Example 53g — Finite mixture Poisson regression

Description Remarks and examples References Also see

Description

To demonstrate a finite mixture model (FMM), we use the following data:

```
. use https://www.stata-press.com/data/r18/gsem_mixture
(U.S. Medical Expenditure Panel Survey (2003))

. describe

Contains data from https://www.stata-press.com/data/r18/gsem_mixture.dta
 Observations:         3,677                  U.S. Medical Expenditure Panel
                                                Survey (2003)
    Variables:            12                  26 Jan 2023 08:46
                                              (_dta has notes)
-------------------------------------------------------------------------------
Variable      Storage   Display    Value
    name         type    format    label      Variable label
-------------------------------------------------------------------------------
drvisits        int     %9.0g                 Number of doctor visits
private         byte    %8.0g                 Has private supplementary
                                                insurance
medicaid        byte    %8.0g                 Has Medicaid public insurance
age             byte    %8.0g                 Age in years
educ            byte    %8.0g                 Years of education
actlim          byte    %8.0g                 Has activity limitations
chronic         byte    %8.0g                 Number of chronic conditions
income          float   %9.0g                 Income in $1,000s
offer           byte    %8.0g                 Employer offers insurance
hpvisits        int     %8.0g                 Number of visits to health
                                                professionals other than
                                                doctors
female          byte    %8.0g                 Female
phylim          byte    %8.0g                 Has physical limitation
-------------------------------------------------------------------------------
Sorted by:

. notes

_dta:
  1.  Data on annual number of doctor visits for individuals age 65 and older
      from the U.S. Medical Expenditure Panel Survey for 2003.
  2.  Data are analyzed in Cameron, A. C., and P. K. Trivedi. 2010.
      Microeconometrics Using Stata. Rev. ed. College Station, TX: Stata Press.
  3.  Additional information on finite mixture models for count data and a
      similar example are found in Deb, P., and P. K. Trivedi. 1997. Demand for
      medical care by the elderly: A finite mixture approach. Journal of
      Applied Econometrics 12: 313-336.
      https://doi.org/10.1002/(SICI)1099-1255(199705)12:3<313::AID-JAE440>3.0.C
      > O;2-G.
```

See *Finite mixture models* in [SEM] **Intro 5** for background.

Remarks and examples

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We are interested in fitting a Poisson regression to model the annual number of doctor visits as a function of whether an individual has private supplementary insurance, whether he or she has Medicaid, age, age squared, education level, whether he or she has activity limitations, and the number of chronic conditions. If we believed that the same model applied to the entire population, we could fit the model by typing

```
. poisson drvisits private medicaid c.age##c.age educ actlim chronic
```

or, equivalently, by using `gsem`,

```
. gsem (drvisits <- private medicaid c.age##c.age educ actlim chronic), poisson
```

However, we believe that the model may differ across groups in the population. We do not have any information that identifies what these groups are or that tells us which individuals in our sample belong to each group. We can consider a categorical latent variable that identifies these groups and refer to the levels of this latent variable as latent classes. With an FMM, we can incorporate the categorical latent variable into our model to account for differences across the latent classes.

Following Cameron and Trivedi (2022), we will fit an FMM with a Poisson regression component for each latent class. We will estimate distinct coefficients for the Poisson model in each class, and we will estimate the probability of belonging to each of these classes using a multinomial logistic regression. We fit the model as follows:

```
. gsem (drvisits <- private medicaid c.age##c.age educ actlim chronic),
> poisson lclass(C 2) startvalues(randomid, draws(5) seed(15))
Computing starting values using randomid:
```

(iteration log omitted)

```
Generalized structural equation model                  Number of obs = 3,677
Log likelihood = -11502.686
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
1.C	(base outcome)					
2.C						
_cons	.877227	.0494614	17.74	0.000	.7802845	.9741696

