

Discrete Choice Modeling

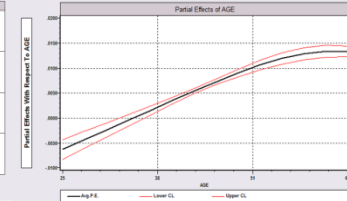
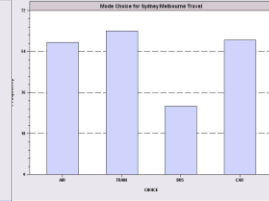
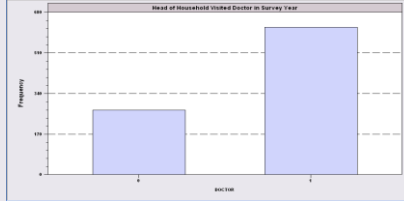
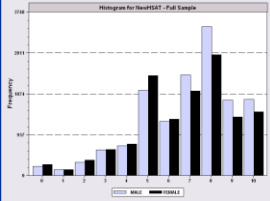
Nested Logit

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Discrete Choice Modeling

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William Greene
Stern School of Business
New York University



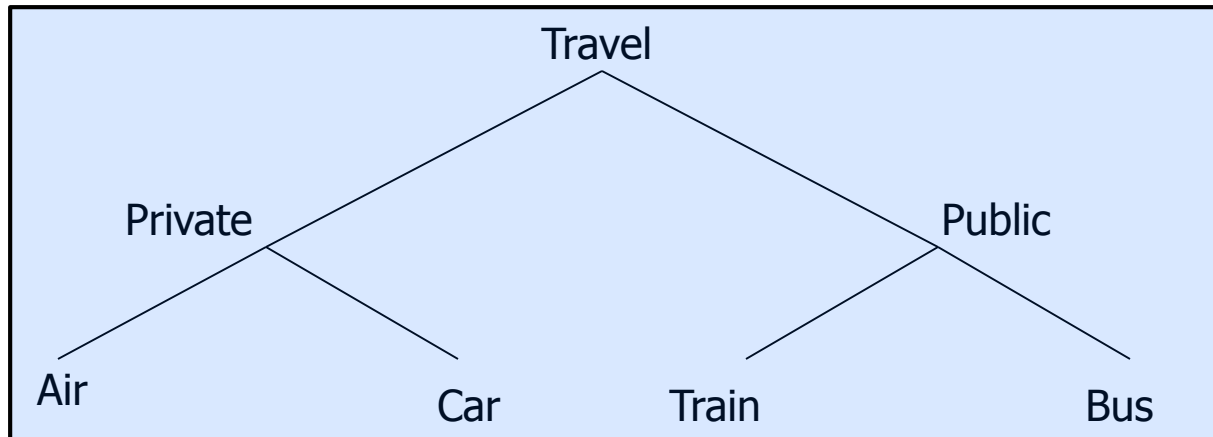
Extended Formulation of the MNL

Sets of similar alternatives

LIMB

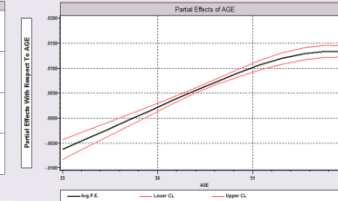
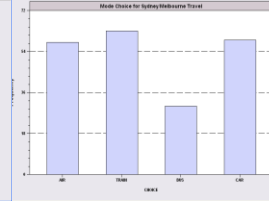
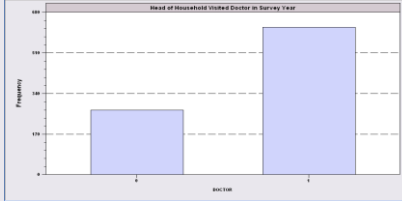
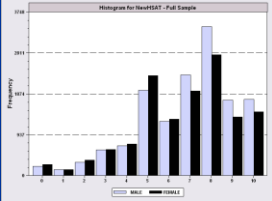
BRANCH

TWIG



Compound Utility: $U(Alt) = U(Alt|Branch) + U(branch)$

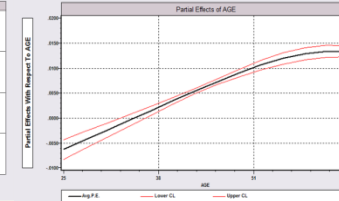
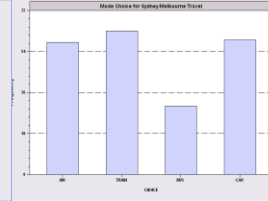
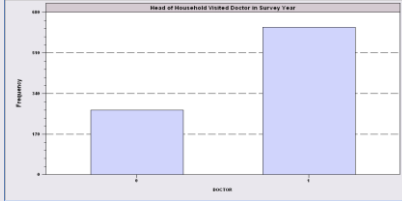
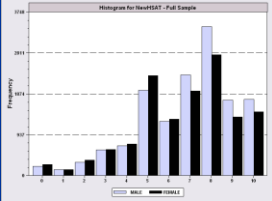
Behavioral implications – Correlations within branches



Correlation Structure for a Two Level Model

- ❑ Within a branch
 - Identical variances (IIA (MNL) applies)
 - Covariance (all same) = variance at higher level
- ❑ Branches have different variances (scale factors)
- ❑ Nested logit probabilities: Generalized Extreme Value

$$\text{Prob}[\text{Alt}, \text{Branch}] = \text{Prob}(\text{branch}) * \text{Prob}(\text{Alt} | \text{Branch})$$



Probabilities for a Nested Logit Model

Utility functions; (Drop observation indicator, i.)

Twig level: $k | j$ denotes alternative k in branch j

$$U(k | j) = \alpha_{k|j} + \beta' \mathbf{x}_{k|j}$$

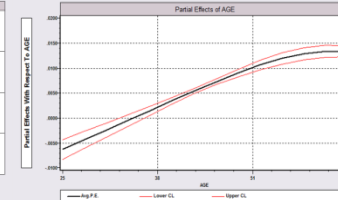
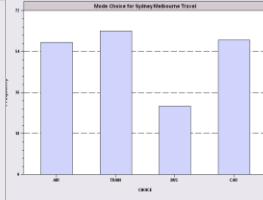
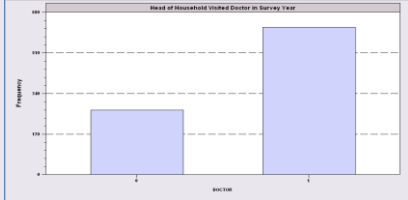
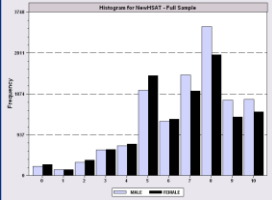
$$\text{Branch level } U(j) = \gamma' \mathbf{y}_j$$

$$\text{Twig level probability: } P(k | j) = P_{k|j} = \frac{\exp(\alpha_{k|j} + \beta' \mathbf{x}_{k|j})}{\sum_{m=1}^{K|j} \exp(\alpha_{m|j} + \beta' \mathbf{x}_{m|j})}$$

$$\text{Inclusive value for branch } j = IV(j) = \log \left[\sum_{m=1}^{K|j} \exp(\alpha_{m|j} + \beta' \mathbf{x}_{m|j}) \right]$$

$$\text{Branch level probability: } P(j) = \frac{\exp \left[\lambda_j (\gamma' \mathbf{y}_j + IV(j)) \right]}{\sum_{b=1}^B \exp \left[\lambda_b (\gamma' \mathbf{y}_b + IV(b)) \right]}$$

