

Latent Class Analysis Using Stata

Chuck Huber
StataCorp
chuber@stata.com

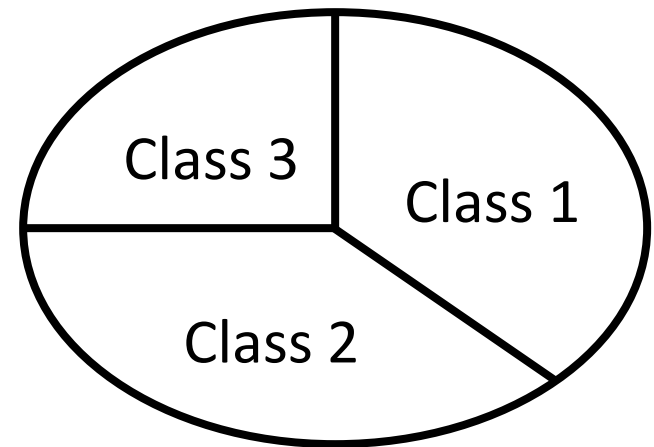
University College London
October 16, 2019

Outline

- Latent class analysis (LCA)
 - Estimation and postestimation options
 - **margins** and **marginsplot**
- Latent class analysis with covariates
- Latent class analysis by groups
- Latent profile analysis

Latent Class Analysis

- A latent class model is characterized by having a categorical latent variable and categorical observed variables.
- The levels of the categorical latent variable represent groups in the population and are called classes.
- We are interested in identifying and understanding these unobserved classes.

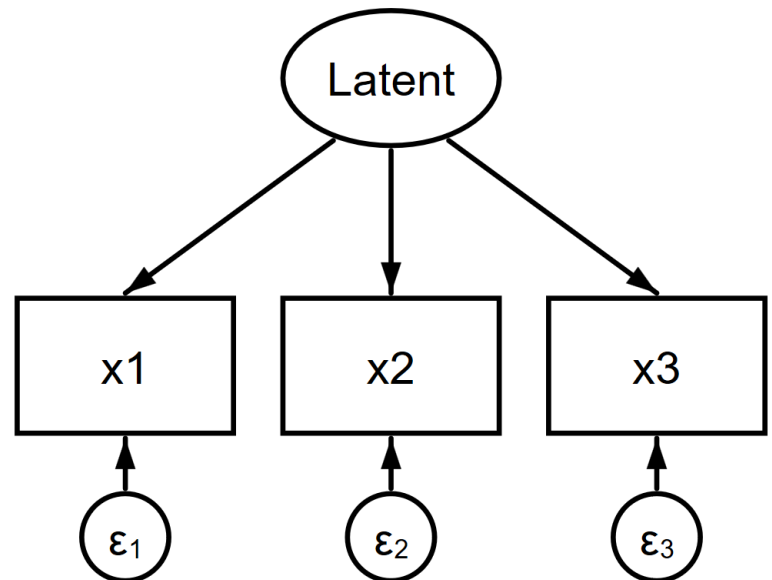


Latent Class Analysis

- Behavioral Research
 - Classify people who are more likely to exhibit specific behaviors
 - Different kinds of social phobias
 - Categories of eating disorders
- Medicine and Health
 - Identify patients with different disease risk profiles
- Marketing Research
 - Differentiate subsets of customers and their buying habits
- And many, many more...

Latent and Observed Variables

- Latent variables are hypothetical constructs that we cannot measure directly (e.g. “intelligence” or “depression”)
- Observed variables are variables that we observe (e.g. “SAT scores” or “Feel sad”)



Latent and Observed Variables

	Continuous Latent	Categorical Latent
Continuous Observed	Factor analysis	Latent Profile Analysis
Categorical Observed	Latent trait analysis or Item Response Theory	Latent Class Analysis

Example Data

AGGRESSIVE BEHAVIOR

Volume 37, pages 19–35 (2011)

The Three Latent Classes of Adolescent Delinquency and the Risk Factors for Membership in Each Class

Penelope Anne Hasking^{1*}, Lawrence M. Scheier^{2,3}, and Arbi ben Abdallah³

¹*School of Psychology and Psychiatry, Monash University, Clayton, Victoria, Australia*

²*LARS Research Institute, Inc., Las Vegas, Nevada*

³*Department of Psychiatry, Epidemiology and Prevention Research Group, Washington University School of Medicine, St. Louis, Missouri*

This study used latent class analysis to examine subpopulation membership based on self-reports of delinquent behaviors obtained from Australian youth. Three discrete identifiable classes were derived based on 51 indicators of physical violence, property damage, minor infractions, drug use, and social delinquency. One class of youth engaged in primarily rule breaking and norm violations including underage alcohol use, typical of this age period. A second class was more actively delinquent emphasizing drug use, trespassing, and various forms of disobedience. A third class of highly delinquent youth differed from their counterparts by endorsing drug use, thievery that involved stealing money, goods, and cars, property damage, gambling, precocious sexual experiences, involvement with pornographic materials, and fighting. Multinomial logistic regression predicting class membership indicated highly delinquent youth were more likely to be older males, use venting coping strategies, and be fun or novelty seeking compared with rule breakers. Findings are discussed in terms of refining current taxonomic arguments regarding the structure of delinquency and implications for prevention of early-stage antisocial behavior. *Aggr. Behav.* 37:19–35, 2011. © 2010 Wiley-Liss, Inc.

Example Data

- Class 1
 - “Possible rule breaking and norm violations”
 - May include underage drinking
- Class 2
 - “More actively delinquent”
 - Occasional drug use, skipping school, and non-violent crime
- Class 3
 - “Highly delinquent”
 - Regular drug use, theft, and violent crime

Example Data

```
. use atrisk.dta
```

```
. describe
```

```
Contains data from atrisk.dta
```

```
obs:      10,000
```

```
vars:      8
```

```
size:     90,000
```

```
20 Mar 2018 15:17
```

variable name	storage type	display format	value label	variable label
id	int	%9.0g		Student identification number
age	byte	%9.0g		Age (years)
male	byte	%9.0g	male	Male
alcohol	byte	%9.0g		Ever consumed alcohol
truant	byte	%9.0g		>10 unexcused absences from school
vandalism	byte	%9.0g		Ever engaged in an act of vandalism
theft	byte	%9.0g		Ever stolen something worth more than \$25
weapon	byte	%9.0g		Ever used a weapon in a fight

```
Sorted by: id
```

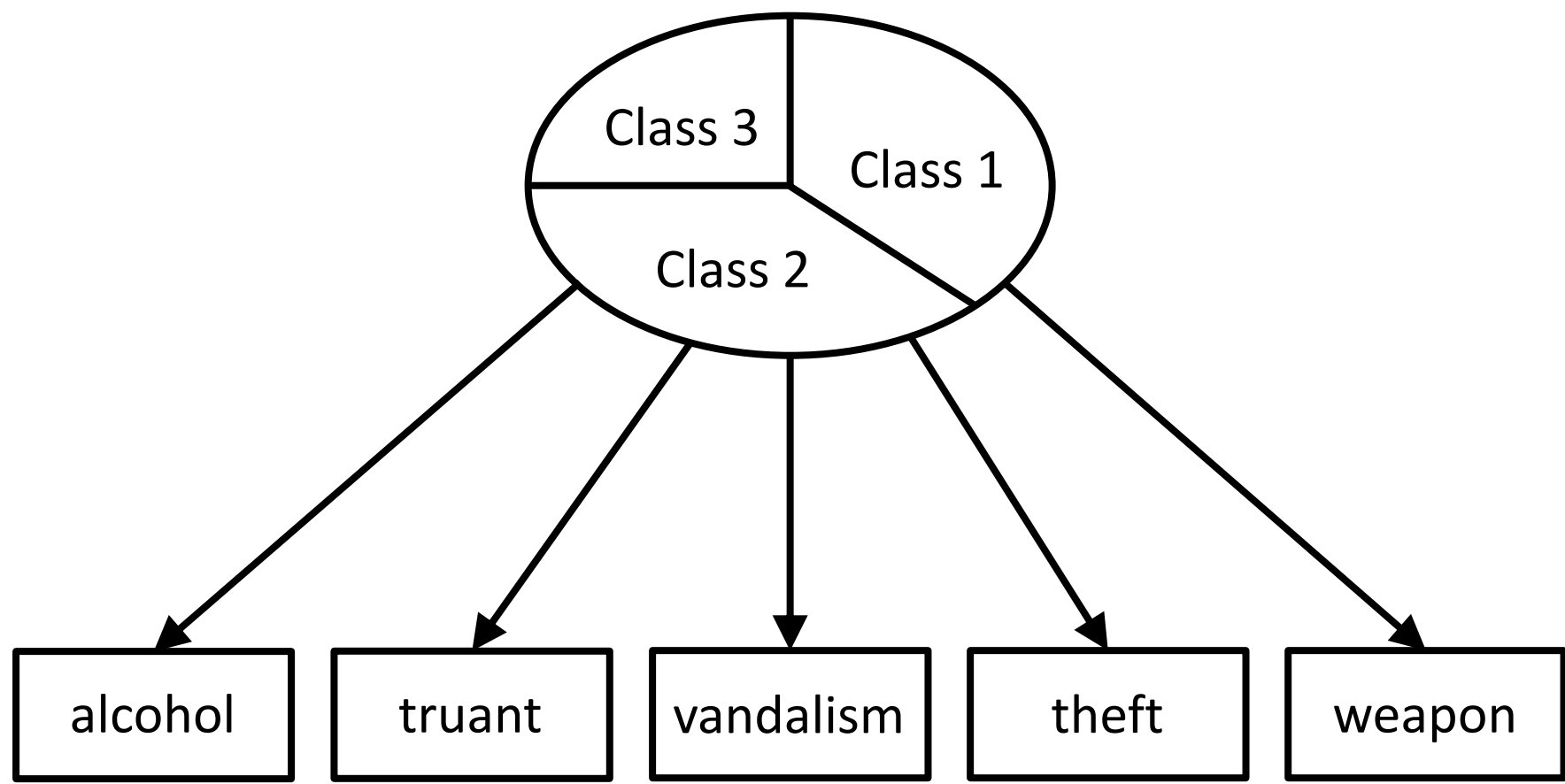
Note that we do not have a variable for class membership.