```
Class:    1
Response: drvisits
Family:   Poisson
Link:     Log
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
drvisits						
private	.138229	.0247626	5.58	0.000	.0896951	.1867629
medicaid	.1269723	.0341525	3.72	0.000	.0600345	.19391
age	.2628874	.0466774	5.63	0.000	.1714014	.3543735
c.age#c.age	-.0017418	.0003108	-5.60	0.000	-.002351	-.0011326
educ	.0241679	.0030705	7.87	0.000	.0181499	.030186
actlim	.1831598	.0238817	7.67	0.000	.1363525	.2299671
chronic	.1970511	.0088783	22.19	0.000	.17965	.2144523
_cons	-8.051256	1.741677	-4.62	0.000	-11.46488	-4.637632

```
Class:    2
Response: drvisits
Family:   Poisson
Link:     Log
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
drvisits						
private	.2077415	.0306353	6.78	0.000	.1476974	.2677856
medicaid	.1071618	.0407211	2.63	0.008	.02735	.1869736
age	.3798087	.0562035	6.76	0.000	.269652	.4899655
c.age#c.age	-.0024869	.0003736	-6.66	0.000	-.0032191	-.0017547
educ	.029099	.003972	7.33	0.000	.021314	.0368841
actlim	.1244235	.0310547	4.01	0.000	.0635574	.1852895
chronic	.3191166	.0089757	35.55	0.000	.3015247	.3367086
_cons	-14.25713	2.101964	-6.78	0.000	-18.37691	-10.13736

Notes:

1. We used the `lclass(C 2)` to specify that our categorical latent variable is named C and has two latent classes.
2. The first table in the output provides the estimated coefficients in the multinomial logit model for `C`.
3. The next two tables are the results for the Poisson regression models for the first and second classes. By default, the coefficients and intercepts vary across the classes. We can specify `lcinvariant(cons)` if we want intercepts to be constrained to be equal across classes, or we can specify `lcinvariant(coef)` if we want all coefficients constrained to be equal across classes. See [SEM] **gsem lclass options** for details on the `lcinvariant()` option.
4. We added the `startvalues(randomid), draws(5) seed(15))` option to request that starting values be computed using random class assignments. In this option, `draws(5)` specifies that five random draws be taken and that the one with the best log likelihood after the EM iterations be selected. If you fit FMMs and other models with categorical latent variables, taking multiple draws of random starting values can help to prevent convergence at a local maximum rather than the global maximum. `gsem` provides a variety of options for obtaining starting values. See [SEM] **Intro 12** and [SEM] **gsem estimation options** for more information on starting values.
5. The `fmm:` prefix can be used to fit finite mixture regression models with a single response variable. We could have fit this same model with `fmm: poisson` by typing

```
. fmm 2, startvalues(randomid, draws(5) seed(15)): ///
  poisson drvisits private medicaid c.age##c.age educ actlim chronic
```

We can use `estat lcprob` to estimate the proportion of individuals in each class.

```
. estat lcprob
Latent class marginal probabilities                    Number of obs = 3,677
```

	Margin	Delta-method std. err.	[95% conf. interval]	
C				
1	.2937527	.0102614	.2740502	.3142586
2	.7062473	.0102614	.6857414	.7259498

We find that about 29% of the population is in class 1 and about 71% is in class 2.

To better understand these classes, we use `estat lcmean` to estimate the marginal predicted counts (means) for each class.

```
. estat lcmean
Latent class marginal means                            Number of obs = 3,677
```

	Margin	Delta-method std. err.	z	P>|z|	[95% conf. interval]	
1						
drvisits	13.95943	.1767506	78.98	0.000	13.613	14.30585
2						
drvisits	3.801692	.0587685	64.69	0.000	3.686508	3.916876

Class 1 appears to represent those who visit the doctor frequently and class 2, those who visit less frequently.

We can also predict the posterior probabilities of class membership and then use those to determine the predicted class for each individual.

```
. predict postpr_dr*, classposteriorpr
. generate pclass_dr = 1 + (postpr_dr2>0.5)
. tabulate pclass_dr
```

pclass_dr	Freq.	Percent	Cum.
1	1,061	28.86	28.86
2	2,616	71.14	100.00
Total	3,677	100.00	

We see that 1,061 individuals in our sample are predicted to be in class 1, the class that frequently visits the doctor.

Our dataset also includes the variable `hpvisits`, which records the number of visits individuals make to health professionals other than doctors. We fit a similar model to the one above but with `hpvisits` as our response variable.