$\lambda_j = 1$ for all branches returns the original MNL model



Discrete Choice Modeling

Nested Logit

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Model Form RU1

Twig Level Probability

$$\text{Prob}(\text{Choice} = k \mid j) = \frac{\exp(\beta' \mathbf{x}_{k|j})}{\sum_{m=1}^{K|j} \exp(\beta' \mathbf{x}_{m|j})}$$

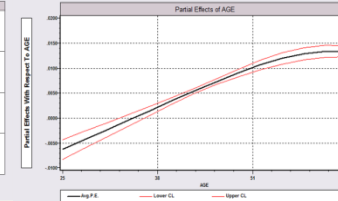
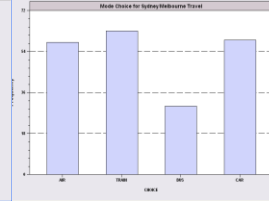
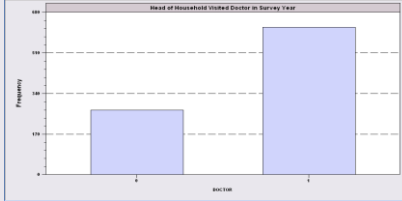
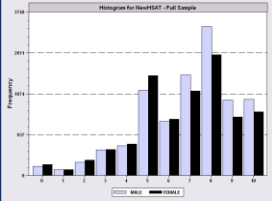
Inclusive Value for the Branch

$$IV(j) = \log \left[\sum_{m=1}^{K|j} \exp(\beta' \mathbf{x}_{m|j}) \right]$$

Branch Probability

$$\text{Prob}(\text{Branch} = j) = \frac{\exp \left[\lambda_j (\mathbf{y}' \mathbf{y}_j + IV(j)) \right]}{\sum_{b=1}^B \exp \left[\lambda_b (\mathbf{y}' \mathbf{y}_b + IV(b)) \right]}$$

$\lambda_j = 1$ Returns the Multinomial Logit Model



Moving Scaling Down to the Twig Level

RU2 Normalization

Twig Level Probability :

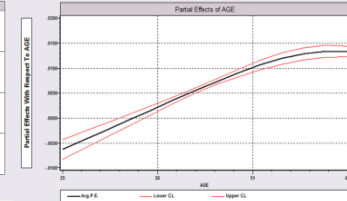
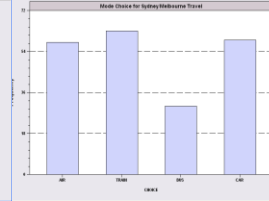
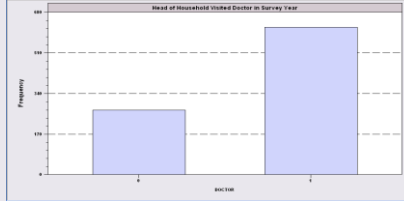
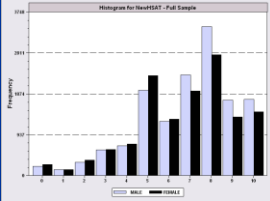
$$P_{klj} = \frac{\exp \left[\frac{\beta' x_{klj}}{\mu_j} \right]}{\sum_{m=1}^{klj} \exp \left[\frac{\beta' x_{mlj}}{\mu_j} \right]}$$

Inclusive Value for the Branch :

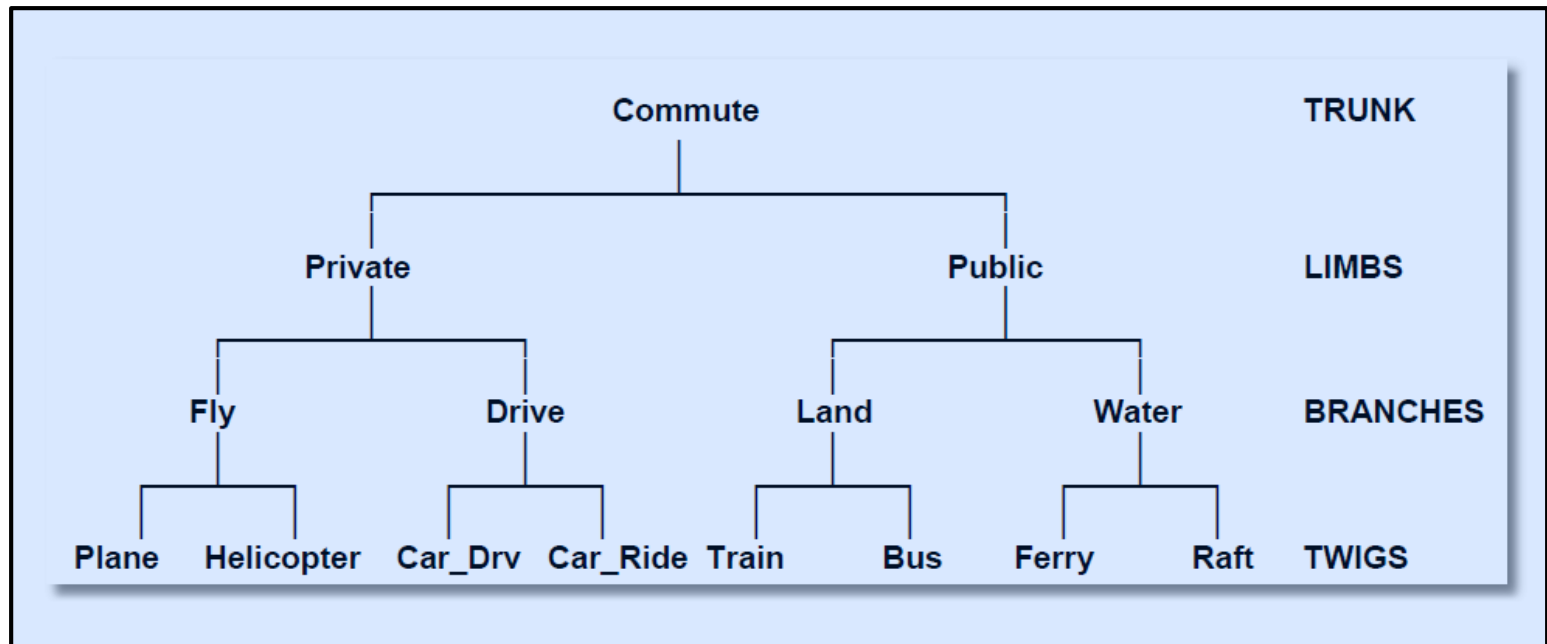
$$IV(j) = \log \left(\sum_{m=1}^{klj} \exp \left[\frac{\beta' x_{mlj}}{\mu_j} \right] \right)$$

Branch Probability :

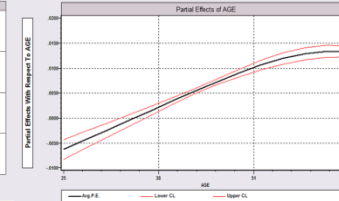
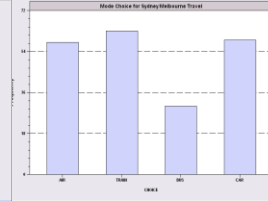
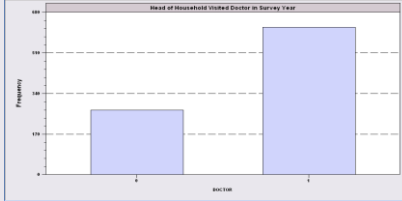
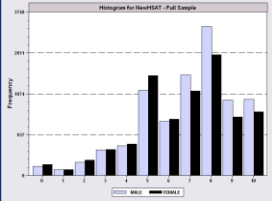
$$P_j = \frac{\exp \left[\mathbf{y}' \mathbf{y}_j + \mu_j IV(j) \right]}{\sum_{b=1}^B \exp \left[\mathbf{y}' \mathbf{y}_b + \mu_b IV(b) \right]}$$



