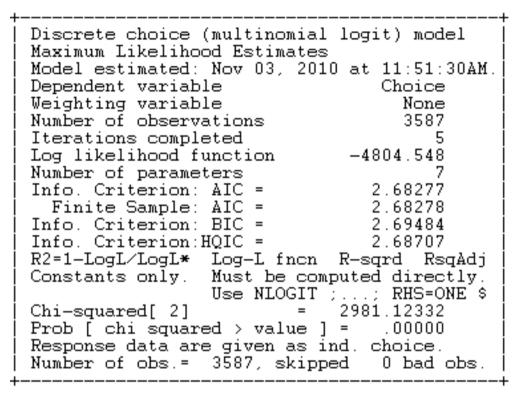
Branch1(alt1, alt2), Branch2(alt3, (...))

IV parameter normalization: the IV parameter will be 1 which normalizes the scale of the car branch to 1.

We choose to normalize the IV parameter of the car branch because it has the highest scale.



First NL model (V)



Variable	Coefficient	Standard Error	 b⁄St.Er.	P[Z >z]
ASCCART	22658772	.08285265	-2.735	.0062
FUEL	20241829	.01429703	-14.158	.0000
ASCCARNT	.37994204	.09911161	3.833	.0001
ASCBUS	.03145882	.07732794	.407	.6841
FARE	19347334	.01625132	-11.905	.0000
ASCTN	409564D-05	.07231932	.000	1.0000
ASCBUSW	.11125885	.06571070	1.693	.0904

- Nlogit will start by calibrating an MNL to generate initial coefficients for the iterative calibration.
- It gives exactly the same results as if you run an MNL with those 6 alternatives.





	+
FIML Nested Multinomial Logit Model Maximum Likelihood Estimates	İ
Model estimated: Nov 03, 2010 at 11:53:1	8AM.
Dependent variable CHOICE	
Weighting variable None	
Number of observations 3587	
Iterations completed 15	
Log likelihood function -4768.225	
Number of parameters 8	
Info. Criterion: AIC = 2.66307	
Finite Sample: AIC = 2.66309	
Info. Criterion: BIC = 2.67687	
Info. Criterion:HQIC = 2.66799	
Restricted log likelihood -6324.968	
McFadden Pseudo R-squared (.2461267)	
Chi squared 3113.487	
Degrees of freedom 8	
Prob[ChiSqd > value] = .0000000	
Constants only. Must be computed direct	ly.
Use NLOGIT ;; RHS=ON	
At start values -4804.5480 .00756 ****	***
Response data are given as ind. choice.	

$$Pseudo R^{2} = 1 - \frac{L(*)}{L(0)} = 1 - \left(\frac{-4768.225}{-6324.968}\right) = 0.2437$$

First NL model (VI)



Then the output shows the results for the Nested structure that we want to fit.



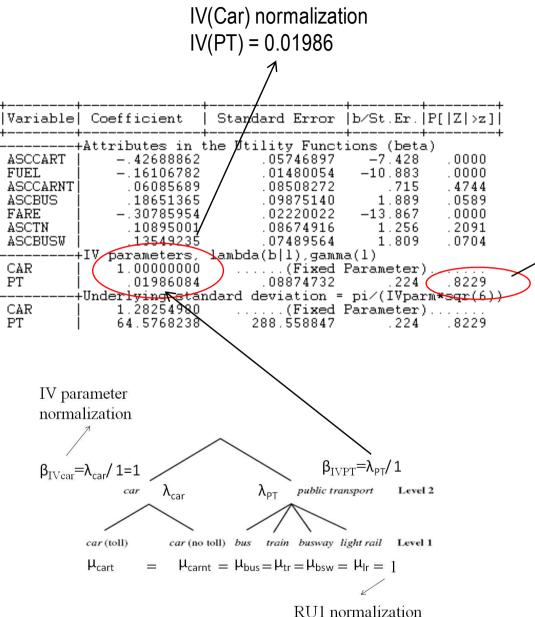
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- The pseudo R-Squared with no information base model is presented immediately.
- In Nested Logits we will use only this, because a model with just the alternative specific constants in nests is not the same as in an MNL.