```
. gsem (hpvisits <- private medicaid c.age##c.age educ actlim chronic),
> poisson lclass(C 2) startvalues(classid pclass_dr)
```

(iteration log omitted)

```
Generalized structural equation model                    Number of obs = 3,677
Log likelihood = -8510.4898
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
1.C	(base outcome)					
2.C						
_cons	2.241837	.059523	37.66	0.000	2.125174	2.3585

```
Class:     1
Response:  hpvisits
Family:    Poisson
Link:      Log
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
hpvisits						
private	.3218525	.0347116	9.27	0.000	.253819	.389886
medicaid	.0715449	.0566317	1.26	0.206	-.0394511	.182541
age	.0975749	.0743567	1.31	0.189	-.0481615	.2433113
c.age#c.age	-.0004749	.0004971	-0.96	0.339	-.0014492	.0004993
educ	.0278151	.0046572	5.97	0.000	.0186872	.0369429
actlim	.7088077	.0353277	20.06	0.000	.6395666	.7780488
chronic	-.0077779	.0127981	-0.61	0.543	-.0328617	.0173059
_cons	-2.430713	2.766794	-0.88	0.380	-7.853529	2.992103

```
Class:     2
Response:  hpvisits
Family:    Poisson
Link:      Log
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
hpvisits						
private	.4448319	.0451971	9.84	0.000	.3562473	.5334165
medicaid	-.4490187	.074252	-6.05	0.000	-.5945499	-.3034875
age	.4160345	.0797576	5.22	0.000	.2597125	.5723565
c.age#c.age	-.0026784	.0005287	-5.07	0.000	-.0037147	-.0016421
educ	.1250644	.0062921	19.88	0.000	.1127322	.1373967
actlim	.3357366	.0442285	7.59	0.000	.2490503	.4224229
chronic	.206585	.0152161	13.58	0.000	.176762	.2364081
_cons	-18.21906	2.991859	-6.09	0.000	-24.083	-12.35513

This time, we used the `startvalues(classid pclass_dr)` option to specify how starting values are calculated. This means that we are using the variable `pclass_dr` as an initial guess of class membership to be used when computing starting values.

We again use `estat lcprob` to estimate the predicted proportion of the population in each class.

```
. estat lcprob
Latent class marginal probabilities                    Number of obs = 3,677
```

	Margin	Delta-method std. err.	[95% conf.	interval]
C				
1	.0960559	.0051683	.0863925	.106674
2	.9039441	.0051683	.893326	.9136075

This time about 10% is in class 1, and 90% is in class 2.

We can predict the class for each individual based on this model and compare the classifications from the two models.

```
. predict postpr_hp*, classposteriorpr
. generate pclass_hp = 1 + (postpr_hp2>0.5)
. tabulate pclass_hp pclass_dr
```

pclass_hp	pclass_dr 1	2	Total
1	169	180	349
2	892	2,436	3,328
Total	1,061	2,616	3,677

Many individuals are predicted to be in class 2 based on both models, meaning that they are in the group that visits the doctor infrequently and in the group that visits other health professionals infrequently. However, there are also 892 that are classified differently by the two models. These individuals are in the class that visits the doctor frequently based on the first model but in the class that visits other healthcare professionals infrequently based on the second model.

In [SEM] **Example 54g**, we consider simultaneously modeling `drvisits` and `hpvisits` and using a single categorical latent variable that identifies groups in the population.

References

Cameron, A. C., and P. K. Trivedi. 2022. *Microeconometrics Using Stata*. 2nd ed. College Station, TX: Stata Press.

Deb, P., and P. K. Trivedi. 1997. Demand for medical care by the elderly: A finite mixture approach. *Journal of Applied Econometrics* 12: 313–336. https://doi.org/10.1002/(SICI)1099-1255(199705)12:3⟨313::AID-JAE440⟩3.0.CO;2-G.

Also see

[SEM] **Example 54g** — Finite mixture Poisson regression, multiple responses

[SEM] **Intro 5** — Tour of models

[SEM] **gsem** — Generalized structural equation model estimation command

[SEM] **estat lcmean** — Latent class marginal means

[SEM] **estat lcprob** — Latent class marginal probabilities

[FMM] **fmm intro** — Introduction to finite mixture models

[FMM] **fmm: poisson** — Finite mixtures of Poisson regression models

For suggested citations, see the FAQ on citing Stata documentation.