Higher Level Trees

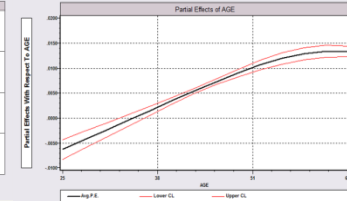
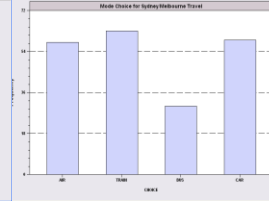
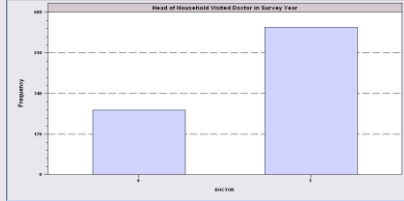
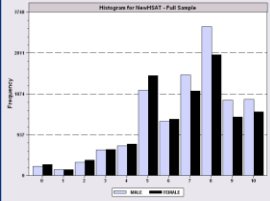


E.g., Location (Neighborhood)
Housing Type (Rent, Buy, House, Apt)
Housing (# Bedrooms)



Estimation Strategy for Nested Logit Models

- ❑ **Two step estimation (ca. 1980s)**
 - For each branch, just fit MNL
 - ❑ Loses efficiency – replicates coefficients
 - For branch level, fit separate model, just including γ and the inclusive values in the branch level utility function
 - ❑ Again loses efficiency
- ❑ **Full information ML (current)**
 - Fit the entire model at once, imposing all restrictions