Example Data

```
. summarize
```

Variable	Obs	Mean	Std. Dev.	Min	Max
id	10,000	5000.5	2886.896	1	10000
age	10,000	15.4826	1.70452	13	18
male	10,000	.5011	.5000238	0	1
alcohol	10,000	.3548	.4784766	0	1
truant	10,000	.094	.2918433	0	1
vandalism	10,000	.077	.2666048	0	1
theft	10,000	.0288	.1672524	0	1
weapon	10,000	.0265	.1606248	0	1

Conceptual Path Diagram



Statistics > LCA (latent class analysis)

LCA (latent class analysis)

Model Group if/in Weights SE/Robust Reporting Maximization Advanced

Type of analysis:
LCA

Latent class specification

C Name for latent categorical variable

3 Number of classes 1 Base class

Multiple latent categorical variables

Measurement model

Measurement type:
Logistic -- Bernoulli family, logit link

Measurement variables:
alcohol truant vandalism theft weapon

Parameters that are equal across classes:

Model has predictors for class membership

Predictors:

Allow different predictors for each class

? R [] OK Cancel Submit

```
gsem (alcohol truant vandalism theft weapon <- _cons)    ///  
    , family(bernoulli) link(logit) lclass(C 3)
```

The coefficients for class

Generalized structural equation model
Log likelihood = -14411.803

Number of obs = 10,000

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
1.C	(base outcome)					
2.C _cons	-2.413129	.5429566	-4.44	0.000	-3.477304	-1.348954
3.C _cons	-3.679325	.4864832	-7.56	0.000	-4.632815	-2.725835

LCA Postestimation

```
. estat lcprob
```

```
Latent class marginal probabilities
```

```
Number of obs = 10,000
```

		Delta-method		
	Margin	Std. Err.	[95% Conf. Interval]	
C				
1	.8970422	.0358031	.8029742	.9490482
2	.0803164	.0405096	.0289462	.2037259
3	.0226414	.0112419	.0084863	.0590022

Class : 1

Response : alcohol
 Family : Bernoulli
 Link : logit

Response : truant
 Family : Bernoulli
 Link : logit

Response : vandalism
 Family : Bernoulli
 Link : logit

Response : theft
 Family : Bernoulli
 Link : logit

Response : weapon
 Family : Bernoulli
 Link : logit

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
alcohol _cons	-.7861047	.0489882	-16.05	0.000	-.8821198	-.6900895
truant _cons	-2.93729	.1906323	-15.41	0.000	-3.310922	-2.563657
vandalism _cons	-2.952349	.1000292	-29.51	0.000	-3.148402	-2.756295
theft _cons	-4.516317	.1614524	-27.97	0.000	-4.832758	-4.199876
weapon _cons	-4.427085	.1749759	-25.30	0.000	-4.770032	-4.084139

Class : 2

Response : alcohol
 Family : Bernoulli
 Link : logit

Response : truant
 Family : Bernoulli
 Link : logit

Response : vandalism
 Family : Bernoulli
 Link : logit

Response : theft
 Family : Bernoulli
 Link : logit

Response : weapon
 Family : Bernoulli
 Link : logit

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
alcohol _cons	.8948312	.4756056	1.88	0.060	-.0373386	1.827001
truant _cons	-.0699578	.4886625	-0.14	0.886	-1.027719	.887803
vandalism _cons	-1.155054	.371044	-3.11	0.002	-1.882286	-.4278206
theft _cons	-3.309095	2.03741	-1.62	0.104	-7.302346	.6841566
weapon _cons	-2.167636	.4837753	-4.48	0.000	-3.115818	-1.219454

Class : 3

Response : alcohol
 Family : Bernoulli
 Link : logit

Response : truant
 Family : Bernoulli
 Link : logit

Response : vandalism
 Family : Bernoulli
 Link : logit

Response : theft
 Family : Bernoulli
 Link : logit

Response : weapon
 Family : Bernoulli
 Link : logit

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
alcohol _cons	1.104349	.2815121	3.92	0.000	.5525958	1.656103
truant _cons	-.2185809	.2018425	-1.08	0.279	-.614185	.1770231
vandalism _cons	.3428592	.501954	0.68	0.495	-.6409527	1.326671
theft _cons	.938004	1.133686	0.83	0.408	-1.283979	3.159987
weapon _cons	-.6708939	.4134047	-1.62	0.105	-1.481152	.1393644

LCA Postestimation

```
. estat lcmean
```

Latent class marginal means

Number of obs = 10,000

		Delta-method		
		Margin	Std. Err.	[95% Conf. Interval]
1	alcohol	.3130057	.0105341	.2927387 .3340132
	truant	.0503407	.0091135	.0351984 .0715143
	vandalism	.0496256	.0047177	.0411543 .0597321
	theft	.010811	.0017266	.0079016 .0147758
	weapon	.0118082	.0020417	.0084088 .0165588
2	alcohol	.7098862	.0979499	.4906664 .8614041
	truant	.4825177	.1220163	.2635266 .7084366
	vandalism	.2395672	.0675949	.1321265 .3946469
	theft	.0352605	.069307	.0006735 .6646658
	weapon	.1026947	.0445792	.0424595 .2280326
3	alcohol	.7510741	.052632	.6347376 .8397142
	truant	.4455713	.0498627	.3511051 .5441406
	vandalism	.5848849	.1218717	.3450312 .7902895
	theft	.7186963	.2291994	.2168736 .9593004
	weapon	.3382967	.0925415	.1852534 .5347848

Estimation and Postestimation

- First you estimate the parameters (fit the model)

```
gsem (alcohol truant vandalism theft weapon <- _cons)    ///  
      , family(bernoulli) link(logit) lclass(C 3)
```

- Then you calculate quantities such as goodness-of-fit statistics, model predictions, residuals, etc

```
estat lcmean  
estat lcprob
```

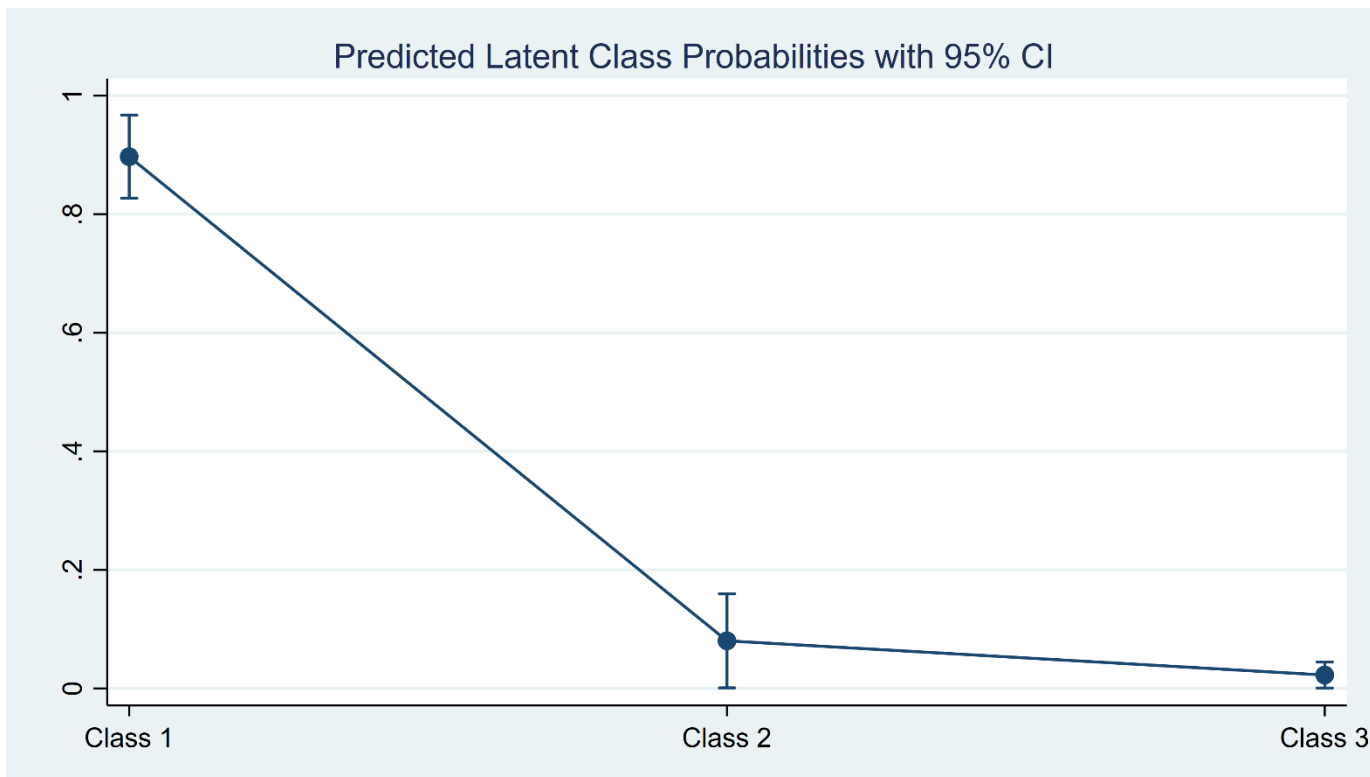
`margins` and `marginsplot`

- You can use `margins` to calculate marginal predictions after you fit almost any kind of model in Stata.
- You can use `marginsplot` to graph those marginal predictions.

margins and marginsplot

```
margins, predict(classpr class(1))    ///  
      predict(classpr class(2))    ///  
      predict(classpr class(3))
```

