Performing and interpreting discrete choice analyses in Stata

Joerg Luedicke

StataCorp LLC

May 24, 2019 Munich

< ロ > < 同 > < 回 > < 回 >

Discrete choice analysis with alternative-specific variables

. webuse transport

(Transportation choice data)

. list id t alt choice trcost trtime age income in 1/12, sepby(t) noobs

id	t	alt	choice	trcost	trtime	age	income
1	1	Car	1	4.14	0.13	3.0	3
1	1	Public	0	4.74	0.42	3.0	3
1	1	Bicycle	0	2.76	0.36	3.0	3
1	1	Walk	0	0.92	0.13	3.0	3
1	2	Car	1	8.00	0.14	3.2	5
1	2	Public	0	3.14	0.12	3.2	5
1	2	Bicycle	0	2.56	0.18	3.2	5
1	2	Walk	0	0.64	0.39	3.2	5
1	3	Car	1	1.76	0.18	3.4	5
1	3	Public	0	2.25	0.50	3.4	5
1	3	Bicycle	0	0.92	1.05	3.4	5
1	3	Walk	0	0.58	0.59	3.4	5

Examples of things we want to learn from discrete choice analyses

- How does the probability of choosing public transportation change if yearly income increases from \$30,000 to \$40,000?
- How does travel time and cost affect the probability of choosing each transportation mode?
- If travel cost related to car travel increases, how does that affect the probability of using a car?
- If travel time is increasing for public transportation, how does that affect the probability of choosing car travel?

Some estimation results from a discrete choice model

<snip>

	choice	Coef.	Std. Err.	Z	P> z	[95% Conf.	Interval]
alt	trcost trtime	8388216 -1.508756	.0438587 .2641554	-19.13 -5.71	0.000	9247829 -2.026492	7528602 9910212

<snip>

- We can conclude that people generally don't like to waste either time or money!
- In this talk, we will see how we can use margins to discover more interesting results

< ロ > < 同 > < 回 > < 回 >

Theoretical motivation of discrete choice models

- Random utility models
- $U_{ijt} = V_{ijt} + \epsilon_{ijt}$
 - $U_{ijt} \rightarrow \text{Utility of person } i \text{ for the } j \text{th alternative at time } t$
 - $V_{ijt} \rightarrow \text{Observed component of utility}$
 - $\epsilon_{ijt} \rightarrow$ Unobserved component of utility
- Decision makers choose alternative *j* if $U_{ijt} > U_{ikt}$ $\forall k \neq j$
- Specification of *V_{ijt}* and assumptions about *e_{ijt}* constitute different discrete choice estimators (e.g., logit or probit)
- New estimation command in Stata 16: **cmxtmixlogit** for fitting panel-data mixed logit models

・ 何 ト ・ ヨ ト ・ ヨ ト … ヨ

The mixed logit model (1)

- The mixed multinomial logit model uses random coefficients to model the correlation of choices across alternatives, thereby relaxing IIA
- With mixed logit, for the random utility model $U_{ijt} = V_{ijt} + \epsilon_{ijt}$ we have:

$$\blacktriangleright V_{ijt} = x_{ijt}\beta_i$$

- ϵ_{ijt} ~ iid type I extreme value
- The random coefficients β_i induce correlation across the alternatives
- We estimate the parameters of a specified distribution for β_i

The mixed logit model (2)

• The probability of unit *i* choosing alternative *j* at time *t* is

$$P_{ijt} = \int P_{ijt}(\beta) f(\beta) d\beta$$

(1)

• $P_{ijt}(\beta)$ is the probability of unit *i* choosing alternative *j* at time *t*, conditional on β_i

$$\bullet P_{ijt}(\beta) = e^{x_{ijt}\beta_i} / \sum_{j=1}^{J} e^{x_{ijt}\beta_j}$$

- * $f(\beta)$ is the mixing distribution of the random coefficients
- The integral in (1) needs to be approximated because it has no closed form solution
- ▶ Using Monte Carlo integration, we draw β_i from $f(\beta)$ and have simulated probabilities $\hat{P}_{ijt} = 1/M \sum_{m=1}^{M} P_{ijt}(\beta^m)$

• The simulated likelihood for the *i*th unit is $L_i = \prod_{t=1}^T \sum_{j=1}^J d_{ijt} \hat{P}_{ijt}$

< 回 > < 三 > < 三 >

cmxtmixlogit

- Random coefficient distributions $f(\beta)$:
 - (multivariate) normal
 - lognormal
 - truncated normal
 - uniform
 - triangle
- Estimates the parameters of the mixed logit model by maximum simulated likelihood
- Halton, Hammersley, and pseudo-random draws with uni- and multidimensional antithetics
- Full support of factor variables and time-series operators
- Support of complex survey data
- Case-specific variables
- margins

cmset - declaring cm data

note: data have been **xtset**

cmchoiceset - exploring choice sets

- . cmchoiceset
- Tabulation of choice-set possibilities

Choice set	Freq.	Percent	Cum.
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	1,053 210 90 147	70.20 14.00 6.00 9.80	70.20 84.20 90.20 100.00
Total	1,500	100.00	

Total is number of cases.