Discrete Choice Modeling

Nested Logit

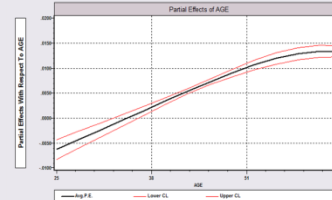
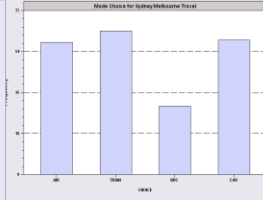
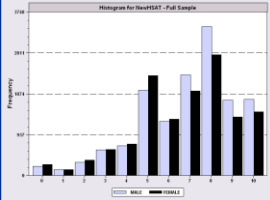
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Discrete choice (multinomial logit) model
Dependent variable                Choice
Log likelihood function            -172.94366
Estimation based on N =          210, K = 10
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
Constants only    -283.7588    .3905 .3787
Chi-squared[ 7]      =      221.63022
Prob [ chi squared > value ] =    .00000
Response data are given as ind. choices
Number of obs.=    210, skipped    0 obs
  
```

MNL Baseline

Variable	Coefficient	Standard Error	b/St.Er.	P[Z >z]
GC	.07578***	.01833	4.134	.0000
TTME	-.10289***	.01109	-9.280	.0000
INVT	-.01399***	.00267	-5.240	.0000
INVC	-.08044***	.01995	-4.032	.0001
A_AIR	4.37035***	1.05734	4.133	.0000
AIR_HIN1	.00428	.01306	.327	.7434
A_TRAIN	5.91407***	.68993	8.572	.0000
TRA_HIN3	-.05907***	.01471	-4.016	.0001
A_BUS	4.46269***	.72333	6.170	.0000
BUS_HIN4	-.02295	.01592	-1.442	.1493



Discrete Choice Modeling

Nested Logit

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FIML Nested Multinomial Logit Model

Dependent variable MODE

Log likelihood function -166.64835

The model has 2 levels.

Random Utility Form 1:IVparms = LMDAb|l

Number of obs.= 210, skipped 0 obs

FIML Parameter Estimates

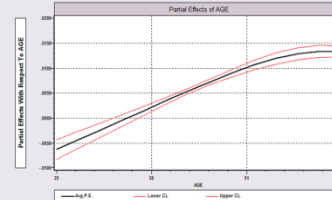
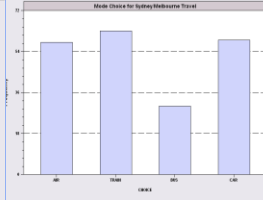
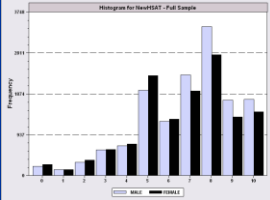
Variable	Coefficient	Standard Error	b/St.Er.	P[Z >z]
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Attributes in the Utility Functions (beta)

GC	.06579***	.01878	3.504	.0005
TTME	-.07738***	.01217	-6.358	.0000
INVT	-.01335***	.00270	-4.948	.0000
INVC	-.07046***	.02052	-3.433	.0006
A_AIR	2.49364**	1.01084	2.467	.0136
AIR_HIN1	.00357	.01057	.337	.7358
A_TRAIN	3.49867***	.80634	4.339	.0000
TRA_HIN3	-.03581***	.01379	-2.597	.0094
A_BUS	2.30142***	.81284	2.831	.0046
BUS_HIN4	-.01128	.01459	-.773	.4395

IV parameters, lambda(b|l), gamma(l)

PRIVATE	2.16095***	.47193	4.579	.0000
PUBLIC	1.56295***	.34500	4.530	.0000

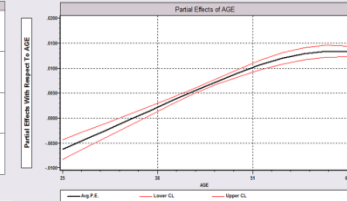
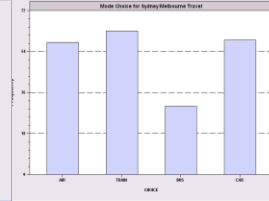
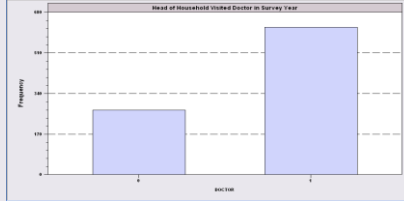
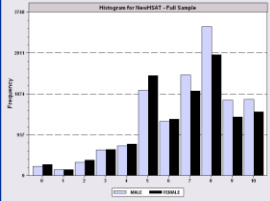


Elasticities Decompose Additively

$$\frac{\partial \log P(alt = j, limb = l, branch = b, trunk = r)}{\partial x(k) | alt = J, limb = L, branch = B, trunk = R} = D(k | J, B, L, R) = \Delta(k) \times F ,$$

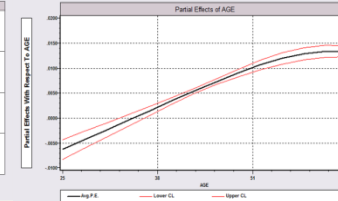
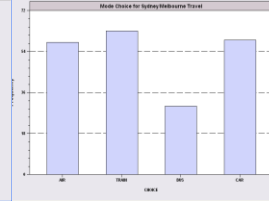
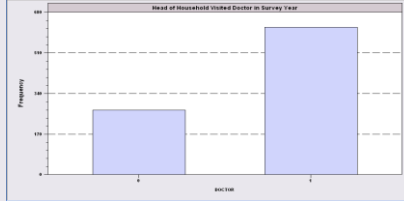
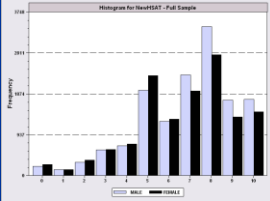
where $\Delta(k)$ = coefficient on $x(k)$ in $U(J|B,L,R)$

and $F = \mathbf{1}(r=R) \times \mathbf{1}(l=L) \times \mathbf{1}(b=B) \times [\mathbf{1}(j=J) - P(J|BLR)]$ (trunk effect),
 $\mathbf{1}(r=R) \times \mathbf{1}(l=L) \times [\mathbf{1}(b=B) - P(B|LR)] \times P(J|BLR) \times \tau_{B|LR}$ (limb effect),
 $\mathbf{1}(r=R) \times [\mathbf{1}(l=L) - P(L|R)] \times P(B|LR) \times P(J|BLR) \times \tau_{B|LR} \times \sigma_{L|R}$ (branch effect),
 $[\mathbf{1}(r=R) - P(R)] \times P(L|R) \times P(B|LR) \times P(J|BLR) \times \tau_{B|LR} \times \sigma_{L|R} \times \phi_R$ (twig effect).



Testing vs. the MNL

- ❑ Log likelihood for the NL model
- ❑ Constrain IV parameters to equal 1 with
; IVSET(list of branches)=[1]
- ❑ Use likelihood ratio test
- ❑ For the example:
 - $\text{LogL (NL)} = -166.68435$
 - $\text{LogL (MNL)} = -172.94366$
 - $\text{Chi-squared with 2 d.f.} = 2(-166.68435 - (-172.94366))$
 $= 12.51862$
 - The critical value is 5.99 (95%)
 - The MNL (and a fortiori, IIA) is rejected



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Nested Logit

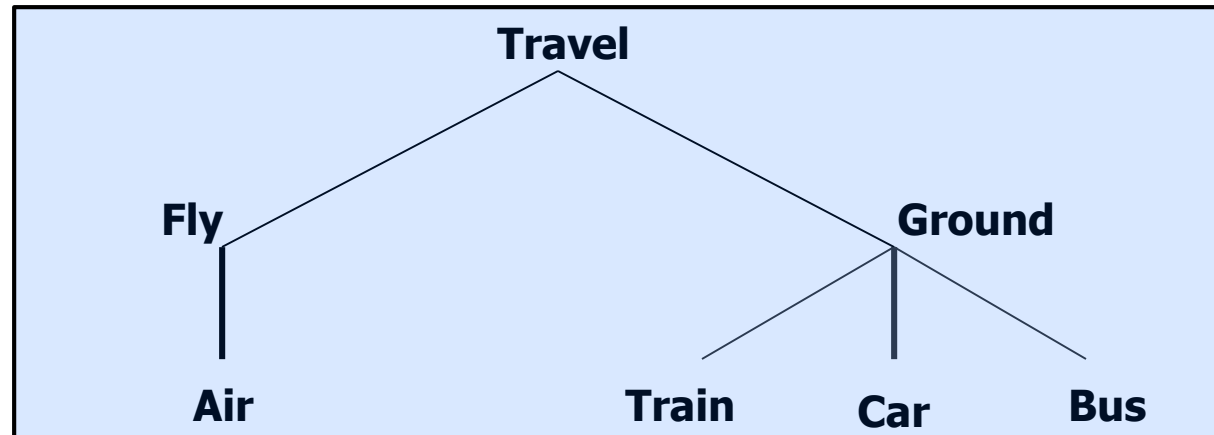
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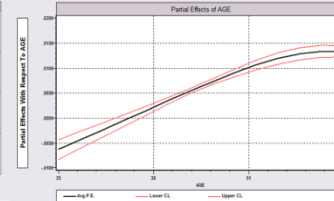
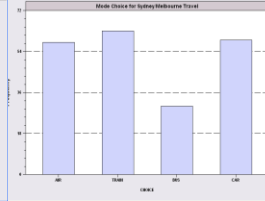
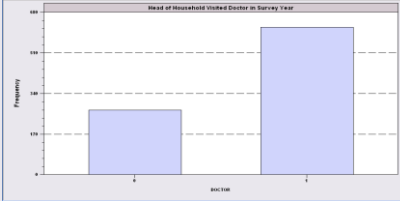
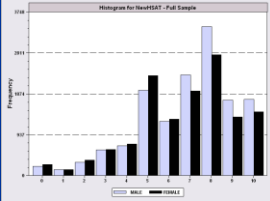
Degenerate Branches

LIMB

BRANCH

TWIG





NL Model with a Degenerate Branch

 FIML Nested Multinomial Logit Model

Dependent variable MODE

Log likelihood function -148.63860

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Variable	Coefficient	Standard Error	b/St.Er.	P[Z >z]
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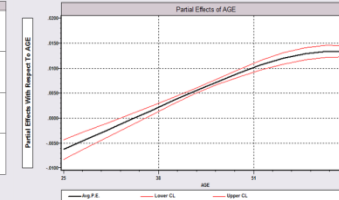
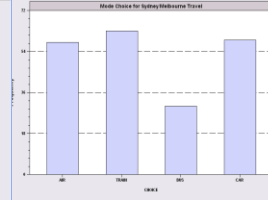
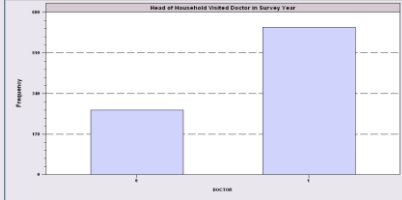
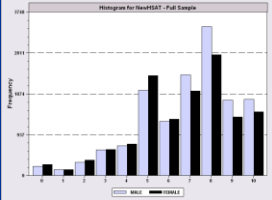
|Attributes in the Utility Functions (beta)

GC	.44230***	.11318	3.908	.0001
TTME	-.10199***	.01598	-6.382	.0000
INVT	-.07469***	.01666	-4.483	.0000
INVC	-.44283***	.11437	-3.872	.0001
A_AIR	3.97654***	1.13637	3.499	.0005
AIR_HIN1	.02163	.01326	1.631	.1028
A_TRAIN	6.50129***	1.01147	6.428	.0000
TRA_HIN2	-.06427***	.01768	-3.635	.0003
A_BUS	4.52963***	.99877	4.535	.0000
BUS_HIN3	-.01596	.02000	-.798	.4248

|IV parameters, lambda(b|1), gamma(1)

FLY	.86489***	.18345	4.715	.0000
GROUND	.24364***	.05338	4.564	.0000

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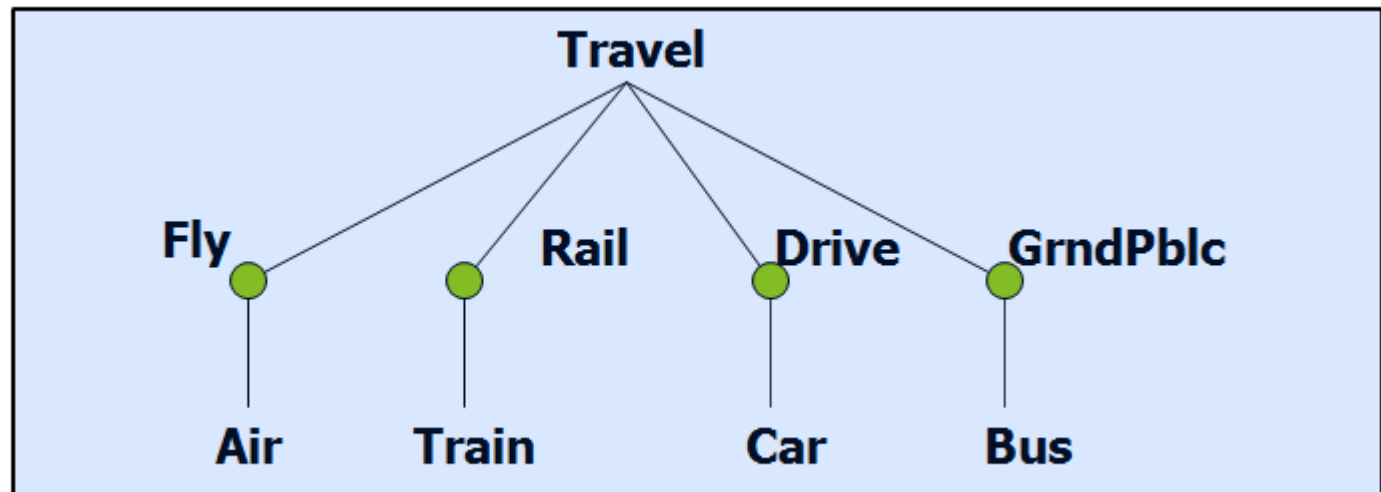
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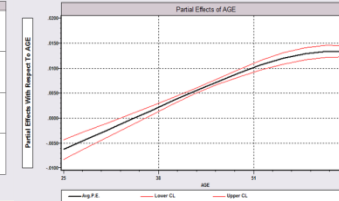
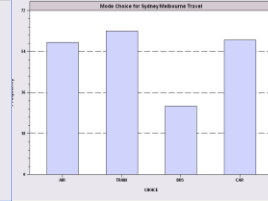
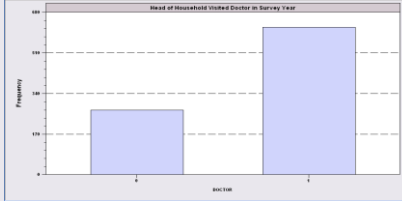
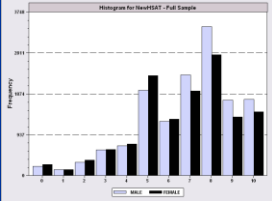
Using Degenerate Branches to Reveal Scaling

LIMB

BRANCH

TWIG





Discrete Choice Modeling

Nested Logit

[Part 8] 17/26

Scaling in Transport Modes

FIML Nested Multinomial Logit Model

Dependent variable **MODE**

Log likelihood function **-182.42834**

The model has 2 levels.

Nested Logit form: IVparms=Tauba|l,r,S|l,r

& Fr.No normalizations imposed a priori

Number of obs.= 210, skipped 0 obs