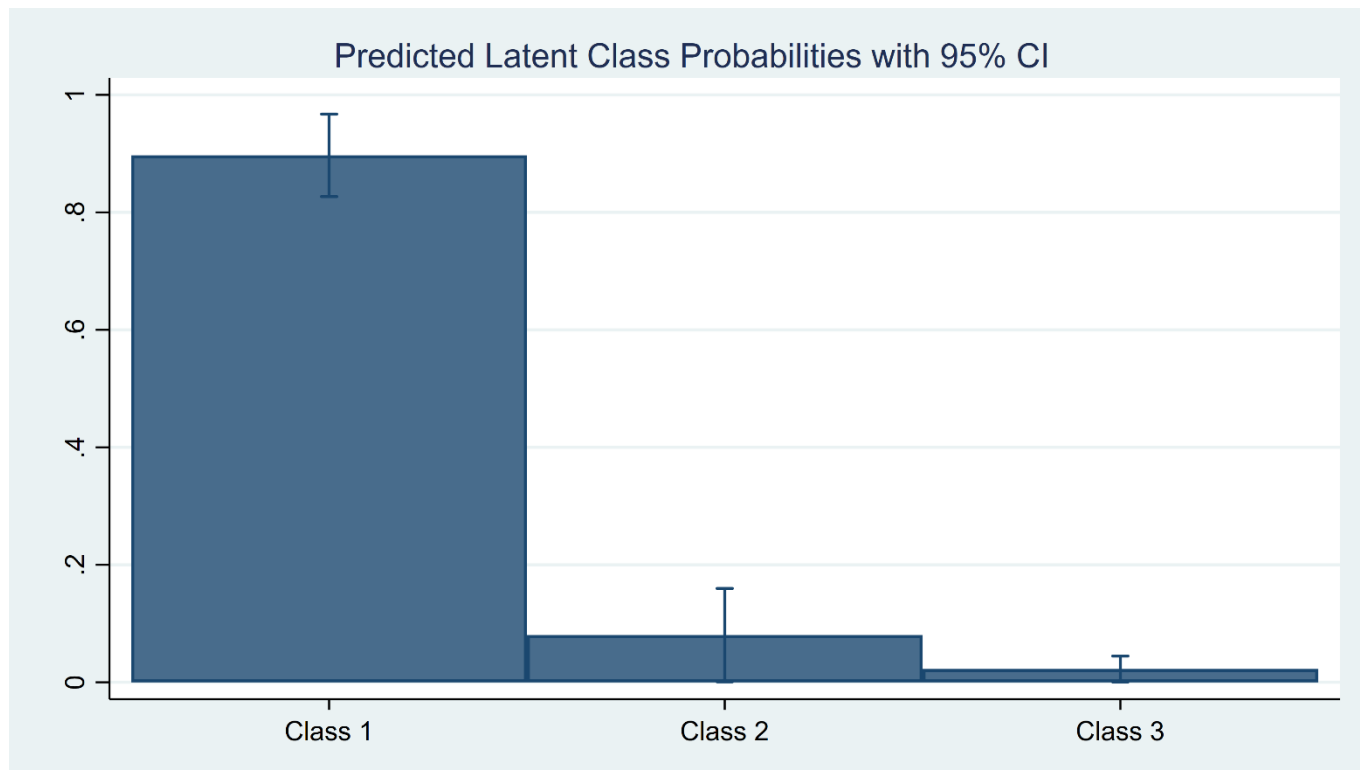
```
marginsplot, xtitle("") ytitle("")    ///  
            xlabel(1 "Class 1" 2 "Class 2" 3 "Class 3")    ///  
            title("Predicted Latent Class Probabilities with 95% CI")
```



margins and marginsplot

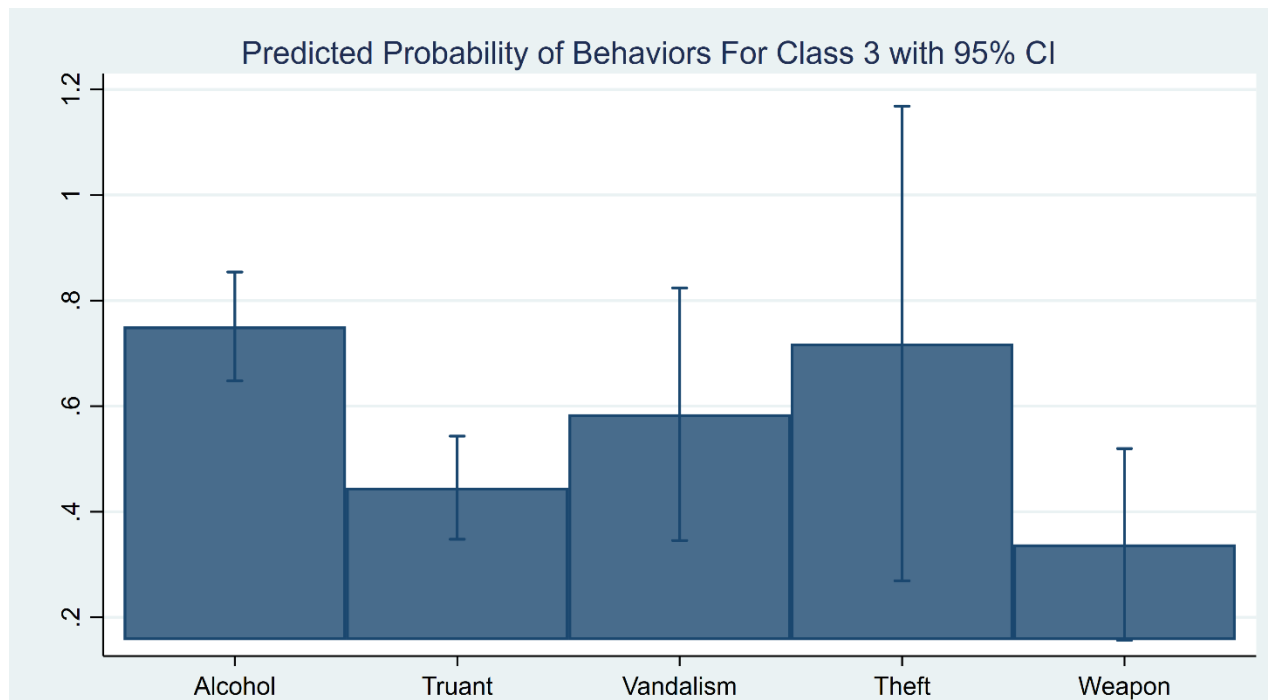
```
margins, predict(classpr class(1))    ///  
      predict(classpr class(2))    ///  
      predict(classpr class(3))
```

```
marginsplot, recast(bar) xtitle("") ytitle("")    ///  
            xlabel(1 "Class 1" 2 "Class 2" 3 "Class 3")    ///  
            title("Predicted Latent Class Probabilities with 95% CI")
```



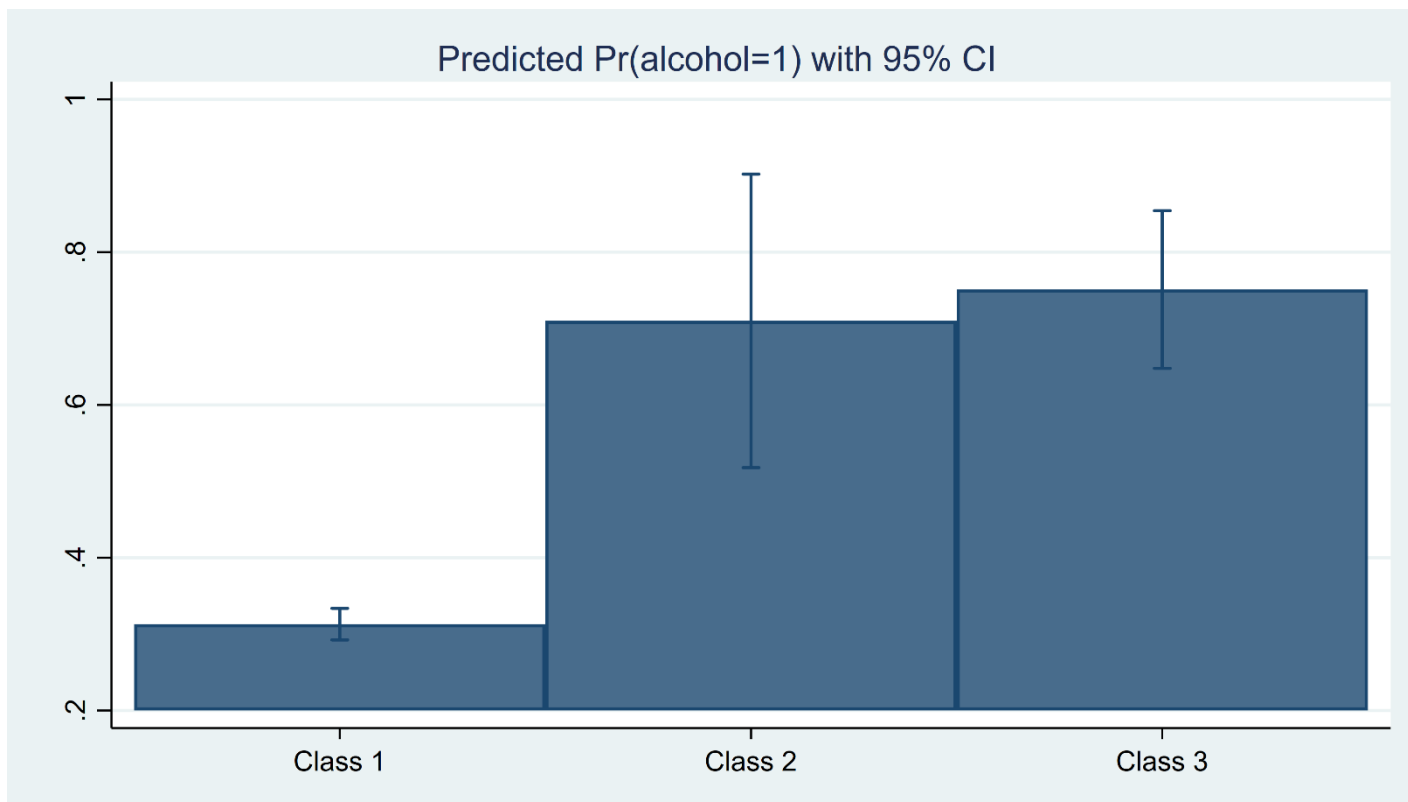
margins and marginsplot

```
margins, predict(outcome(alcohol) class(3)) ///  
      predict(outcome(truant) class(3))      ///  
      predict(outcome(vandalism) class(3))   ///  
      predict(outcome(theft) class(3))       ///  
      predict(outcome(weapon) class(3))  
  
marginsplot, recast(bar) xtitle("") ytitle("") ///  
      xlabel(1 "Alcohol" 2 "Truant" 3 "Vandalism" 4 "Theft" 5 "Weapon") ///  
      title("Predicted Probability of Behaviors For Class 3 with 95% CI")
```



margins and marginsplot

```
margins, predict(outcome(alcohol) class(1))      ///  
      predict(outcome(alcohol) class(2))      ///  
      predict(outcome(alcohol) class(3))  
  
marginsplot, recast(bar) xtitle("") ytitle("")    ///  
      xlabel(1 "Class 1" 2 "Class 2" 3 "Class 3")  ///  
      title("Predicted Pr(alcohol=1) with 95% CI")
```



LCA Postestimation

```
. predict cpr*, classposteriorpr  
  
. format %9.4f cpr1 cpr2 cpr3  
  
. list id alcohol truant vandalism theft weapon cpr1 cpr2 cpr3    ///  
>      in 1/10, abbreviate(10) separator(0) noobs
```

id	alcohol	truant	vandalism	theft	weapon	cpr1	cpr2	cpr3
1	0	0	0	0	0	0.9852	0.0144	0.0004
2	0	0	1	0	1	0.4245	0.3579	0.2176
3	0	0	0	0	0	0.9852	0.0144	0.0004
4	1	0	0	0	0	0.9248	0.0725	0.0027
5	1	1	0	0	1	0.0621	0.8196	0.1184
6	0	0	0	0	0	0.9852	0.0144	0.0004
7	0	0	0	0	0	0.9852	0.0144	0.0004
8	0	0	0	0	0	0.9852	0.0144	0.0004
9	0	0	0	0	0	0.9852	0.0144	0.0004
10	1	0	0	0	0	0.9248	0.0725	0.0027

LCA Postestimation

```
. estat lcgof
```

Fit statistic	Value	Description
Likelihood ratio		
chi2_ms(14)	20.646	model vs. saturated
p > chi2	0.111	
Information criteria		
AIC	28857.607	Akaike's information criterion
BIC	28980.183	Bayesian information criterion

How many classes?

```
quietly gsem (alcohol truant vandalism theft weapon <- ), logit lclass(C 1)
estimates store oneclass
```

```
quietly gsem (alcohol truant vandalism theft weapon <- ), logit lclass(C 2)
estimates store twoclass
```

```
quietly gsem (alcohol truant vandalism theft weapon <- ), logit lclass(C 3)
estimates store threeclass
```

```
. estimates stats oneclass twoclass threeclass
```

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
<u>oneclass</u>	10,000	.	-14863.47	5	29736.93	29772.98
<u>twoclass</u>	10,000	.	-14430.33	11	28882.66	28961.97
<u>threeclass</u>	10,000	.	-14411.8	17	28857.61	28980.18

Note: N=Obs used in calculating BIC; see [\[R\] BIC note](#).