э

cmsample - reasons for sample exclusion

```
. preserve
```

```
. webuse transport, clear
(Transportation choice data)
. replace trcost = . in 5
(1 real change made, 1 to missing)
. replace alt = . in 2
(1 real change made, 1 to missing)
. replace choice = 0 if t==3 & id==1
(1 real change made)
. replace income = 1 in 1
(1 real change made)
```

cmsample - reasons for sample exclusion

note: data have been **xtset**

-

イロト 不得 トイヨト イヨト

cmsample - reasons for sample exclusion

. cmsample trcost trtime, choice(choice) casevars(age income)

Reason for exclusion	Freq.	Percent	Cum.
observations included caseid variable missing varlist missing choice variable all 0 casevars not constant within case*	5,988 1 4 3	99.80 0.02 0.07 0.07 0.05	99.80 99.82 99.88 99.95 100.00
Total	6,000	100.00	

* indicates an error

. restore

э

Panel-data mixed logit model using cmxtmixlogit (1)

. cmxtmixlogit	choice trcost, random(trtim	e) casevars(age income	e) nolog
Mixed logit ch	noice model	Number of 005	= 6,000
		Number of cases	,
Panel variable	e: id	Number of panels	= 500
Time variable:	t t	Cases per panel: mi	.n = 3
		av	rg = 3.0
		ma	ax = 3
Alternatives v	variable: alt	Alts per case: mi	n = 4
		av	rg = 4.0
		ma	ax = 4
Integration se	equence: Hammersley		
Integration po	pints: 594	Wald chi2(8)	= 432.68
Log simulated	likelihood = -1005.9899	Prob > chi2	= 0.0000
	[
choice	Coef. Std. Err.	z P> z [95% (Conf. Interval]
(anin)			

<snip>

э

Panel-data mixed logit model using cmxtmixlogit (2)

<snip>

choice	Coef.	Std. Err.	Z	P> z	[95% Conf.	Interval]
alt						
trcost	8388216	.0438587	-19.13	0.000	9247829	7528602
trtime	-1.508756	.2641554	-5.71	0.000	-2.026492	9910212
/Normal						
sd(trtime)	1.945596	.2594145			1.498161	2.526661
Car	(base alte	rnative)				

<snip>

э

Panel-data mixed logit model using cmxtmixlogit (3)

<snip>

Car	(base alte	rnative)				
Public						
age	.1538915	.0672638	2.29	0.022	.0220569	.2857261
income	3815444	.0347459	-10.98	0.000	4496451	3134437
_cons	5756547	.3515763	-1.64	0.102	-1.264732	.1134222
Bicycle						
age	.20638	.0847655	2.43	0.015	.0402426	.3725174
income	5225054	.0463235	-11.28	0.000	6132978	4317131
_cons	-1.137393	.4461318	-2.55	0.011	-2.011795	2629909
Walk						
age	.3097417	.1069941	2.89	0.004	.1000372	.5194463
income	9016697	.0686042	-13.14	0.000	-1.036132	7672078
_cons	4183279	.5607111	-0.75	0.456	-1.517302	.6806458

э

What would be the expected choice probabilities if every person in the population had a yearly income of \$30,000?

. margins, at	(income=3)						
Predictive man Model VCE	rgins : OIM			Number o	of obs	=	6,000
-	: Pr(alt), pro: : income	edict() =	3				
	1	Delta-method					
	Margin	Std. Err.	Z	P> z	[95%	Conf.	Interval]
_outcome							
Car	.3331611	.0196734	16.93	0.000	.294	1602	.3717203
Public	.2210964	.0184285	12.00	0.000	.1849	9772	.2572156
Bicycle	.1676081	.0181511	9.23	0.000	.1320)325	.2031837
Walk	.2781343	.0243791	11.41	0.000	.2303	3521	.3259166

< ロ > < 同 > < 回 > < 回 >

What would be the differences between an income of \$40,000 and \$30,000 over time?