```
NLOGIT ; Lhs=mode
; Rhs=gc,ttme,invvt,invvc,one
; Choices=air,train,bus,car
; Tree=Fly(Air),
;       Rail(train),
;       LoclMass(bus),
;       Drive(Car)
; ivset:(drive)=[1]$
```

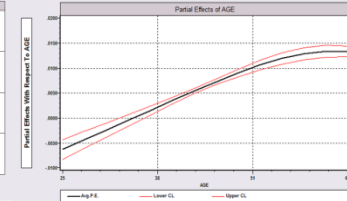
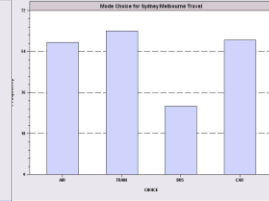
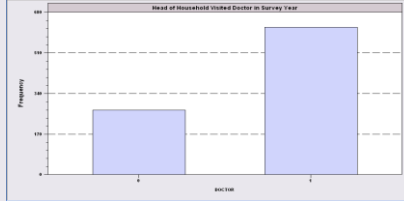
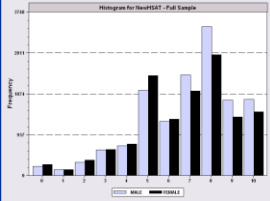
Variable	Coefficient	Standard Error	b/St.Er.	P[Z >z]
----------	-------------	----------------	----------	----------

|Attributes in the Utility Functions (beta)

GC	.09622**	.03875	2.483	.0130
TTME	-.08331***	.02697	-3.089	.0020
INVT	-.01888***	.00684	-2.760	.0058
INVC	-.10904***	.03677	-2.966	.0030
A_AIR	4.50827***	1.33062	3.388	.0007
A_TRAIN	3.35580***	.90490	3.708	.0002
A_BUS	3.11885**	1.33138	2.343	.0192

|IV parameters, tau(b|l,r),sigma(l|r),phi(r)

FLY	1.65512**	.79212	2.089	.0367
RAIL	.92758***	.11822	7.846	.0000
LOCLMASS	1.00787***	.15131	6.661	.0000
DRIVE	1.00000	(Fixed Parameter).....		



Discrete Choice Modeling

Nested Logit

[Part 8] 18/26

```
NLOGIT ; lhs=mode;rhs=gc,ttme,invtr,invtr ; rh2=one,hinc; choices=air,train,bus,car
; tree=Travel[Private(Air,Car),Public(Train,Bus)] ; ru1
; simulation = * ; scenario:gc(car)=[*]1.5
```

Simulation

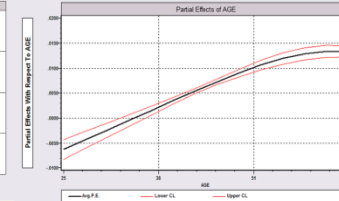
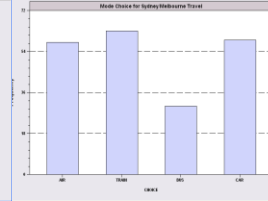
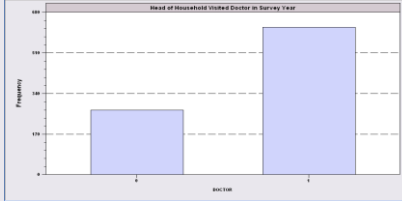
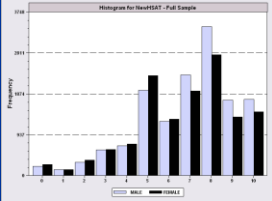
```
|Simulations of Probability Model|
|Model: FIML: Nested Multinomial Logit Model|
|Number of individuals is the probability times the|
|number of observations in the simulated sample.|
|Column totals may be affected by rounding error.|
|The model used was simulated with 210 observations.|
```

Specification of scenario 1 is:

Attribute	Alternatives affected	Change type	Value
GC	CAR	Scale base by value	1.500

Simulated Probabilities (shares) for this scenario:

Choice	Base	Scenario	Scenario - Base
	%Share Number	%Share Number	ChgShare ChgNumber
AIR	26.515 56	8.854 19	-17.661% -37
CAR	29.200 61	6.836 14	-22.364% -47
TRAIN	29.782 63	12.487 26	-17.296% -37
BUS	14.504 30	71.824 151	57.320% 121
Total	100.000 210	100.000 210	.000% 0



Discrete Choice Modeling

Nested Logit

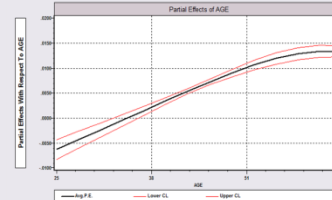
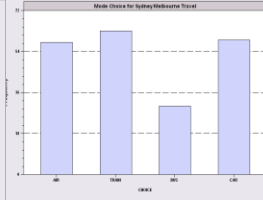
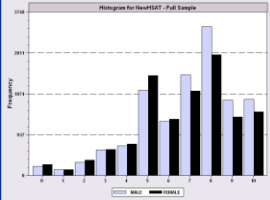
[Part 8] 19/26

Nested Logit Approach for Best/Worst