Options for Starting Values

Starting values options for models with categorical latent variables are as follows:

`startvalues(factor [, maxopts])` specifies that starting values be computed by assigning each observation to an initial latent class that is determined by running a `factor` analysis on all the observed variables in the specified model. This is the default for models with categorical latent variables.

`startvalues(classid varname [, maxopts])` specifies that starting values be computed by assigning each observation to an initial latent class specified in *varname*. *varname* is required to have each class represented in the estimation sample.

`startvalues(classpr varlist [, maxopts])` specifies that starting values be computed using the initial class probabilities specified in *varlist*. *varlist* is required to contain k variables for a model with k latent classes. The values in *varlist* are normalized to sum to 1 within each observation.

`startvalues(randomid [, draws(#) seed(#) maxopts])` specifies that starting values be computed by randomly assigning observations to initial classes.

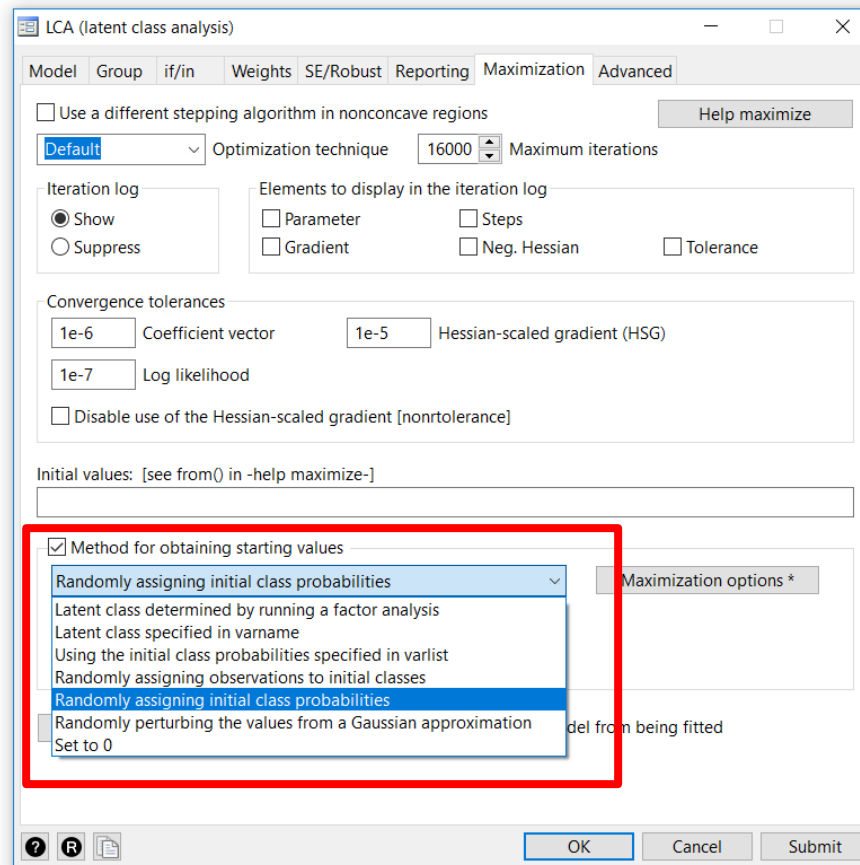
`startvalues(randompr [, draws(#) seed(#) maxopts])` specifies that starting values be computed by randomly assigning initial class probabilities.

`startvalues(jitter [#c [#v], draws(#) seed(#) maxopts])` specifies that starting values be constructed by randomly perturbing the values from a Gaussian approximation to each outcome.

$\#_c$ is the magnitude for randomly perturbing coefficients, intercepts, cutpoints, and scale parameters; the default value is 1.

$\#_v$ is the magnitude for randomly perturbing variances for Gaussian outcomes; the default value is 1.

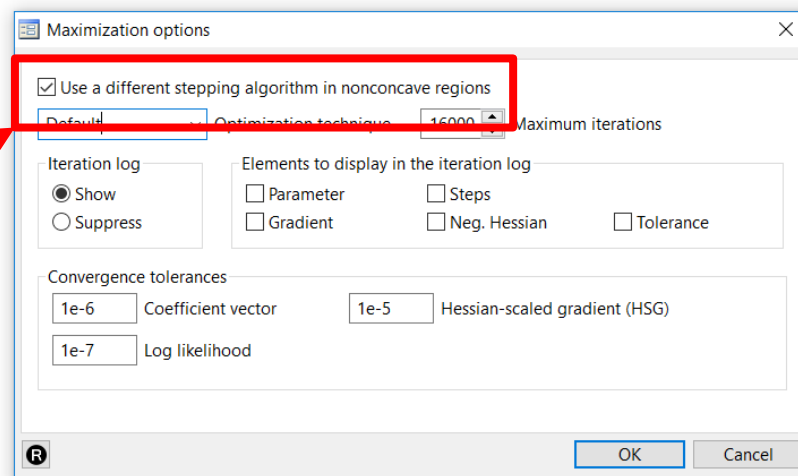
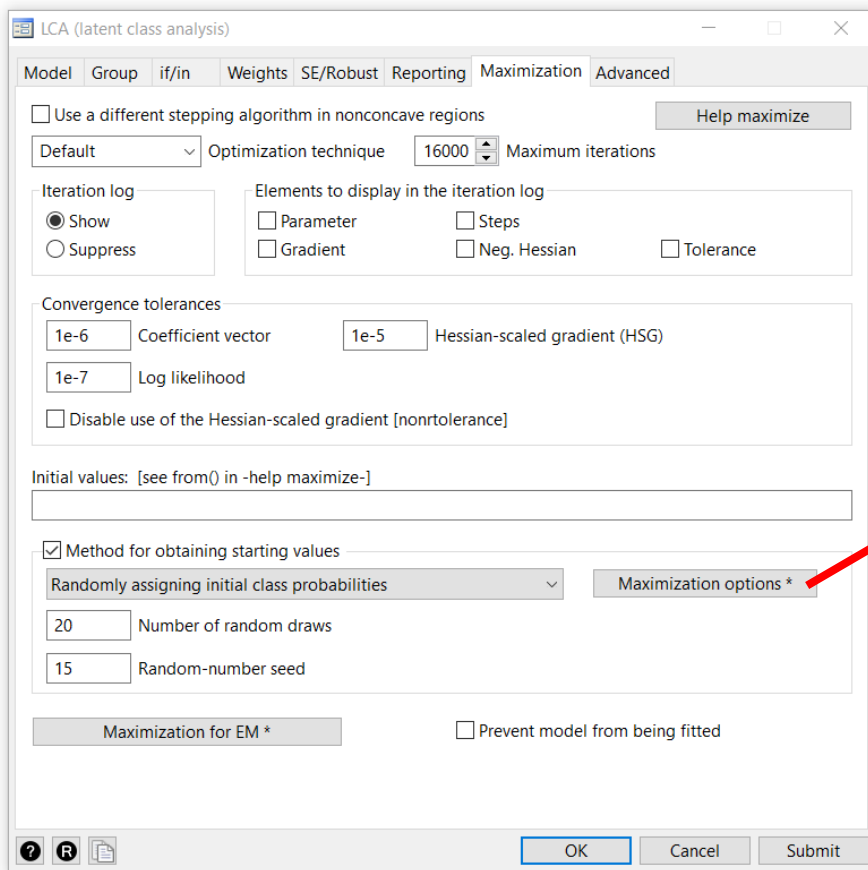
Options for Starting Values



```
gsem (alcohol truant vandalism theft weapon <- _cons)
, logit lclass(C 3)
startvalues(randompr, draws(20) seed(15))
```

```
///
///
```

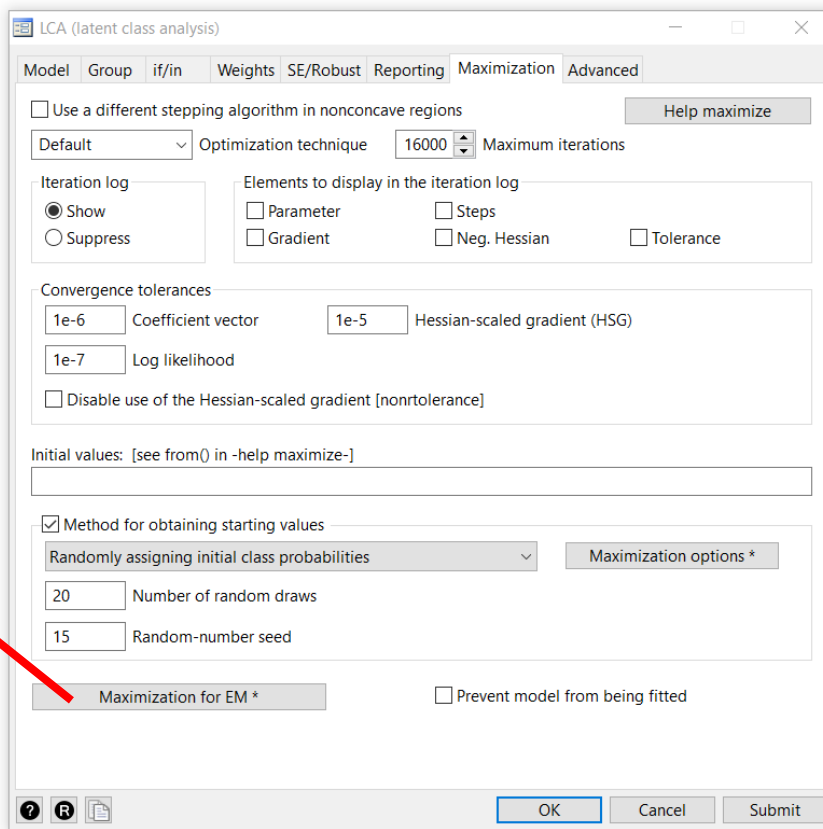
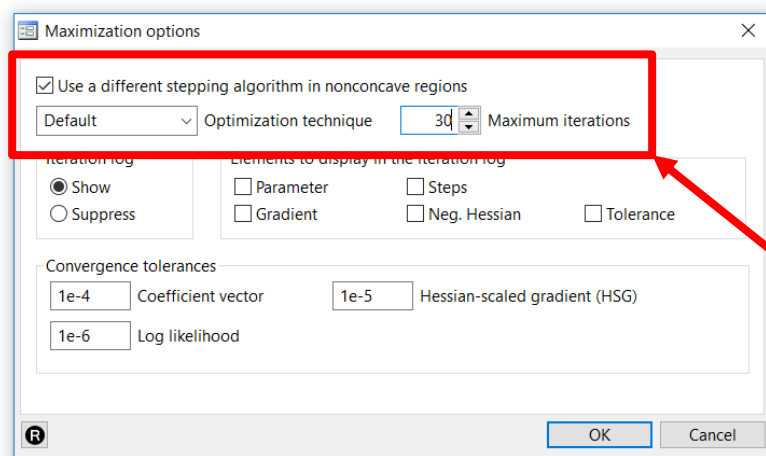
Options for Starting Values



```

gsem (alcohol truant vandalism theft weapon <- _cons)    ///
, logit lclass(C 3)                                     ///
startvalues(randompr, draws(20) seed(15) difficult)
    
```

