Title

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	.9462354	.2230296	4.24	0.000	.5091055	1.383365
_cons	-.6516817	.4582374	-1.42	0.155	-1.549811	.246447
3.Class						
totchr	1.180529	.2592237	4.55	0.000	.6724597	1.688598
_cons	-3.351774	.6142963	-5.46	0.000	-4.555772	-2.147775

```
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	.0112207	.2807387	0.04	0.968	-.5390171	.5614585
c.age#c.age	.0000205	.0018687	0.01	0.991	-.0036421	.0036831
totchr	.5379614	.1147848	4.69	0.000	.3129874	.7629355
_cons	5.699671	10.47168	0.54	0.586	-14.82445	26.22379
var(e.lmed~p)	2.326567	.2087899			1.951314	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	.4981827
c.age#c.age	-.0017135	.0007679	-2.23	0.026	-.0032185	-.0002085
totchr	.2870954	.0351779	8.16	0.000	.218148	.3560427
sex						
Female	-.1060824	.0560499	-1.89	0.058	-.2159382	.0037735
_cons	-3.057939	4.331861	-0.71	0.480	-11.54823	5.432352
var(e.lmed~p)	.739862	.0805511			.5976924	.9158487

```
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	-.1855109	.2573091	-0.72	0.471	-.6898275	.3188057
c.age#c.age	.0010118	.0017054	0.59	0.553	-.0023306	.0043543
totchr	.1000722	.0861763	1.16	0.246	-.0688302	.2689746
sex						
Female	-.2824172	.1344932	-2.10	0.036	-.546019	-.0188154
_cons	18.37937	9.628842	1.91	0.056	-.4928178	37.25155
var(e.lmed~p)	.3186381	.0987861			.1735414	.5850492

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