```
nlogit
;lhs=choice,cset,altij
;choices=A,B,C,D
;model:
U(A) = Seat + in28*inch28 + in30*inch30 + scr*cabscr + limmov*limmov + pay*pay + h1*hour1 + h3*hour3 /
U(B) = Scrn + in28*inch28 + in30*inch30 + scr*cabscr + limmov*limmov + pay*pay + h1*hour1 + h3*hour3 /
U(C) = Alco + in28*inch28 + in30*inch30 + scr*cabscr + limmov*limmov + pay*pay + h1*hour1 + h3*hour3 /
U(D) =      in28*inch28 + in30*inch30 + scr*cabscr + limmov*limmov + pay*pay + h1*hour1 + h3*hour3 $
```

Note that you could potentially run any model for this data. For example, if one wanted to test for differences in scale between the best and worst alternatives, one could use the NL model (note however that you need the altij variable to take different values for best and worst now – see **altn** in the two examples above).

Uses the result that if $U(i,j)$ is the lowest utility, $-U(i,j)$ is the highest.



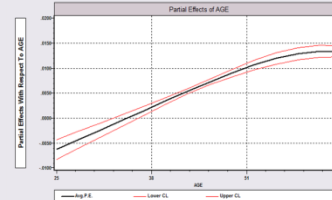
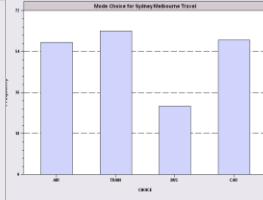
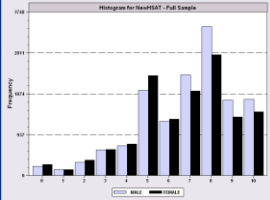
Discrete Choice Modeling

Nested Logit

[Part 8] 20/26

Nested Logit Approach.

Resp	Set	Altij	Altn	Cset	Bestworst		Inch28	Inch30	CabScr	LimMov	Pay	Hour1	Hour3	Choice
1	1	1	1	4	1		0	1	0	0	0	0	0	0
1	1	2	2	4	1		0	0	0	1	0	0	0	0
1	1	3	3	4	1		0	0	0	0	0	0	0	1
1	1	4	4	4	1		0	0	0	0	0	0	0	0
1	1	1	5	4	-1		0	-1	0	0	0	0	0	0
1	1	2	6	4	-1		0	0	0	-1	0	0	0	1
1	1	3	7	4	-1		0	0	0	0	0	0	0	0
1	1	4	8	4	-1		0	0	0	0	0	0	0	0
1	2	1	1	4	1		1	0	0	0	0	0	0	0
1	2	2	2	4	1		0	0	1	0	0	0	0	0
1	2	3	3	4	1		0	0	0	0	1	0	0	1
1	2	4	4	4	1		0	0	0	0	0	0	1	0
1	2	1	5	4	-1		-1	0	0	0	0	0	0	1
1	2	2	6	4	-1		0	0	-1	0	0	0	0	0
1	2	3	7	4	-1		0	0	0	0	-1	0	0	0
1	2	4	8	4	-1		0	0	0	0	0	0	-1	0



Discrete Choice Modeling

Nested Logit

[Part 8] 21/26

Nested Logit Approach – Different Scaling for Worst

nlogit

;lhs=choice,cset,**altn**

;choices=Ab,Bb,Cb,Db, Aw,Bw,Cw,Dw

;tree =Bst(Ab,Bb,Cb,Db),Wst(Aw,Bw,Cw,Dw)

;ru1

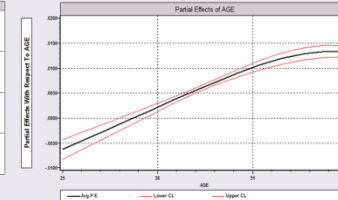
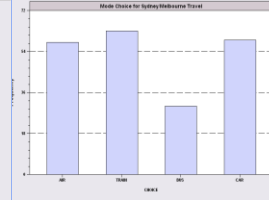
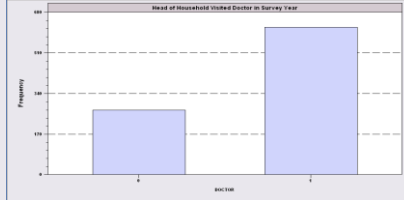
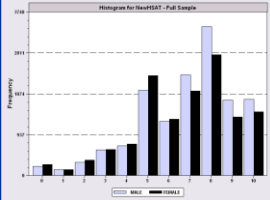
;ivset:(Bst)=[1.0]

;model:

U(Ab) = Seat + in28*inch28 + in30*inch30 + scr*cabscr + limmov*limmov + pay*pay + h1*hour1 + h3*hour3 /
 U(Bb) = Scrn + in28*inch28 + in30*inch30 + scr*cabscr + limmov*limmov + pay*pay + h1*hour1 + h3*hour3 /
 U(Cb) = Alco + in28*inch28 + in30*inch30 + scr*cabscr + limmov*limmov + pay*pay + h1*hour1 + h3*hour3 /
 U(Db) = in28*inch28 + in30*inch30 + scr*cabscr + limmov*limmov + pay*pay + h1*hour1 + h3*hour3 /
 U(Aw) = Seat + in28*inch28 + in30*inch30 + scr*cabscr + limmov*limmov + pay*pay + h1*hour1 + h3*hour3 /
 U(Bw) = Scrn + in28*inch28 + in30*inch30 + scr*cabscr + limmov*limmov + pay*pay + h1*hour1 + h3*hour3 /
 U(Cw) = Alco + in28*inch28 + in30*inch30 + scr*cabscr + limmov*limmov + pay*pay + h1*hour1 + h3*hour3 /
 U(Dw) = in28*inch28 + in30*inch30 + scr*cabscr + limmov*limmov + pay*pay + h1*hour1 + h3*hour3 \$

8 choices are two blocks of 4.

Best in one brance, worst in the
second branch



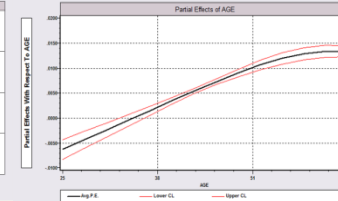
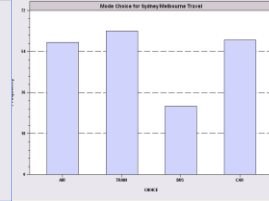
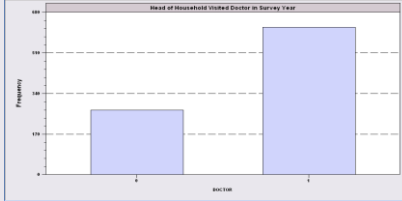
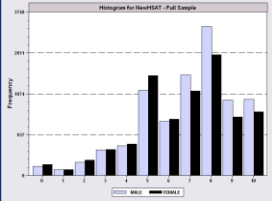
An Error Components Model

Random terms in utility functions share random components

$$\begin{aligned}
 U(\text{Air}, i) &= \alpha_{\text{AIR}} + \beta_1 \text{INVC}_{i, \text{AIR}} + \dots + \varepsilon_{i, \text{AIR}} + \boxed{w_{i,1}} \\
 U(\text{Car}, i) &= \beta_1 \text{INVC}_{i, \text{CAR}} + \dots + \varepsilon_{i, \text{CAR}} + \boxed{w_{i,1}} \\
 U(\text{Train}, i) &= \alpha_{\text{TRAIN}} + \beta_1 \text{INVC}_{i, \text{TRAIN}} + \dots + \varepsilon_{i, \text{TRAIN}} + \boxed{w_{i,2}} \\
 U(\text{Bus}, i) &= \alpha_{\text{BUS}} + \beta_1 \text{INVC}_{i, \text{BUS}} + \dots + \varepsilon_{i, \text{BUS}} + \boxed{w_{i,2}}
 \end{aligned}$$

$$\text{Cov} \begin{pmatrix} \text{Air} \\ \text{Car} \\ \text{Train} \\ \text{Bus} \end{pmatrix} = \begin{bmatrix} \boxed{\sigma_\varepsilon^2 + \theta_1^2} & \boxed{\theta_1^2} & 0 & 0 \\ \boxed{\theta_1^2} & \boxed{\sigma_\varepsilon^2 + \theta_1^2} & 0 & 0 \\ 0 & 0 & \boxed{\sigma_\varepsilon^2 + \theta_2^2} & \boxed{\theta_2^2} \\ 0 & 0 & \boxed{\theta_2^2} & \boxed{\sigma_\varepsilon^2 + \theta_2^2} \end{bmatrix}$$

This model is estimated by maximum simulated likelihood.



The Multinomial Probit Model

$$U(i, t, j) = \alpha_j + \beta' \mathbf{x}_{itj} + \gamma_j' \mathbf{z}_{it} + \varepsilon_{i,t,j}$$

$$[\varepsilon_1, \varepsilon_2, \dots, \varepsilon_J] \sim \text{Multivariate Normal}[\mathbf{0}, \mathbf{\Sigma}]$$

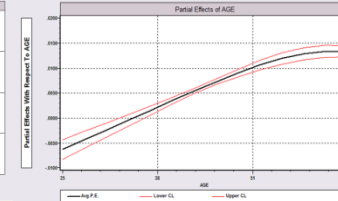
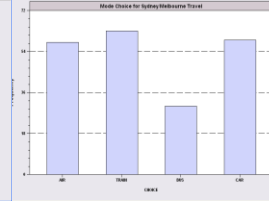
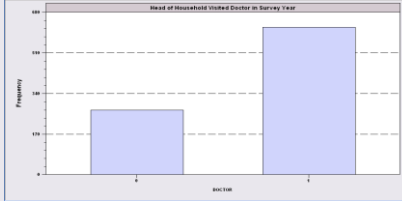
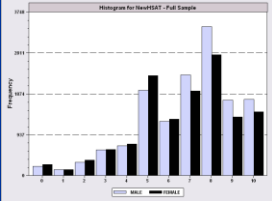
Correlation across choices

Heteroscedasticity

Some restrictions needed for identification

Sufficient: Last row of $\mathbf{\Sigma}$ = last row of $\mathbf{I}$

One additional diagonal element = 1.



Multinomial Probit Probabilities

$$U(i, j) > U(i, 1)$$

$$U(i, j) > U(i, 2)$$

...

$$U(i, j) > U(i, J)$$

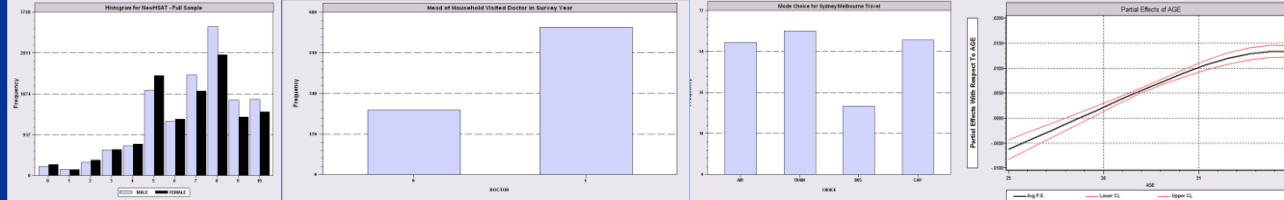
$$\text{Prob}(\text{event}) = \int_{-\infty}^{U(i,1)-U(i,J)} \int_{-\infty}^{U(i,1)-U(i,J-1)} \dots \int_{-\infty}^{U(i,1)-U(i,1)} \phi_{J-1}(\varepsilon_J, \varepsilon_{J-1} \dots \varepsilon_1 | \Sigma_{(j)}) d\varepsilon$$

Requires (J-1)-variate multivariate normal integration with a full covariance matrix.

The GHK simulator uses simulation to compute these probabilities accurately

using a simulation of the form $\text{Prob}(\text{event}) \approx \frac{1}{R} \sum_{r=1}^R \prod_{j=1}^{J-1} \Phi[h(w_{kr})]$.

w_{kr} = sequences of random $N[0,1]$ draws using a simulator.



Discrete Choice Modeling

Nested Logit

[Part 8] 26/26

The problem of just reporting coefficients