Options for the EM Algorithm



```

gsem (alcohol truant vandalism theft weapon <- _cons)    ///
, logit lclass(C 3)                                     ///
startvalues(randompr, draws(20) seed(15) difficult)    ///
emopts(iterate(30) difficult)

```

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- Latent class analysis (LCA)
 - Estimation and postestimation options
 - **margins** and **marginsplot**
- Latent class analysis with covariates
- Latent class analysis by groups
- Latent profile analysis

LCA With Covariates

```
. use atrisk.dta
```

```
. describe
```

Contains data from atrisk.dta

```
obs:      10,000
vars:      8
size:      90,000
```

20 Mar 2018 15:17

variable name	storage type	display format	value label	variable label
id	int	%9.0g		Student identification number
age	byte	%9.0g		Age (years)
male	byte	%9.0g	male	Male
alcohol	byte	%9.0g		Ever consumed alcohol
truant	byte	%9.0g		>10 unexcused absences from school
vandalism	byte	%9.0g		Ever engaged in an act of vandalism
theft	byte	%9.0g		Ever stolen something worth more than \$25
weapon	byte	%9.0g		Ever used a weapon in a fight

Sorted by: id

LCA With Covariates

LCA (latent class analysis)

Model Group if/in Weights SE/Robust Reporting Maximization Advanced

Type of analysis:
LCA

Latent class specification

C Name for latent categorical variable

3 Number of classes 1 Base class

Multiple latent categorical variables

Measurement model

Measurement type:
Logistic -- Bernoulli family, logit link

Measurement variables:
alcohol truant vandalism theft weapon

Parameters that are equal across classes:

Model has predictors for class membership

Predictors:
age

Allow different predictors for each class

OK Cancel Submit

```
gsem (alcohol truant vandalism theft weapon <- _cons)    ///  
      (C <- age), family(bernoulli) link(logit)         ///  
      lclass(C 3)
```

LCA With Covariates

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
1.C	(base outcome)					
2.C						
→ age	.2719666	.0540686	5.03	0.000	.165994	.3779391
_cons	-6.981905	.9669605	-7.22	0.000	-8.877113	-5.086698
3.C						
→ age	.2890307	.0506078	5.71	0.000	.1898412	.3882202
_cons	-8.29407	.9687997	-8.56	0.000	-10.19288	-6.395258

LCA With Covariates

```
. estat lcprob
```

```
Latent class marginal probabilities      Number of obs = 10,000
```

		Delta-method		
	Margin	Std. Err.	[95% Conf. Interval]	
C				
1	.9152694	.0130999	.8858127	.9376619
2	.0625325	.016597	.036884	.1040892
3	.0221981	.0116365	.0078758	.0609655

LCA With Covariates

```
. estat lcmean
```

Latent class marginal means

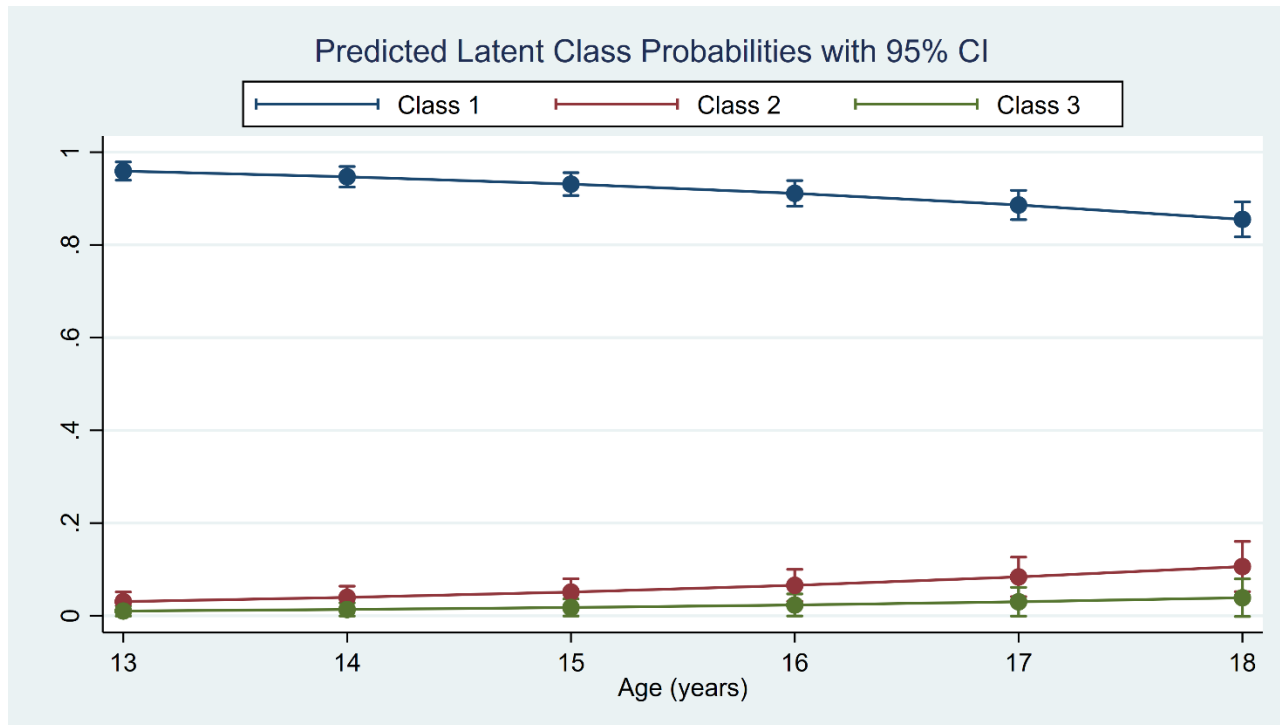
Number of obs = 10,000

		Delta-method		
		Margin	Std. Err.	[95% Conf. Interval]
1	alcohol	.3177198	.0067361	.3046662 .3310664
	truant	.055649	.0048065	.0469451 .0658553
	vandalism	.0509588	.0032663	.0449244 .0577547
	theft	.0108852	.0015597	.0082168 .0144076
	weapon	.0125271	.0016357	.0096948 .0161733
2	alcohol	.7622907	.0497867	.6517565 .8460291
	truant	.530044	.0724128	.3894933 .6659856
	vandalism	.2915297	.0641079	.1829752 .4305484
	theft	3.46e-06	.002712	0 1
	weapon	.1313218	.042565	.0678219 .2390298
3	alcohol	.7357761	.0373358	.6564975 .8022686
	truant	.4469371	.0417226	.3672857 .5294088
	vandalism	.5463925	.0447149	.4582233 .6317444
	theft	.8486219	.4398189	.0067831 .9997827
	weapon	.3073444	.0374031	.2392267 .3850415

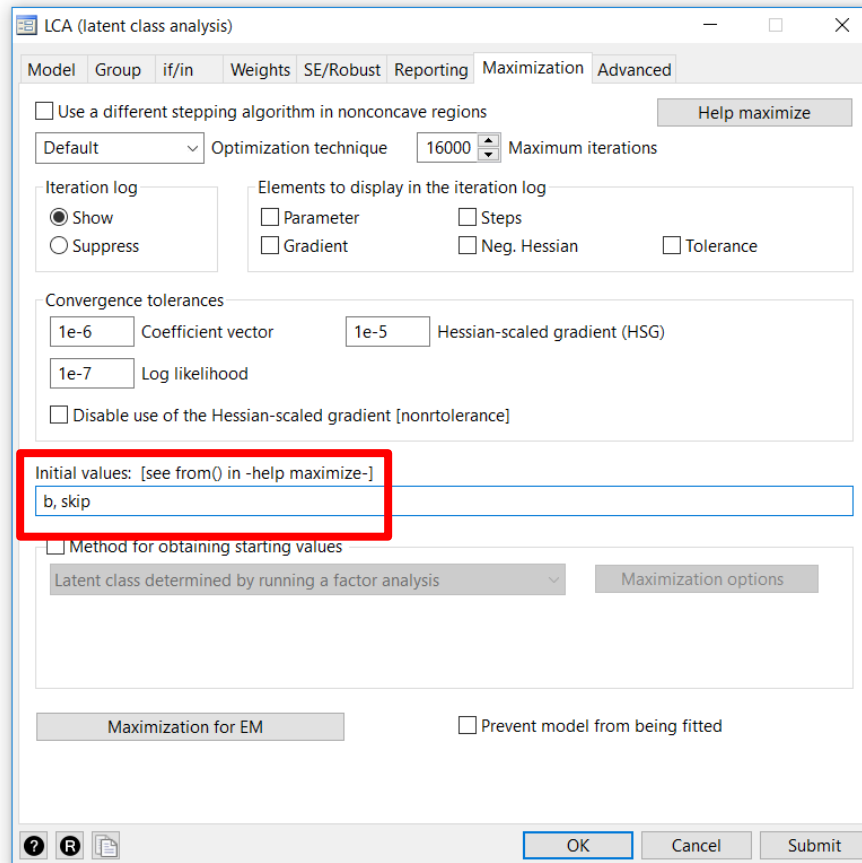
margins and marginsplot

```
margins, predict(classpr class(1))    ///  
      predict(classpr class(2))    ///  
      predict(classpr class(3))    ///  
      at(age=(13(1)18))
```

```
marginsplot, title("Predicted Latent Class Probabilities with 95% CI")  ///  
            legend(order(1 "Class 1" 2 "Class 2" 3 "Class 3"))        ///  
            rows(1) position(12) ring(1)    ytitle("")
```