First NL model (VII)



■We can't reject the hypothesis that the IV_{PT} is zero.



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□ There is too much correlation between the alternatives in the PT branch. Huge common variance.



First NL model (IX)

data.

zero.

MNI

You may proceed with

several Wald tests to the

The first test is exactly the

from the previous slide, we

are testing the hypothesis

of the coefficient being

The second one is about

testing the hypothesis that

the IV_{PT} is 1, which would

mean equal scales, (equal

variances) between both

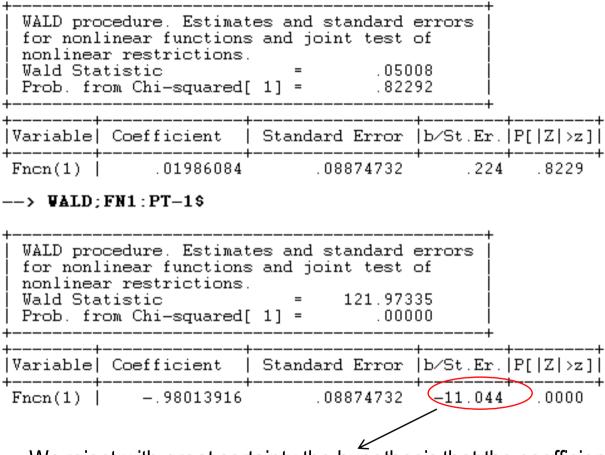
levels thus pointing to an

same as the output test



FFIIP

--> VALD; FN1: PT-0\$



We reject with great certainty the hypothesis that the coefficient may be 1, an MNL is definitely not advisable! Hence we should search for a new structure of the NL.

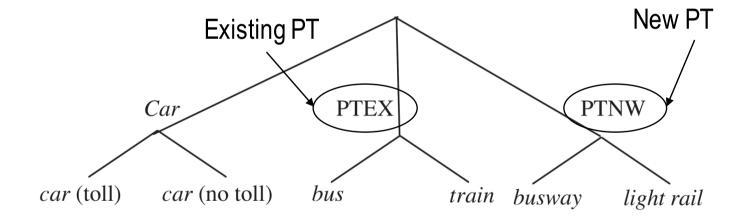
44



Second Nested Model (I)

□ We are not yet satisfied with the Nested Model we have just tested.

□ A second alternative model can be having three branches. We may study the following structure:









Second Nested Model (II)

NLOGIT ;lhs = choice, cset, altij ;choices = cart, carnt, bus, train, busway, LR ;tree = car(cart, carnt), PTEX(bus, train), PTNW (busway, LR) :RU1 ;start = logit ;ivset: (car)=[1.0] :maxit = 100 ;Prob=MARGPROB ;cprob=ALTPROB :ivb=IVBRANCH ;Utility=U1 :model: U(cart) = asccart + fuel*fuel/ U(carnt) = asccarnt + fuel*fuel / U(bus) = ascbus + fare*fare/ U(train) = asctn + fare*fare/ U(busway) = ascbusw + fare*fare / U(LR) = fare*fare :Crosstab\$





Second Nested Model (III)



Notice that we haven't
been worrying much about
the significance of the
variables, looking mainly at
the model structure.

□ Coefficient of variable

now.

ASCTN is irrelevant for

+			L	LL
Variable	Coefficient	Standard Error	b∕St.Er.	P[Z >z]
ASCCART FUEL	22658772 20241829	.08285265 .01429703	-2.735 -14.158	.0062
ASCCARNT ASCBUS FARE	.37994204 .03145882 19347334	.09911161 .07732794 .01625132	3.833 .407 –11.905	.0001 .6841 .0000
ASCTN ASCBUSW	409564D-05 .11125885		.000	1.0000

Discrete choice (multinomial logit) model

Model estimated: Nov 03, 2010 at 01:41:02PM.

R2=1-LogL/LogL* Log-L fncn R-sqrd RsqAdj Constants only. Must be computed directly.

Response data are given as ind. choice. Number of obs. = 3587, skipped 0 bad obs.