```

Alternative-specific multinomial probit      Number of obs   =      840
Case variable: id                          Number of cases  =      210
Alternative variable: mode                  Alts per case: min =       4
                                           avg   =      4.0
                                           max   =       4

Integration sequence:      Hammersley
Integration points:        200           Wald chi2(5)   =     32.05
Log simulated-likelihood = -190.09418     Prob > chi2    =     0.0000
  
```

choice	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
mode						
travelcost	-.00977	.0027834	-3.51	0.000	-.0152253	-.0043146
termtime	-.0377095	.0094088	-4.01	0.000	-.0561504	-.0192686
air	(base alternative)					
train						
income	-.0291971	.0089246	-3.27	0.001	-.046689	-.0117052
_cons	.5616376	.3946551	1.42	0.155	-.2118721	1.335147
bus						
income	-.0127503	.0079267	-1.61	0.108	-.0282863	.0027857
_cons	-.0571364	.4791861	-0.12	0.905	-.9963239	.882051
car						
income	-.0049086	.0077486	-0.63	0.526	-.0200957	.0102784
_cons	-1.833393	.8186156	-2.24	0.025	-3.43785	-.2289357
/lnl2_2	-.5502039	.3905204	-1.41	0.159	-1.31561	.2152021
/lnl3_3	-.6005552	.3353292	-1.79	0.073	-1.257788	.0566779
/12_1	1.131518	.2124817	5.33	0.000	.7150612	1.547974
/13_1	.9720669	.2352116	4.13	0.000	.5110606	1.433073
/13_2	.5197214	.2861552	1.82	0.069	-.0411325	1.080575

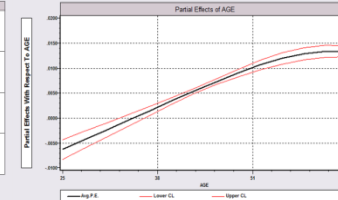
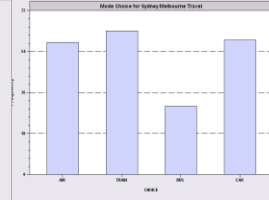
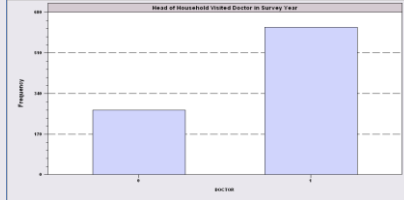
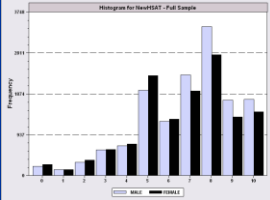
```

Multinomial Probit Model
Dependent variable      MODE
Log likelihood function -189.43560
Restricted log likelihood -291.12182
Chi squared [ 13](P= .000) 203.37243
Significance level      .00000
McFadden Pseudo R-squared .3492909
Estimation based on N = 210, K = 13
Inf. Cr. AIC = 404.9 AIC/N = 1.928
R2=1-LogL/LogL* Log-L fncn R-sqrd R2Adj
No coefficients -291.1218 .3493 .3356
Constants only -283.7588 .3324 .3183
At start values -215.7845 .1221 .1036
Response data are given as ind. choices
Replications for simulated probs. = 100
Pseudo random draws (Mersenne twister).
Number of obs. = 210, skipped 0 obs
  
```

MODE	Coefficient	Standard Error	z	Prob. z >Z*	95% Confidence Interval	
Attributes in the Utility Functions (beta)						
GC	-.02377***	.00905	-2.63	.0086	-.04150	-.00604
TME	-.09303***	.03596	-2.59	.0097	-.16351	-.02255
A_AIR	4.53688**	2.04884	2.21	.0268	.52123	8.55254
AIR_HIN1	.01181	.02848	.41	.6785	-.04401	.06762
A_TRAIN	5.89123***	1.93928	3.04	.0024	2.09031	9.69215
TRA_HIN2	-.06043***	.02181	-2.77	.0056	-.10317	-.01768
A_BUS	4.36644***	1.26372	3.46	.0005	1.88960	6.84328
BUS_HIN3	-.01934	.01811	-1.07	.2854	-.05484	.01615
Std. Devs. of the Normal Distribution						
s[AIR]	2.81207**	1.27772	2.20	.0277	.30777	5.31636
s[TRAIN]	1.91542**	.96835	1.98	.0479	.01749	3.81334
s[BUS]	1.0	(Fixed Parameter)				
s[CAR]	1.0	(Fixed Parameter)				
Correlations in the Normal Distribution						
rAIR_TRA	-.04362	1.18925	-.04	.9707	-2.37451	2.28726
rAIR_BUS	-.12346	1.24418	-.10	.9210	-2.56200	2.31508
rTRA_BUS	.56226	.47185	1.19	.2334	-.36254	1.48707
rAIR_CAR	0.0	(Fixed Parameter)				
rTRA_CAR	0.0	(Fixed Parameter)				
rBUS_CAR	0.0	(Fixed Parameter)				

Stata: AIR = “base alternative”

Normalizes on CAR



Discrete Choice Modeling

Nested Logit

[Part 8] 27/26

