Title

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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

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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
```

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
1.Class	(base outcome)					
2.Class						
totchr	.9462362	.2230292	4.24	0.000	.509107	1.383366
_cons	-.6516843	.4582362	-1.42	0.155	-1.549811	.2464422
3.Class						
totchr	1.18053	.2592234	4.55	0.000	.6724612	1.688598
_cons	-3.351777	.6142948	-5.46	0.000	-4.555773	-2.147781

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

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
lmedexp						
income	.0044082	.0025775	1.71	0.087	-.0006437	.0094601
age	.0112209	.2807385	0.04	0.968	-.5390164	.5614582
c.age#c.age	.0000205	.0018687	0.01	0.991	-.0036421	.0036831
totchr	.5379611	.1147846	4.69	0.000	.3129875	.7629347
_cons	5.699667	10.47167	0.54	0.586	-14.82444	26.22377
var(e.lmed~p)	2.326567	.2087898			1.951315	2.773983

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

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
lmedexp						
income	.0027704	.0013668	2.03	0.043	.0000915	.0054492
age	.2714012	.115707	2.35	0.019	.0446196	.4981828
c.age#c.age	-.0017135	.0007679	-2.23	0.026	-.0032185	-.0002085
totchr	.2870954	.0351779	8.16	0.000	.218148	.3560428
sex						
Female	-.1060824	.0560499	-1.89	0.058	-.2159383	.0037734
_cons	-3.057941	4.331862	-0.71	0.480	-11.54823	5.432352
var(e.lmed~p)	.7398619	.0805511			.5976923	.9158486

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

	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
lmedexp						
income	-.006469	.0041191	-1.57	0.116	-.0145423	.0016044
age	-.185511	.2573091	-0.72	0.471	-.6898276	.3188057
c.age#c.age	.0010118	.0017054	0.59	0.553	-.0023306	.0043543
totchr	.1000723	.0861764	1.16	0.246	-.0688303	.2689748
sex						
Female	-.2824174	.1344932	-2.10	0.036	-.5460192	-.0188156
_cons	18.37937	9.628842	1.91	0.056	-.4928137	37.25155
var(e.lmed~p)	.3186378	.098786			.1735412	.5850485

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	N	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: BIC uses N = number of observations. 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