Choice

2.68277

2.68278

2.69484

2.68707

. 00000

2981.12332

-4804.548

Use NLOGIT :...: RHS=ONE \$

None

3587

5

7

Maximum Likelihood Estimates

Dependent variable

Weighting variable

Number of observations

Log likelihood function

Finite Sample: AIC =

Prob [chi squared > value] =

Iterations completed

Number of parameters

Info. Criterion: AIC =

Info. Criterion: BIC =

Info. Criterion:HOIC =

Chi-squared[2]



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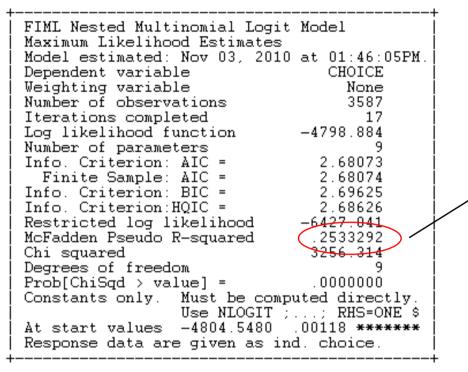
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Second Nested Model (IV)



+	·			+
Variable	Coefficient	Standard Error	b/St.Er.	P[Z >z]
	⊦Attributes in †	the Utility Funct:	ions (beta	n)
ASCCART	34016067	.08514441		.0001
FUEL	19924460			
ASCCARNT	.25725625			.0122
ASCBUS	13734992	.16336122		
FARE	24786595	.02675499		
ASCTN		.16301087		
ASCBUSW	.12774225		1.792	.0731
CAR	FIV parameters, 1.00000000	lambda(b l),gamma		
PTEX	.62271038	(Fixed H .10163515		
PTNU	.79117650	.10190404		
		ndard deviation =		
CAR	1.28254980	(Fixed H		
PTEX	2.05962490	.33615993		
PTNW	1.62106659	.20879441		

 Model has improved against a model with equal shares (no information)





Second Nested Model (V)



--> VALD; FN1:ptex-0\$

for nonl nonlinea Wald Sta	WALD procedure. Estimates and standard errors for nonlinear functions and joint test of nonlinear restrictions. Wald Statistic = 37.53915 Prob. from Chi-squared[1] = .00000				
Variable	Coefficient	Standard Error	b⁄St.Er.	P[Z >z]	
Fncn(1)	.62271038	.10163515	6.127	. 0000	

--> WALD; FN1: ptex-1\$

for nonl nonlinea Wald Sta	<pre>WALD procedure. Estimates and standard errors for nonlinear functions and joint test of nonlinear restrictions. Wald Statistic = 13.78040 Prob. from Chi-squared[1] = .00021 +</pre>				
Variable	Coefficient	Standard Error	b∕St.Er.	P[Z >z]	
Fncn(1)	37728962	.10163515	-3.712	.0002	

--> WALD; FN1: ptnw-0\$

for nonl nonlinea Wald Sta	ocedure. Estimat inear functions restrictions tistic rom Chi-squared	s and joint 		of 71	
Variable	Coefficient	Standard	Error	b∕St.Er.	P[Z >z]
Fncn(1)	.79117650	. 101	L90404	7.764	. 0000

--> VALD; FN1:ptnw-1\$

for non: nonlinea Wald Sta	ocedure. Estimat linear functions ar restrictions atistic rom Chi-squared	s and joint =		of 29	
Variable	Coefficient	Standard	Error	b∕St.Er.	P[Z >z]
Fncn(1)	20882350	. 10:	L90404	-2.049	.0404

The IV parameters are in the expected interval, neither 0 nor 1, meaning that the branches that we defined are significant for the data we are analyzing and for the Utility functions which we have proposed.



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Second Nested Model (VI)

LR CART CARNT BUS TRAIN BUSWAY Total CART NL Three CARNT branches BUS TRAIN BUSWAY LR Total % *Correct Predictions* = $\frac{986}{3587}$ = 27.48% CARNT TRAIN CART BUS BUSWAY LR Total MNL CART model CARNT BUS TRAIN BUSWAY LR Total % Correct Predictions = $\frac{982}{3587}$ = 27.37% No great difference!