Initial Values with the `from()` Option



```
gsem (alcohol truant vandalism theft weapon <- _cons)    ///  
      (C <- age), family(bernoulli) link(logit)          ///  
lclass(C 3) from(b, skip)
```


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vars:      8
```

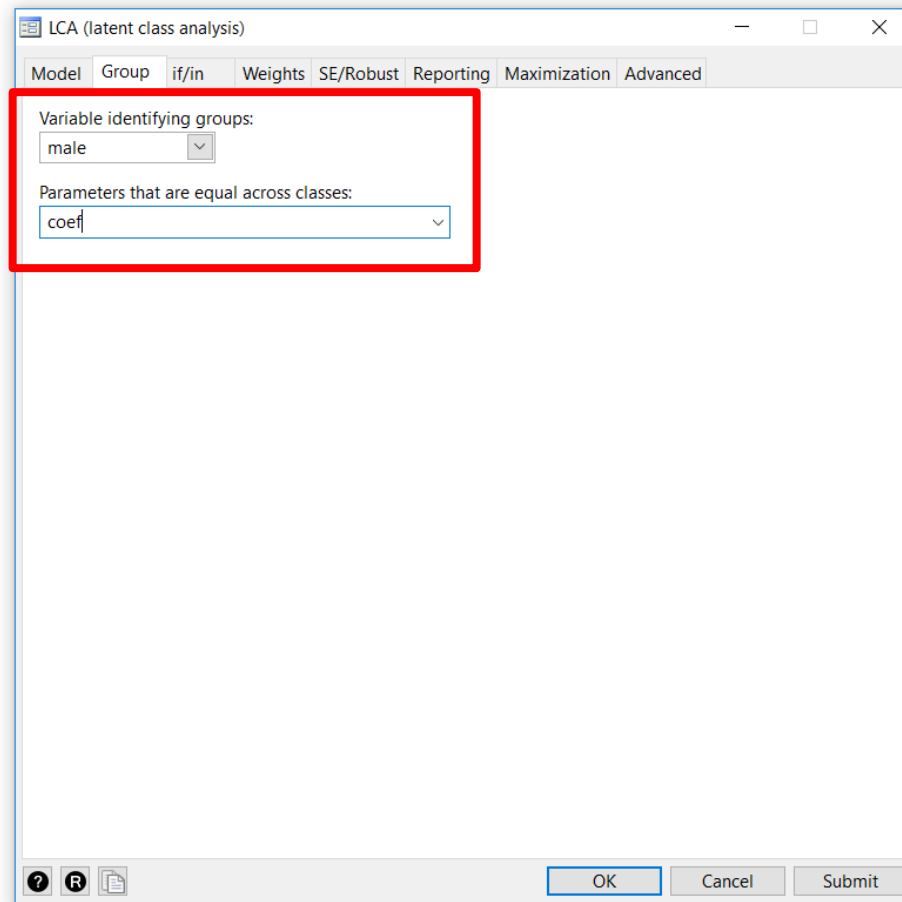
```
20 Mar 2018 15:17
```

```
size:     90,000
```

variable name	storage type	display format	value label	variable label
id	int	%9.0g		Student identification number
age	byte	%9.0g		Age (years)
male	byte	%9.0g	male	Male
alcohol	byte	%9.0g		Ever consumed alcohol
truant	byte	%9.0g		>10 unexcused absences from school
vandalism	byte	%9.0g		Ever engaged in an act of vandalism
theft	byte	%9.0g		Ever stolen something worth more than \$25
weapon	byte	%9.0g		Ever used a weapon in a fight

```
Sorted by: id
```

LCA By Groups



```
gsem (alcohol truant vandalism theft weapon <- _cons)    ///  
      (C <- age), family(bernoulli) link(logit)           ///  
      lclass(C 3) group(male) ginvariant(coef)
```

LCA By Groups

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]	
1.C	(base outcome)					
2.C						
male#c.age						
female	.1996802	.0642796	3.11	0.002	.0736945	.3256659
male	.1996802	.0642796	3.11	0.002	.0736945	.3256659
male						
female	-7.764133	1.374316	-5.65	0.000	-10.45774	-5.070524
male	-5.166688	1.259612	-4.10	0.000	-7.635483	-2.697893
3.C						
male#c.age						
female	.3405638	.0548289	6.21	0.000	.2331011	.4480265
male	.3405638	.0548289	6.21	0.000	.2331011	.4480265
male						
female	-8.4182	1.083083	-7.77	0.000	-10.541	-6.295396
male	-8.763309	.9569931	-9.16	0.000	-10.63898	-6.887637

LCA By Groups

```
. estat lcprob
```

Latent class marginal probabilities

Number of obs = 10,000

		Delta-method		
male		Margin	Std. Err.	[95% Conf. Interval]
0	C			
	1	.9433078	.0113769	.9164295 .9619008
	2	.00929	.010251	.0010557 .0768111
	3	.0474022	.017409	.0228395 .0957914
1	C			
	1	.8587708	.0407295	.7589482 .9215296
	2	.1115619	.0384299	.0554715 .2116591
	3	.0296674	.0099256	.0153168 .0566891

```
. estat lcmean
```

Latent class marginal means

Number of obs = 10,000

	Margin	Delta-method Std. Err.	[95% Conf. Interval]	
0.male#1.C				
alcohol	.3024592	.0078545	.28729	.3180719
truant	.0467973	.0047443	.0383293	.0570251
vandalism	.0518493	.0039382	.0446519	.0601339
theft	.008876	.0019226	.0058015	.0135578
weapon	.009861	.0019113	.00674	.0144063
0.male#2.C				
alcohol	.8587083	.1022934	.5379601	.9694413
truant	.3125136	.1537263	.1005828	.6488477
vandalism	.6237619	.2253174	.20162	.9158532
theft	.811037	.366611	.0379878	.997861
weapon	.4970692	.2013821	.1693018	.8273751
0.male#3.C				
alcohol	.7052357	.0726249	.5467674	.825936
truant	.5974203	.1603976	.2865114	.8457754
vandalism	.3259337	.0611469	.2188929	.4548385
theft	.2014416	.0843749	.0827666	.4135572
weapon	.1799448	.057378	.0928923	.3198147
1.male#1.C				
alcohol	.326503	.0138507	.2999583	.3542082
truant	.0558936	.0115078	.0371758	.083221
vandalism	.0473091	.0058805	.0370294	.0602639
theft	.01436	.0024698	.0102431	.0200978
weapon	.0151411	.0028376	.0104769	.0218358
1.male#2.C				
alcohol	.7256983	.0832924	.5381264	.8572958
truant	.4556383	.091347	.2891031	.6327225
vandalism	.2130356	.0651992	.1121517	.3671416
theft	3.78e-07	.000225	0	1
weapon	.0785246	.0324125	.034207	.1701435
1.male#3.C				
alcohol	.7215414	.0501339	.6137411	.8086366
truant	.4624785	.0570091	.3543796	.5742239
vandalism	.6546292	.0627237	.523907	.7655226
theft	.6673	.2103064	.2385516	.9277502
weapon	.2956006	.0507453	.2065255	.4035547

Outline

- Latent class analysis (LCA)
 - Estimation and postestimation options
 - **margins** and **marginsplot**
- Latent class analysis with covariates
- Latent class analysis by groups
- Latent profile analysis

Latent and Observed Variables

	Continuous Latent	Categorical Latent
Continuous Observed	Factor analysis	Latent Profile Analysis
Categorical Observed	Latent trait analysis or Item Response Theory	Latent Class Analysis

Latent Profile Analysis

LCA (latent class analysis)

Model | Group | if/in | Weights | SE/Robust | Reporting | Maximization | Advanced

Type of analysis:
 LCA

Latent class specification

A Name for latent categorical variable

2 Number of classes 1 Base class

Multiple latent categorical variables

Measurement model

Measurement type:

- Regress -- Gaussian family, identity link
- Gaussian family, log link
- Complementary log-log -- Bernoulli family, cloglog link
- Logistic -- Bernoulli family, logit link
- Probit -- Bernoulli family, probit link
- Binomial family, cloglog link
- Binomial family, logit link
- Binomial family, probit link
- Poisson -- poisson family, log link
- Negative binomial -- nbinomial constant family, log link
- Negative binomial mean -- nbinomial mean family, Log link
- Ordinal logistic -- ordinal family, logit link
- Ordinal probit -- ordinal family, probit link
- Ordinal family, cloglog link
- Multinomial logistic -- multinomial family, logit link
- Beta family, logit link
- Beta family, probit link
- Beta family, cloglog link
- Exponential -- exponential family, log link
- Weibull -- weibull family, log link
- Gamma -- gamma family, log link
- Loglogistic -- loglogistic family, log link
- Lognormal -- lognormal family, log link

OK Cancel Submit

Latent Profile Analysis

Diabetologia 16, 17–24 (1979)

An Attempt to Define the Nature of Chemical Diabetes Using a Multidimensional Analysis

G. M. Reaven and R. G. Miller

Departments of Medicine and Statistics, Stanford University and Veterans Administration Hospital, Palo Alto, California, USA

Summary. The relationship between chemical diabetes and overt diabetes in 145 nonobese adult subjects has been examined. The degree of glucose intolerance, insulin response to oral glucose, and insulin resistance in normal subjects and patients with nonketotic diabetes were first determined. These variables were then analyzed by a computer program which permits direct visualization of the three-dimensional shape of the data set. The picture obtained was that of a boomerang with two wings and a fat middle. The patients were then divided into three groups (normal, chemical diabetes, overt diabetes) on the basis of their oral glucose tolerance. Two-dimensional views of the relationship between the metabolic variables in these subjects resembled the initial three-dimensional image, i. e., a central

core with two wings going off in opposite directions. The two wings represented patients with chemical diabetes and overt diabetes, respectively. Following this, the patients were reclassified on the basis of all three metabolic variables (plasma glucose response to oral glucose, plasma insulin response to oral glucose, and degree of insulin resistance) by means of a computer classification which employed a cluster analysis technique. This again resulted in the definition of three groups, in which there was a divergence between subjects classified as having chemical diabetes as contrasted to overt diabetes. This apparent separation between subjects with chemical and overt diabetes may explain why patients with chemical diabetes rarely develop overt diabetes.

Diabetologia

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Latent Profile Analysis

