

example 1b — Covariates for class membership

[Description](#)[Remarks and examples](#)[Also see](#)

Description

In this example, we demonstrate how to fit an FMM with covariates that model the probability of class membership.

Remarks and examples

[stata.com](#)

We continue with [example 1a](#), where we settled on the three-component mixture model as being the best fit for these data. In that example, we used variables from our data to predict the mean of medical expenditures for each latent class. However, the prior probability of being in a given class was the same for each individual.

Assuming that the probabilities of belonging to a particular class are the same for all individuals does not seem realistic for these data. It seems more reasonable to think that individual characteristics predict the probability of being in a given group. We specify `totchr` in the `lcprob()` option to model the latent class probabilities based on the number of chronic conditions a person has.

```
. use http://www.stata-press.com/data/r15/mus03sub
(Abbreviated dataset mus03data from Cameron and Trivedi (2010))
. fmm 3, lcprob(totchr): regress lmedexp income c.age##c.age totchr i.sex
```

Fitting class model:

(iteration log omitted)

```
Finite mixture model          Number of obs      =          2,955
Log likelihood = -4712.3871
```

| | Coef. | Std. Err. | z | P> z | [95% Conf. Interval] | |
|---------|----------------|-----------|-------|-------|----------------------|-----------|
| 1.Class | (base outcome) | | | | | |
| 2.Class | | | | | | |
| totchr | .9376084 | .2222695 | 4.22 | 0.000 | .5019683 | 1.373249 |
| _cons | -.6114399 | .4542569 | -1.35 | 0.178 | -1.501767 | .2788872 |
| 3.Class | | | | | | |
| totchr | 1.16097 | .2588803 | 4.48 | 0.000 | .6535739 | 1.668366 |
| _cons | -3.270603 | .6134585 | -5.33 | 0.000 | -4.47296 | -2.068246 |

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Class : 1
 Response : lmedexp
 Model : regress

| | Coef. | Std. Err. | z | P> z | [95% Conf. Interval] | |
|---------------|-----------|-----------|-------|-------|----------------------|----------|
| lmedexp | | | | | | |
| income | .0048917 | .0026337 | 1.86 | 0.063 | -.0002702 | .0100537 |
| age | .0261976 | .284515 | 0.09 | 0.927 | -.5314416 | .5838368 |
| c.age#c.age | -.0000843 | .0018944 | -0.04 | 0.965 | -.0037973 | .0036286 |
| totchr | .5412491 | .1163553 | 4.65 | 0.000 | .3131969 | .7693012 |
| sex | | | | | | |
| female | .1793964 | .1507783 | 1.19 | 0.234 | -.1161237 | .4749164 |
| _cons | 5.035174 | 10.61396 | 0.47 | 0.635 | -15.76781 | 25.83815 |
| var(e.lmed~p) | 2.311098 | .2100365 | | | 1.934015 | 2.761703 |

Class : 2
 Response : lmedexp
 Model : regress

| | Coef. | Std. Err. | z | P> z | [95% Conf. Interval] | |
|---------------|-----------|-----------|-------|-------|----------------------|-----------|
| lmedexp | | | | | | |
| income | .0027131 | .0013618 | 1.99 | 0.046 | .0000439 | .0053822 |
| age | .2675077 | .1152288 | 2.32 | 0.020 | .0416634 | .4933519 |
| c.age#c.age | -.001688 | .0007648 | -2.21 | 0.027 | -.0031869 | -.0001891 |
| totchr | .2878736 | .0354297 | 8.13 | 0.000 | .2184327 | .3573145 |
| sex | | | | | | |
| female | -.1326158 | .0602376 | -2.20 | 0.028 | -.2506795 | -.0145522 |
| _cons | -2.895759 | 4.313613 | -0.67 | 0.502 | -11.35029 | 5.558767 |
| var(e.lmed~p) | .7413402 | .0801554 | | | .5997686 | .9163288 |

Class : 3
 Response : lmedexp
 Model : regress

| | Coef. | Std. Err. | z | P> z | [95% Conf. Interval] | |
|---------------|-----------|-----------|-------|-------|----------------------|-----------|
| lmedexp | | | | | | |
| income | -.0061289 | .0041295 | -1.48 | 0.138 | -.0142226 | .0019648 |
| age | -.2012074 | .2578283 | -0.78 | 0.435 | -.7065417 | .3041268 |
| c.age#c.age | .0011186 | .0017078 | 0.65 | 0.512 | -.0022287 | .0044659 |
| totchr | .106383 | .0878267 | 1.21 | 0.226 | -.0657542 | .2785202 |
| sex | | | | | | |
| female | -.3027395 | .1371042 | -2.21 | 0.027 | -.5714588 | -.0340202 |
| _cons | 18.93315 | 9.651339 | 1.96 | 0.050 | .0168759 | 37.84943 |
| var(e.lmed~p) | .3241542 | .1006027 | | | .176432 | .5955603 |

In the first table, we see that `totchr` is significant in both class probability equations. We use `estimates store fmm3f` and then `estimates stats fmm3 fmm3f` to compare this model with the three-component one we fit in [example 1a](#).

```
. estimates store fmm3f
. estimates stats fmm3 fmm3f
```

Akaike's information criterion and Bayesian information criterion

| Model | Obs | ll(null) | ll(model) | df | AIC | BIC |
|-------|-------|----------|-----------|----|----------|----------|
| fmm3 | 2,955 | . | -4727.674 | 23 | 9501.348 | 9639.147 |
| fmm3f | 2,955 | . | -4712.387 | 25 | 9474.774 | 9624.555 |

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

Both the AIC and the BIC favor the model that uses a predictor to model class probabilities. We continue with this new model in [example 1c](#), where we illustrate some postestimation features.

Also see

[\[FMM\] fmm intro](#) — Introduction to finite mixture models

[\[FMM\] fmm: regress](#) — Finite mixtures of linear regression models

[\[FMM\] estat lcmean](#) — Latent class marginal means

[\[FMM\] estat lcpb](#) — Latent class marginal probabilities