Specifying utility functions at higher levels of the NL tree (I)

- Up to now we have only specified the utility functions at level 1, the level of the alternatives. But what if there are variables which better explain the choice between the branches (level 2) and not the conditional probabilities (probability in each nest)?
- The nested Logit model allows to specify these utility functions. Let's consider the same Nested Logit structure of the current example, but let's now include as explanatory variables on the option to use Car the number of licensed drivers at the home of the respondent and the number of vehicles available. Intuitively these should motivate the choice for driving in either tolled or non tolled roads.





Specifying utility functions at higher levels of the NL tree (II)

NLOGIT

;lhs = choice, cset, altij

;choices = cart, carnt, bus, train, busway, LR

;tree = car(cart, carnt), PTEX(bus, train), PTNW (busway, LR)

```
:RU1
;start = logit
;ivset: (car)=[1.0]
:maxit = 100
:Prob=MARGPROB
:cprob=ALTPROB
;ivb=IVBRANCH
;Utility=U1
:model:
U(Car)=ndrivlic*ndrivlic+numbvehs*numbvehs/
U(ptex)=asptex/
U(cart) = asccart + fuel*fuel/
U(carnt) = asccarnt + fuel*fuel /
U(bus) = ascbus + fare*fare/
U(train) = asctn + fare*fare/
U(busway) = ascbusw + fare*fare /
```

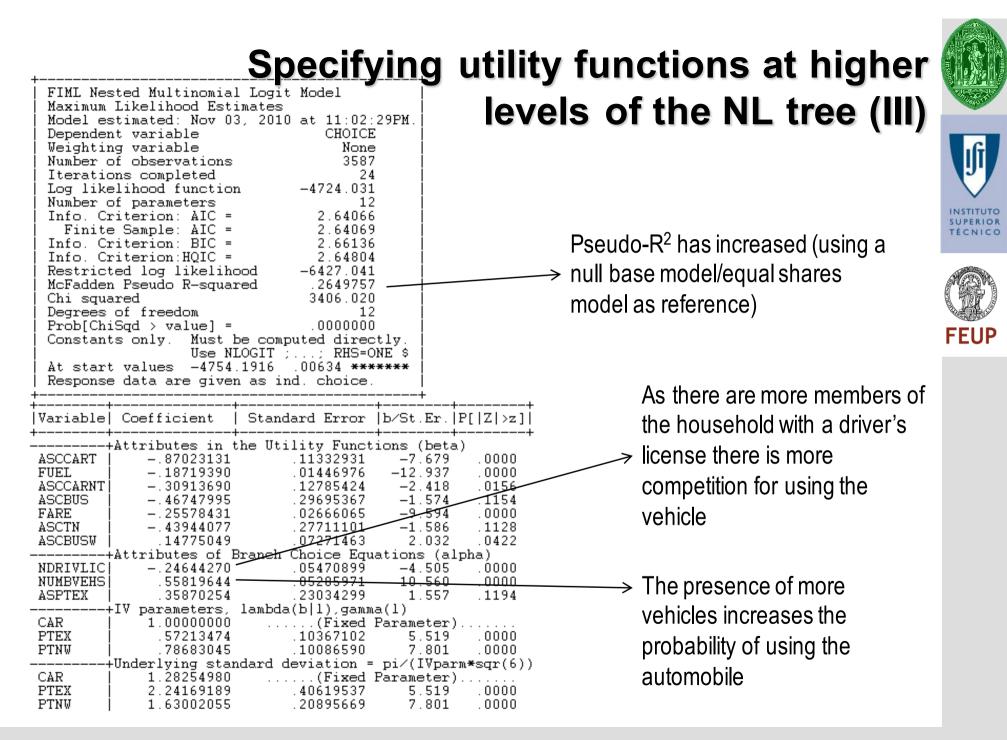
U(LR) = fare*fare

```
;Crosstab$
```

This is off course something that only a Nested Logit can do.