```
. webuse gsem_lca2  
(Latent profile analysis)
```

```
. describe
```

```
Contains data from http://www.stata-press.com/data/r15/gsem\_lca2.dta  
  obs:           145                Latent profile analysis  
  vars:           7                 18 Jan 2017 12:39  
  size:          3,045              (_dta has notes)
```

variable name	storage type	display format	value label	variable label
patient	int	%9.0g		Patient ID
relwgt	float	%9.0g		Relative weight
fglucose	int	%9.0g		Fasting plasma glucose
glucose	float	%9.0g		Glucose area (mg/10mL/hr)
insulin	float	%9.0g		Insulin area (mIU/10mL/hr)
sspg	float	%9.0g		Steady-state plasma glucose
cclass	byte	%17.0g	class	Clinical classification

Latent Profile Analysis

LCA (latent class analysis)

Model Group if/in Weights SE/Robust Reporting Maximization Advanced

Type of analysis:
LCA

Latent class specification
C Name for latent categorical variable
3 Number of classes 1 Base class
Multiple latent categorical variables

Measurement model
Measurement type:
Regress -- Gaussian family, identity link Censoring...
Measurement variables:
glucose insulin sspg
Parameters that are equal across classes:
Model has predictors for class membership
Predictors:
Allow different predictors for each class

OK Cancel Submit

```
gsem (glucose insulin sspg <- _cons), ///  
family(gaussian) link(identity) ///  
lclass(C 3)
```

Latent Profile Analysis

```
. estat lcprob
```

```
Latent class marginal probabilities
```

```
Number of obs = 145
```

	Delta-method			
	Margin	Std. Err.	[95% Conf. Interval]	
C				
1	.5289099	.0481727	.4345859	.6212135
2	.2899368	.045273	.2097056	.3858759
3	.1811533	.0322278	.126267	.2529898

Latent Profile Analysis

```
. estat lcmean
```

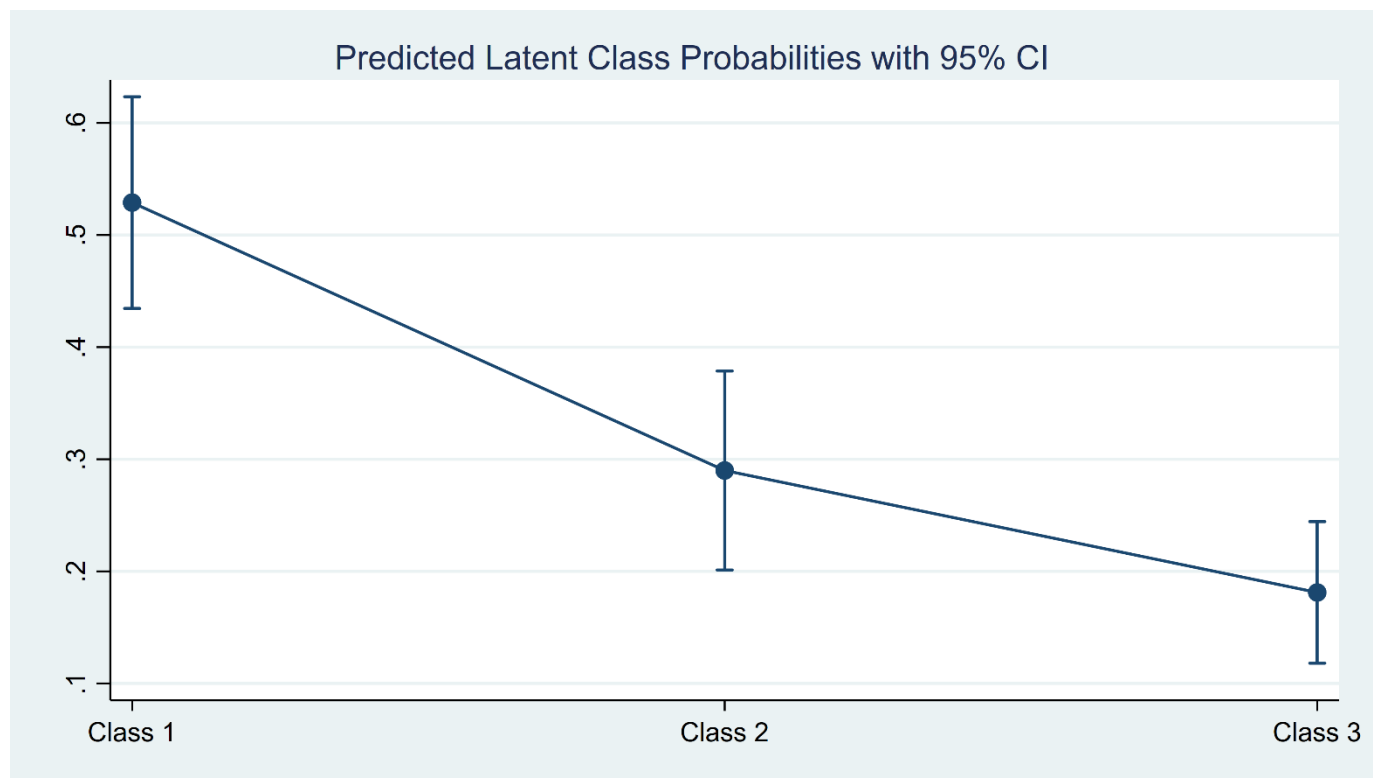
```
Latent class marginal means                Number of obs      =          145
```

		Delta-method				
		Margin	Std. Err.	z	P> z	[95% Conf. Interval]
1	glucose	35.6516	.5603517	63.62	0.000	34.55333 36.74987
	insulin	16.36279	.6088787	26.87	0.000	15.16941 17.55617
	sspg	10.68416	.6630563	16.11	0.000	9.38459 11.98372
2	glucose	50.75437	1.754034	28.94	0.000	47.31653 54.19221
	insulin	29.61048	2.578857	11.48	0.000	24.55602 34.66495
	sspg	22.69286	.8822253	25.72	0.000	20.96373 24.42199
3	glucose	114.761	5.00265	22.94	0.000	104.956 124.566
	insulin	7.574333	.8903958	8.51	0.000	5.829189 9.319477
	sspg	34.17127	1.573196	21.72	0.000	31.08786 37.25468

Latent Profile Analysis

```
margins, predict(classpr class(1))    ///
      predict(classpr class(2))    ///
      predict(classpr class(3))
```

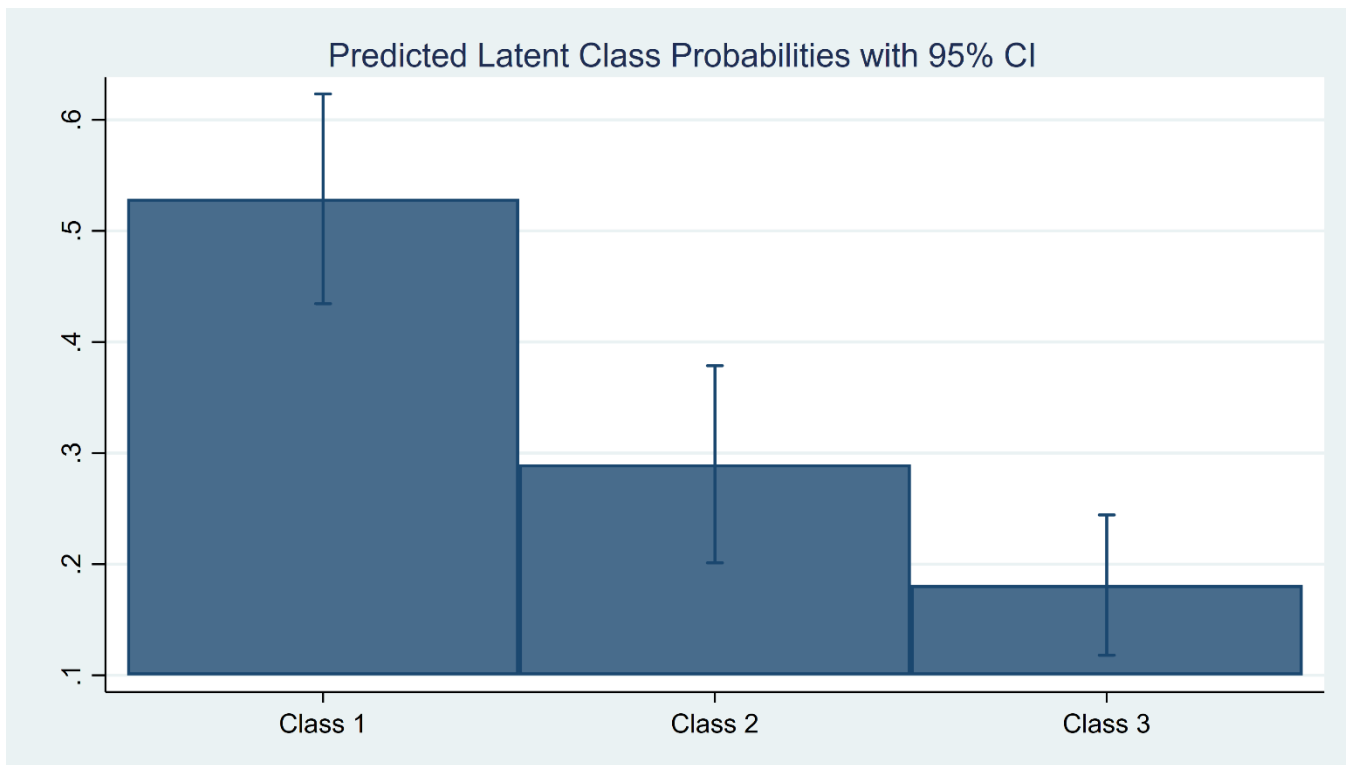
```
marginsplot, xtitle("") ytitle("")    ///
      xlabel(1 "Class 1" 2 "Class 2" 3 "Class 3")    ///
      title("Predicted Latent Class Probabilities with 95% CI")
```



Latent Profile Analysis

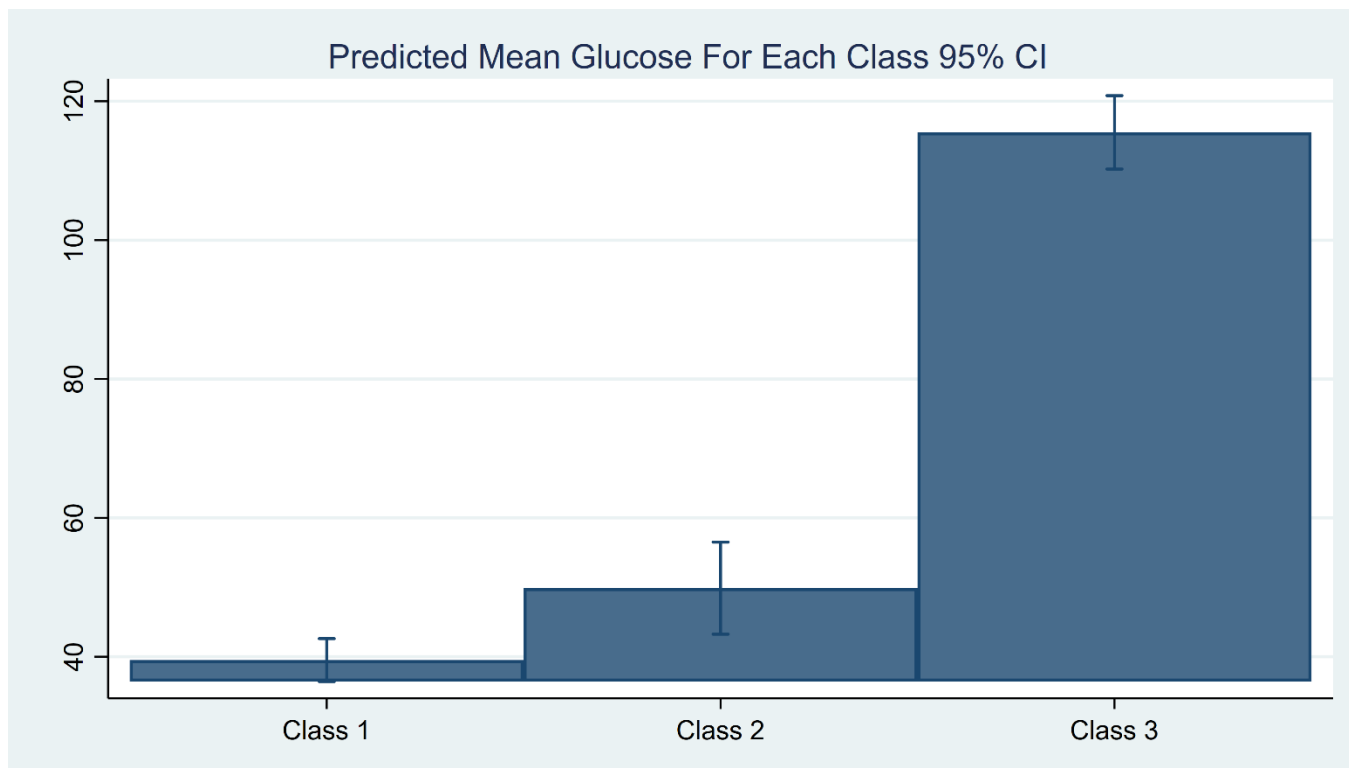
```
margins, predict(classpr class(1))    ///  
      predict(classpr class(2))    ///  
      predict(classpr class(3))
```