```
+-----+
| Multinomial Probit Model
| Dependent variable          MODE
| Number of observations      210
| Log likelihood function     -184.7619
| Response data are given as ind. choice.
+-----+
```

Multinomial Probit Model

Not comparable to MNL

```
+-----+-----+-----+-----+
|Variable| Coefficient | Standard Error |b/St.Er.|P[|Z|>z]|
+-----+-----+-----+-----+-----+
```

-----+Attributes in the Utility Functions (beta)

Variable	Coefficient	Standard Error	b/St.Er.	P[Z >z]
GC	.10822534	.04339733	2.494	.0126
TTME	-.08973122	.03381432	-2.654	.0080
INVC	-.13787970	.05010551	-2.752	.0059
INVT	-.02113622	.00727190	-2.907	.0037
AASC	3.24244623	1.57715164	2.056	.0398
TASC	4.55063845	1.46158257	3.114	.0018
BASC	4.02415398	1.28282031	3.137	.0017

-----+Std. Devs. of the Normal Distribution.

Variable	Std. Dev.	Std. Error	b/St.Er.	P[Z >z]
s[AIR]	3.60695794	1.42963795	2.523	.0116
s[TRAIN]	1.59318892	.81711159	1.950	.0512
s[BUS]	1.00000000	(Fixed Parameter).....		
s[CAR]	1.00000000	(Fixed Parameter).....		

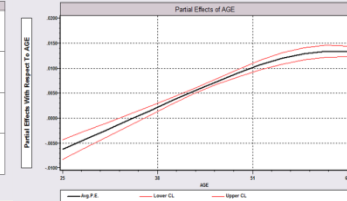
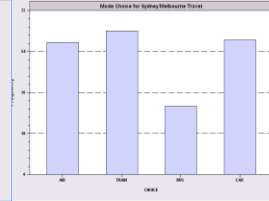
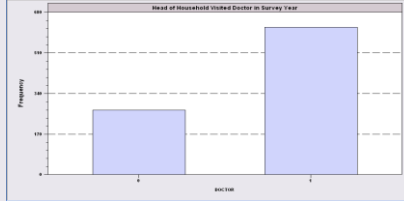
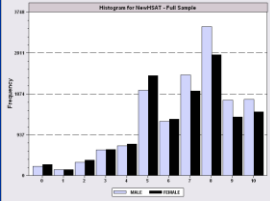
-----+Correlations in the Normal Distribution

Variable	Correlation	Std. Dev.	Std. Error	b/St.Er.	P[Z >z]
rAIR,TRA	.30491746	.49357120	.618	.5367	
rAIR,BUS	.40383018	.63548534	.635	.5251	
rTRA,BUS	.36973127	.42310789	.874	.3822	
rAIR,CAR	.000000	(Fixed Parameter).....			
rTRA,CAR	.000000	(Fixed Parameter).....			
rBUS,CAR	.000000	(Fixed Parameter).....			

Correlation Matrix for

Air, Train, Bus, Car

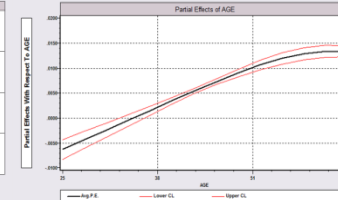
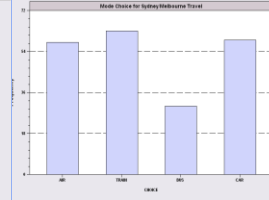
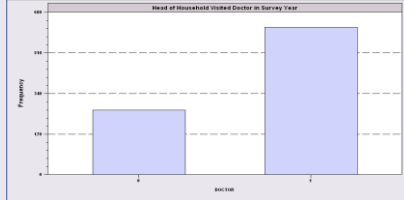
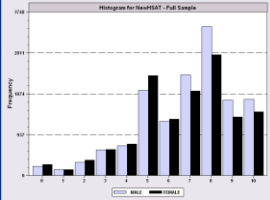
1	.305	.404	0
.305	1	.370	0
.404	.370	1	0
0	0	0	1



Multinomial Probit Elasticities

Elasticity averaged over observations.		
Attribute is INVC in choice AIR		
Effects on probabilities of all choices in model:		
* = Direct Elasticity effect of the attribute.		
	Mean	St.Dev
* Choice=AIR	-4.2785	1.7182
Choice=TRAIN	1.9910	1.6765
Choice=BUS	2.6722	1.8376
Choice=CAR	1.4169	1.3250
Attribute is INVC in choice TRAIN		
Choice=AIR	.8827	.8711
* Choice=TRAIN	-6.3979	5.8973
Choice=BUS	3.6442	2.6279
Choice=CAR	1.9185	1.5209
Attribute is INVC in choice BUS		
Choice=AIR	.3879	.6303
Choice=TRAIN	1.2804	2.1632
* Choice=BUS	-7.4014	4.5056
Choice=CAR	1.5053	2.5220
Attribute is INVC in choice CAR		
Choice=AIR	.2593	.2529
Choice=TRAIN	.8457	.8093
Choice=BUS	1.7532	1.3878
* Choice=CAR	-2.6657	3.0418

Multinomial Logit		
INVC in AIR		
	Mean	St.Dev
* -5.0216	2.3881	
2.2191	2.6025	
2.2191	2.6025	
2.2191	2.6025	
INVC in TRAIN		
1.0066	.8801	
* -3.3536	2.4168	
1.0066	.8801	
1.0066	.8801	
INVC in BUS		
.4057	.6339	
.4057	.6339	
* -2.4359	1.1237	
.4057	.6339	
INVC in CAR		
.3944	.3589	
.3944	.3589	
.3944	.3589	
* -1.3888	1.2161	



Discrete Choice Modeling

Nested Logit

[Part 8] 29/26

Not the Multinomial Probit Model

MPROBIT

The MNP model is frequently motivated using a latent-variable framework. The latent variable for the j th alternative, $j = 1, \dots, J$, is

$$\eta_{ij} = \mathbf{z}_i \boldsymbol{\alpha}_j + \xi_{ij}$$

where the $1 \times q$ row vector $\mathbf{z}_i$ contains the observed independent variables for the i th decision maker. Associated with $\mathbf{z}_i$ are the J vectors of regression coefficients $\boldsymbol{\alpha}_j$. The $\xi_{i,1}, \dots, \xi_{i,J}$ are distributed independently and identically standard normal. The decision maker chooses the alternative k such that $\eta_{ik} \geq \eta_{im}$ for $m \neq k$.

This is identical to the multinomial logit – a trivial difference of scaling that disappears from the partial effects.
(Use ASMProbit for a true multinomial probit model.)