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Specifying utility functions at higher





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--> VALD; FN1: ptex-1\$

<pre>++ WALD procedure. Estimates and standard errors for nonlinear functions and joint test of nonlinear restrictions. Wald Statistic = 17.03332 Prob. from Chi-squared[1] = .00004 ++</pre>				
Variable	Coefficient	Standard Error	b⁄St.Er.	P[Z >z]
Fncn(1)	42786526	.10367102	-4.127	.0000

--> VALD; FN1:ptnv-1\$

-	WALD pro for nonl nonlines Wald Sta Prob. fr				
-	Variable	Coefficient	Standard Error	+ b∕St.Er.	+ P[Z >z]
-	Fncn(1)	21316955	.10086590	-2.113	.0346

The two IV parameters are statistically different from 1 and from 0 (previous table)

levels of the NL tree (IV)

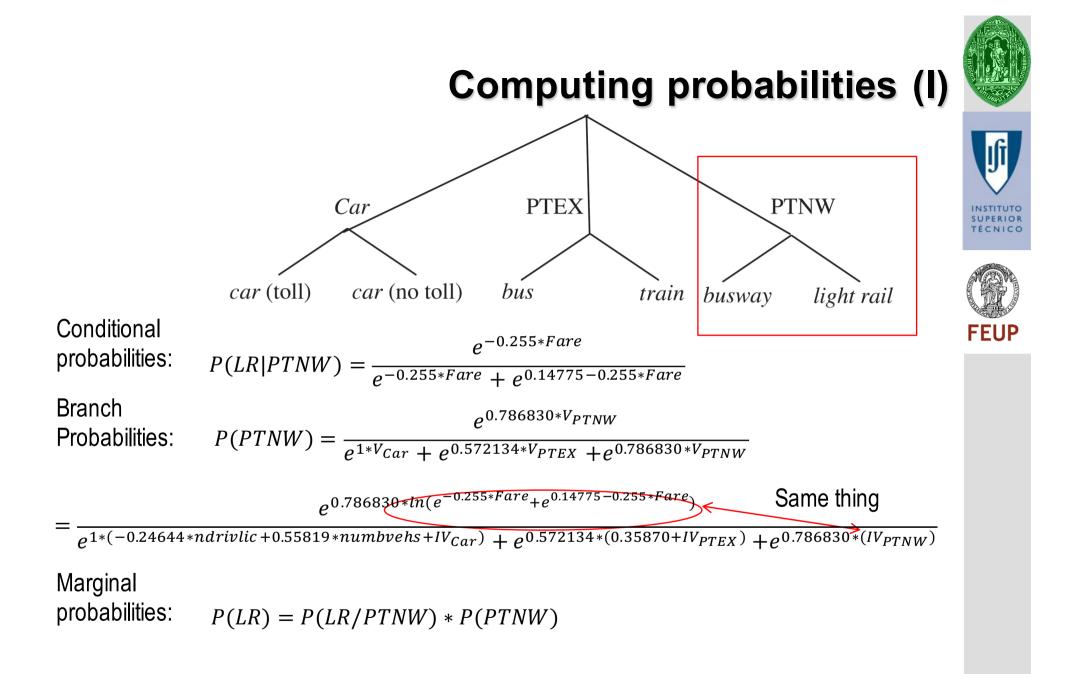
Specifying utility functions at higher levels of the NL tree (V)

	CART	CARNT	BUS	TRAIN	BUSWAY	LR	Total					
CART	193	204	94	87	115	105	798					
CARNT	196	222	91	98	117	114	838					
BUS	87	91	132	55	64	0	428					
TRAIN	91	94	55	129	0	60	428					
BUSWAY	123	114	59	0	185	88	569					
LR	109	113	0	57	88	159	526					
Total	798	838	431	425	569	526	3587					
	% Correct Predictions = $\frac{1022}{3587}$ = 28.49%											



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- This is not to say that the model will predict everything wrong: the shares as you remember are estimated through expectancy, aggregating probabilities across individuals so every probability will contribute.
- Modeling has as much of science as it has of art. It is difficult to say you have reached the best model. This model still does not have many explanatory variables.