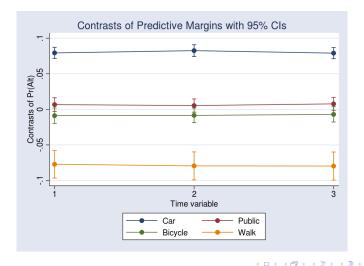
. margins, at	(income=(3 4)) contr	ast(at(r) now	vald) over(t)	
Contrasts of Model VCE	predictive margins : OIM		Number of ob	s = 6,000
Expression over	: Pr(alt), predict() : t			
1at	: 1.t income	=	3	
1at	: 2.t income	=	3	
1at	: 3.t income	-	3	
2at	: 1.t income	=	4	
2at 2. at	: 2.t income : 3.t	=	4	
2at	income	=	4	
	Contrast	Delta-method Std. Err.	[95% Conf.	Interval]
at@_out (2 vs 1) (2 vs 1) (2 vs 1) Put (2 vs 1) Put (2 vs 1) Put (2 vs 1) Bicy (2 vs 1) Bicy (2 vs 1) Bicy (2 vs 1) Bicy (2 vs 1) V	Car#1 .0793997 Car#2 .0825786 Car#3 .0790618 slic#1 .0066981 slic#2 .0033644 slic#2 .008805 rcle#1 .0084672 rcle#3 .0070729 alk#1 .0777273	.0040536 .0042477 .0040101 .0049098 .00474 .0046076 .0055205 .0052449 .0054537 .0098791 .0100246	.0714548 .0742532 .0712022 0039258 0013121 0197005 018747 017762 09558 09558	.0873446 .090904 .0869214 .0163212 .0146547 .019396 .0019396 .0019396 .0036161 0578546 059828

(StataCorp LLC)

We better plot these:

. marginsplot

Variables that uniquely identify margins: t _outcome



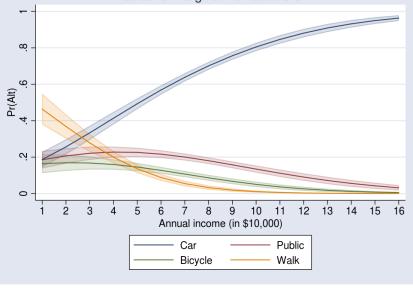
э

What are the averaged choice probabilities over the entire income range?

- . margins, at(income=(1(1)16))
 <output omitted>
- . marginsplot, recast(line) ciopts(recast(rarea) color(%20))
 Variables that uniquely identify margins: income _outcome

3

Predictive Margins with 95% CIs



(StataCorp LLC)

2

イロト イヨト イヨト イヨト

Marginal predictions with alternative-specific variables

- Direct and indirect effects
- If travel costs related to cars increased by 25%, how would that affect the probability of choosing a car?
- How would that increase affect the probability of choosing any of the other transportation modes?

A B b 4 B b

margins specification

```
. margins, alternative(Car) ///
> at(trcost = generate(trcost)) ///
> at(trcost = generate(1.25*trcost)) ///
> subpop(if t==1)
```

3

Applying the counterfactual

. webuse transport (Transportation choice data)

- . generate trcost_cf = trcost
- . qui replace trcost_cf = 1.25*trcost if alt == 1
- . format trcost_cf %3.2f
- . list id t alt choice trcost trcost_cf in 1/12, sepby(t) noobs

id	t	alt	choice	trcost	trcost_f
1	1	Car	1	4.14	5.17
1	1	Public	0	4.74	4.74
1	1	Bicycle	0	2.76	2.76
1	1	Walk	0	0.92	0.92
1	2	Car	1	8.00	10.00
1	2	Public	0	3.14	3.14
1	2	Bicycle	0	2.56	2.56
1	2	Walk	0	0.64	0.64
1	3	Car	1	1.76	2.20
1	3	Public	0	2.25	2.25
1	3	Bicycle	0	0.92	0.92
1	3	Walk	0	0.58	0.58

・ロン・雪と・雪と、 明

margins output

Predictive m Model VCE	2			Number o Subpop.	of obs no. obs	=	6,000 2,000
Expression Alternative	: Pr(alt), pred : Car	ict()					
1at	: trcost	= trcost					
2at	: trcost	= 1.25*t	rcost				
	De	lta-method					
	Margin	Std. Err.	Z	P> z	[95% Co	onf.	Interval]
_outcome#_at		0112004	47 71	0.000	50156	2.0	5662496

