example 1d — Component-specific covariates

Description Remarks and examples Also see

Description

In this example, we demonstrate how to fit FMMs with class-specific covariates using the hybrid syntax; see [FMM] **fmm** for details.

Remarks and examples

We continue with example 1b, where we settled on the three-component mixture model with the variable `totchr` modeling class probabilities as being the best fit for these data. We notice that the variable `sex` in our model from example 1b is not significant in the class 1 model. To omit this variable from the class 1 equation but keep it for the class 2 and class 3 equations, we use the hybrid syntax.

```
. fmm, lcprob(totchr): (regress lmedexp income c.age##c.age totchr)
>                      (regress lmedexp income c.age##c.age totchr i.sex)
>                      (regress lmedexp income c.age##c.age totchr i.sex)
```

(iteration log omitted)

```
Finite mixture model                            Number of obs     =      2,955
Log likelihood = -4713.1378
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1.Class	(base outcome)					
2.Class						
totchr	.9462374	.2230283	4.24	0.000	.50911	1.383365
_cons	-.6516885	.4582329	-1.42	0.155	-1.549808	.2464315
3.Class						
totchr	1.180531	.2592226	4.55	0.000	.6724642	1.688598
_cons	-3.351782	.6142908	-5.46	0.000	-4.55577	-2.147795

```
Class          : 1
Response       : lmedexp
Model          : regress
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lmedexp						
income	.0044082	.0025775	1.71	0.087	-.0006437	.0094601
age	.0112211	.2807381	0.04	0.968	-.5390154	.5614576
c.age#c.age	.0000205	.0018687	0.01	0.991	-.0036421	.0036831
totchr	.5379605	.1147841	4.69	0.000	.3129878	.7629332
_cons	5.699659	10.47166	0.54	0.586	-14.82441	26.22373
var(e.lmed~p)	2.326568	.2087898			1.951317	2.773984

```
Class          : 2
Response       : lmedexp
Model          : regress
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lmedexp						
income	.0027704	.0013668	2.03	0.043	.0000915	.0054492
age	.2714013	.115707	2.35	0.019	.0446196	.4981829
c.age#c.age	-.0017135	.0007679	-2.23	0.026	-.0032185	-.0002085
totchr	.2870955	.0351779	8.16	0.000	.2181481	.3560429
sex						
female	-.1060825	.0560499	-1.89	0.058	-.2159384	.0037734
_cons	-3.057943	4.331862	-0.71	0.480	-11.54824	5.432351
var(e.lmed~p)	.7398617	.0805511			.5976922	.9158483

```
Class          : 3
Response       : lmedexp
Model          : regress
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lmedexp						
income	-.006469	.0041191	-1.57	0.116	-.0145423	.0016043
age	-.1855111	.2573092	-0.72	0.471	-.6898278	.3188056
c.age#c.age	.0010118	.0017054	0.59	0.553	-.0023306	.0043543
totchr	.1000725	.0861765	1.16	0.246	-.0688303	.2689753
sex						
female	-.2824176	.1344932	-2.10	0.036	-.5460194	-.0188158
_cons	18.37938	9.628843	1.91	0.056	-.4928095	37.25156
var(e.lmed~p)	.3186371	.0987857			.173541	.5850469

We store our estimates and compare this model with the model in example 1b.

```
. estimates store fmm3ff
. estimates stats fmm3f fmm3ff
```

Akaike's information criterion and Bayesian information criterion

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
fmm3f	2,955	.	-4712.387	25	9474.774	9624.555
fmm3ff	2,955	.	-4713.138	24	9474.276	9618.066

Note: N=Obs used in calculating BIC; see **[R] BIC note**.

The AIC for this more parsimonious model is about the same as the previous model (`fmm3f`), which was our best model. The BIC here appears to be rewarding us for our parsimony.

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 lcprob** — Latent class marginal probabilities