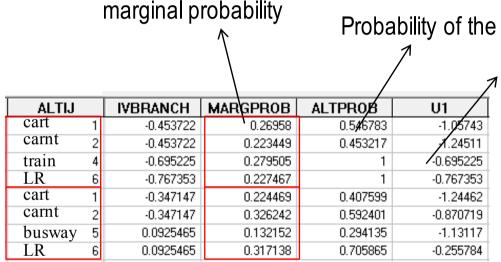


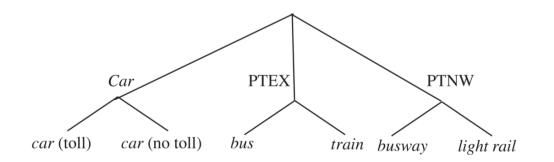


Computing probabilities (II)

□ The marginal probability:

P(Bus) = P(Bus|PT) * P(PT)





Probability of the alternative inside each branch

Utility of each alternative

Remember that in each choice the respondent had 4 alternatives, the first two were cart and carnt, the two other were Public Transport alternatives picked from 4 possible.





Aggregating across alternatives (I)

- □ Regarding aggregation be careful because you can't just copy the Probability attribute to excel, it will only bring 1900 lines. You have to export the variables:
- Go to project -> Export -> Variables then Choose Excel Worksheet, give the name for your file and choose the variables you want to export: ALTIJ and MARGPROB.

Fi	le Hom	e	Insert	Page	Layout		Formulas	Data	Review	View	Develop	er Kor	obat		
Fro	ess Web		From Oth Sources ternal Dat	s - Connect		Refresh All - G	Conned Properti Edit Lini nections	ies Z ↓	AZA Sort	T Eiltar	Clear Reaphly Advanced	Text to Column	Remove s Duplicates	Data Validation Data Too	
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1	ALTIJ, MAR	SPRO	в				Convert T	ext to Co	lumns Wiza	ard - Step	1 of 3			ß	23
2	1,.2730418						The Text	Winard ba	c determiner	Libat your	data is Delimi	ted			
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4	4,.3324234							data type	DOSE NEXC, C	i choose a	ie uata type i	inat best ut	scribes yo	ur uata.	
5	6,.1610541								na khak hask	doggribog	unum alatau				
6	1,.2221990						Choose the file type that best describes your data: O Delimited - Characters such as commas or tabs separate each field.								
7 2,.3080466															
8	5,.1176736														
_	6,.3520808														
_	1,.2060386														
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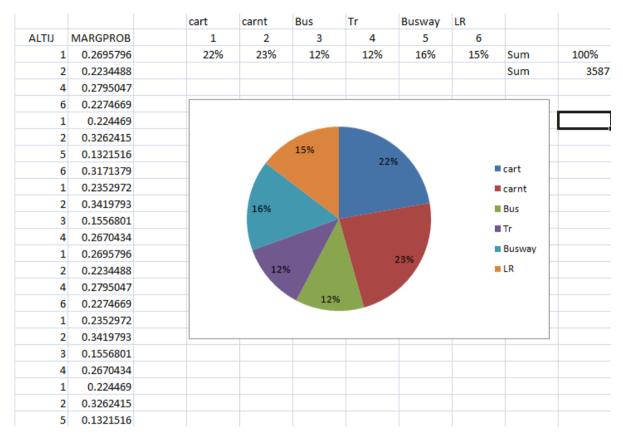








Aggregating across alternatives (II)







Be aware that we are aggregating across alternatives which have been produced synthetically, thus outputting indicative shares which you should be careful on using! An advanced topic on avoiding these issues is combining RP and SP data, but we will not see that on this course.

Bibliography

- Ben-Akiva, M. and Lerman, Steven R. (1985) "Discrete Choice Analysis: Theory and Applications to Travel Demand", MIT Press.
- Hensher, Rose and Greene (2005) "Applied Choice Analysis: A Primer" Cambridge.
- Ortúzar J. and Willumsen L. (2001) Modelling Transport. 3rd Edition. John Wiley and Sons. West Sussex, England.

Case study data is free to be accessed from: http://www.cambridge.org/0521605776





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