_outcome#_at						
Car#1	.5439062	.0113994	47.71	0.000	.5215638	.5662486
Car#2	.4405694	.0101017	43.61	0.000	.4207704	.4603683
Public#1	.2010082	.0104382	19.26	0.000	.1805497	.2214668
Public#2	.2548516	.0117988	21.60	0.000	.2317264	.2779769
Bicycle#1	.1255662	.0095539	13.14	0.000	.1068409	.1442914
Bicycle#2	.1566796	.0110237	14.21	0.000	.1350736	.1782856
Walk#1	.1295194	.0101536	12.76	0.000	.1096187	.1494201
Walk#2	.1478994	.0110109	13.43	0.000	.1263185	.1694803
	1					

<ロ> <四> <四> <三</td>

Contrasts with alternative-specific variables

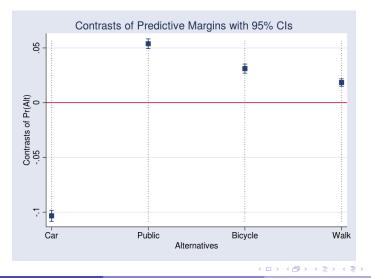
> at(trcos	st = generate st = generate t(at(r) nowal	(trcost)) (1.25*trcost)) d)				
Contrasts of predic Model VCE : OIM	Number of Subpop. n			6,000 2,000		
Expression : Pr(a Alternative : Car	alt), predict	()				
1at : tree	ost	= trcost				
2at : troo	ost	= 1.25*trcost				
		Delta-method Std. Err.	[95% Conf.	Interva	1]	
_at@_outcome (2 vs 1) Car (2 vs 1) Public (2 vs 1) Bicycle (2 vs 1) Walk	1033369 .0538434 .0311134 .01838	.0022563 .0021237	.0269511	.05826 .03527	556 757	

æ

< ロ > < 同 > < 回 > < 回 >

Plotting contrasts

. marginsplot, recast(dot) yline(0) plotopts(msymbol(square))
<output omitted>



(StataCorp LLC)

May 24, 2019 Munich 27 / 32

э

Average marginal effects: how does the probability of choosing a car change with car travel time?

. margins, dyc	dx(trtime)	outcome(Car)	alternativ	e(Car)		
Average margir Model VCE :		3		Number of obs	=	6,000
Expression : Alternative : Outcome : dy/dx w.r.t. :	Car Car	predict()				
		Delta-metho	od			

	Delta-method					
	dy/dx	Std. Err.	Z	P> z	[95% Conf.	Interval]
trtime _cons	1581844	.0269102	-5.88	0.000	2109275	1054414

< ロ > < 同 > < 回 > < 回 >

Average marginal effects: how does the probability of choosing public transportation change with travel time related to car use?

. margins, d	ydx(trtime) outcome(Public)	alternative(Car)		
Average marg. Model VCE		Number of obs	=	6,000
Expression Alternative Outcome dy/dx w.r.t.	: Public			

	Delta-method					
	dy/dx	Std. Err.	Z	P> z	[95% Conf.	Interval]
trtime						
_cons	.1055447	.0171745	6.15	0.000	.0718834	.139206

A B F A B F

4 A N

Average direct & indirect marginal effects

. margins, dydx(trtime) outcome(Car)
Average marginal effects Number of obs = 6,000
Model VCE : OIM
Expression : Pr(alt), predict()
Outcome : Car
dy/dx w.r.t. : trtime

	Delta-method					
	dy/dx	Std. Err.	Z	P> z	[95% Conf.	Interval]
trtime						
alt						
Car	1581844	.0269102	-5.88	0.000	2109275	1054414
Public	.1055447	.0171745	6.15	0.000	.0718834	.139206
Bicycle	.0374872	.0073318	5.11	0.000	.0231171	.0518573
Walk	.0151526	.0043034	3.52	0.000	.006718	.0235871

-

< 日 > < 同 > < 回 > < 回 > < □ > <

Discrete choice estimators in Stata 16

Stata's new cm commands:

- cmclogit
- cmmprobit
- cmroprobit
- cmrologit
- cmmixlogit
- cmxtmixlogit

(formerly asclogit)
(formerly asmprobit)
(formerly asroprobit)
(formerly rologit)
(formerly asmixlogit)
(new in Stata 16)

All cm commands now support margins

New [CM] manual

Other discrete choice estimators:

• nlogit, mlogit, mprobit, logit, probit, ...

Thank you!

< □ > < □ > < □ > < □ > < □ > < □ >

æ