```
marginsplot, recast(bar) xtitle("") ytitle("")    ///  
      xlabel(1 "Class 1" 2 "Class 2" 3 "Class 3")    ///  
      title("Predicted Latent Class Probabilities with 95% CI")
```



Latent Profile Analysis

```
margins, predict(outcome(glucose) class(1))      ///  
      predict(outcome(glucose) class(2))      ///  
      predict(outcome(glucose) class(3))  
  
marginsplot, recast(bar) xtitle("") ytitle("")      ///  
      xlabel(1 "Class 1" 2 "Class 2" 3 "Class 3")      ///  
      title("Predicted Mean Glucose For Each Class 95% CI")
```

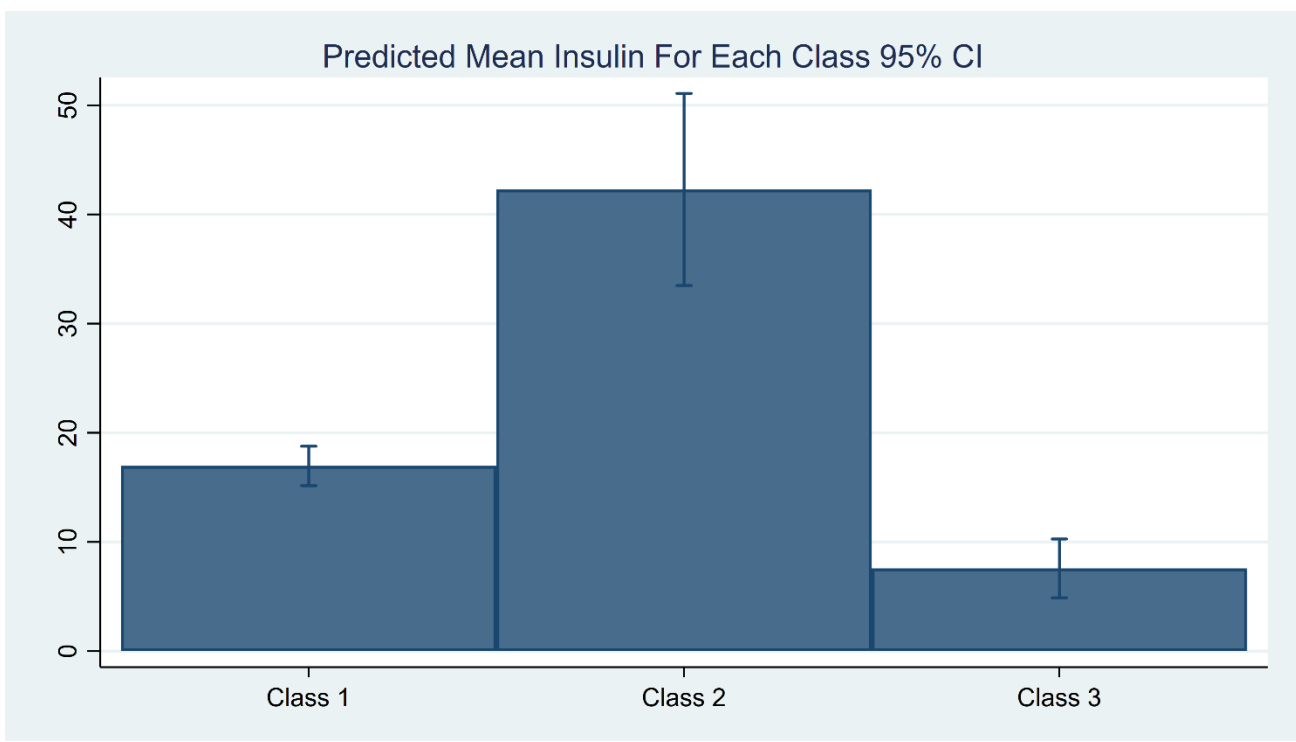


Latent Profile Analysis

```

margins, predict(outcome(insulin) class(1)) ///
predict(outcome(insulin) class(2)) ///
predict(outcome(insulin) class(3))

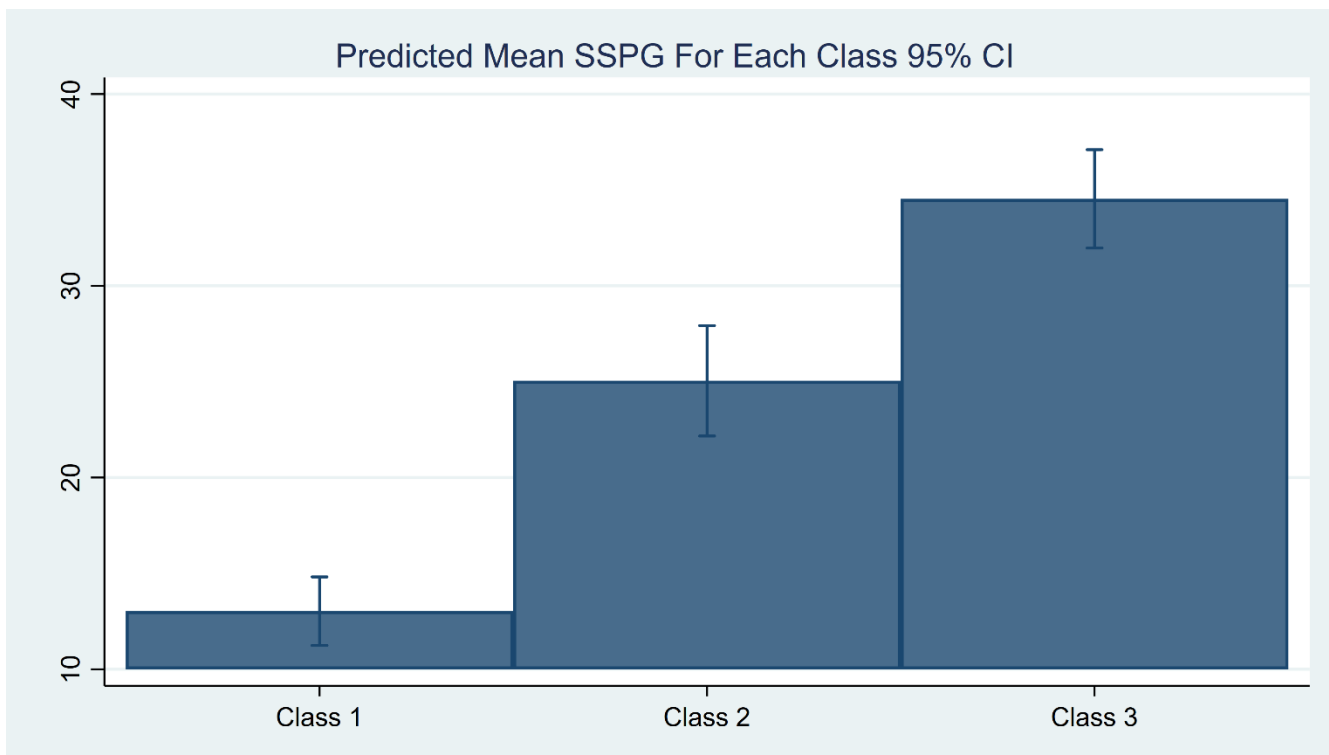
marginsplot, recast(bar) xtitle("") ytitle("") ///
xlabel(1 "Class 1" 2 "Class 2" 3 "Class 3") ///
title("Predicted Mean Insulin For Each Class 95% CI")
    
```



Latent Profile Analysis

```
margins, predict(outcome(sspg) class(1)) ///  
      predict(outcome(sspg) class(2)) ///  
      predict(outcome(sspg) class(3))
```

```
marginsplot, recast(bar) xtitle("") ytitle("") ///  
             xlabel(1 "Class 1" 2 "Class 2" 3 "Class 3") ///  
             title("Predicted Mean SSPG For Each Class 95% CI")
```



Summary

- Latent class analysis (LCA)
 - Estimation and postestimation options
 - **margins** and **marginsplot**
- Latent class analysis with covariates
- Latent class analysis by groups
- Latent profile analysis

Thanks for Coming!

Questions?

You can download the slides, dataset, and do-file here:

<https://tinyurl.com/2019LCA>

You can contact me at:

chuber@stata.com