

Practical considerations for using the full random effects modeling (FREM) approach to covariate modeling

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Objectives

The aim of this work is to investigate practical usage considerations of FREM including the estimation method(s), specification of different parameterizations of the parameter-covariate relationships and the sensitivity to the additional distributional assumptions required by FREM.

Background

- The FREM approach to covariate modeling has been suggested to avoid issues with standard covariate model building approaches, e.g. selection bias^{1,2}
- Implemented in PsN³ and similar to the full fixed effects modeling (FFEM) approach (all parameter-covariate relationships are estimated simultaneously), but through covariance instead of structural effects
- Advantages over FFEM; e.g. with missing data, correlated covariates⁴
- Allows conditional interpretation of the results, i.e. coefficients and variability conditional on only a subset of covariates (even a single covariate) without having to re-fit the final model
- FREM has an unusual implementation of the covariate model with implicit covariate effect relations

Results

- IMPMap was found more stable than FOCE (FREM successful minimization: 100%, 62%)
- Bias and precision of the re-estimated covariate parameters were similar, as were mean run-times (FOCE 16 cores: 14 min, 30 min; IMPMap 8 cores: 40 min, 90 min)
- While modeling covariates as random effects, FREM provided accurate covariate coefficients also for non-normal covariate distributions
- Parameterization corresponding to different parameter-covariate relationships could be implemented as either data or model transformations with the same result (Figure 1)
- FREM allowed both univariate (Figure 2) and multivariate (Figure 3) interpretation of the covariate effects simultaneously. When the same relations as FFEM were selected the results were in close agreement.

FREM coefficients			FFEM coefficients		
	AAG			AAG	
BASE	0.372		BASE	0.372	
MTT	-0.0246		MTT	-0.0249	
SLOPE	-0.506		SLOPE	-0.507	

FREM unexplained variability			FFEM unexplained variability		
	BASE	MTT		BASE	MTT
BASE	0.121		BASE	0.122	
MTT	-0.00356	0.0226	MTT	-0.00357	0.0226
SLOPE	-0.0247	0.0155	SLOPE	-0.0239	0.0160
		0.150			0.149

Figure 2. Illustrative example of FREM results (blue, left) calculated to be interpreted as univariate FFEM results (red, right), i.e. an effect only conditional on knowledge of a single covariate.

References

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Conclusion

The investigation gives information to implementation of FREM with respect to practical aspects such as estimation method, parameterizations, expected performance and robustness towards covariate distribution. Further, it supports FREM for unbiased covariate confirmatory analyses.

Data and Methods

- A simulation study (n=150) in NONMEM was performed, based on real data and the final parameters of a docetaxel model for neutrophil counts⁵. All 18 covariate-parameter relationships were re-estimated with FFEM and FREM using IMPMap and FOCE. Bias, precision, termination and run-time were evaluated.
- Covariate correlations were low in data (< 40%)
- Implementation details of parameterizations of covariate-parameter relations in FREM were investigated. Both transformation of covariate observations and the FREM model were tested.
- Univariate FFEM coefficients (FFEM with only one covariate per execution) were compared to FREM coefficients
- Non-normal covariate models were tested

Parameter model	FREM covariate model (or covariate data)	
	Normal	Log-normal
	Normal $P = \theta + (C - \bar{C})\beta + \eta$ Exponential $P = \theta e^{(C - \bar{C})\beta + \eta}$	$P = \theta + (\ln C - \ln \bar{C})\beta + \eta$ $P = \theta \left(\frac{C}{C_{GM}} \right)^\beta e^\eta$

Figure 1. Interaction of parameter and covariate model on implicit covariate relation parameterization. P , individual parameter model; β , coefficient of covariate effect; C , individual covariate; \bar{C} , mean of covariate; C_{GM} , geometric mean of covariate; $\ln \bar{C}$, mean of log-transformed covariate.

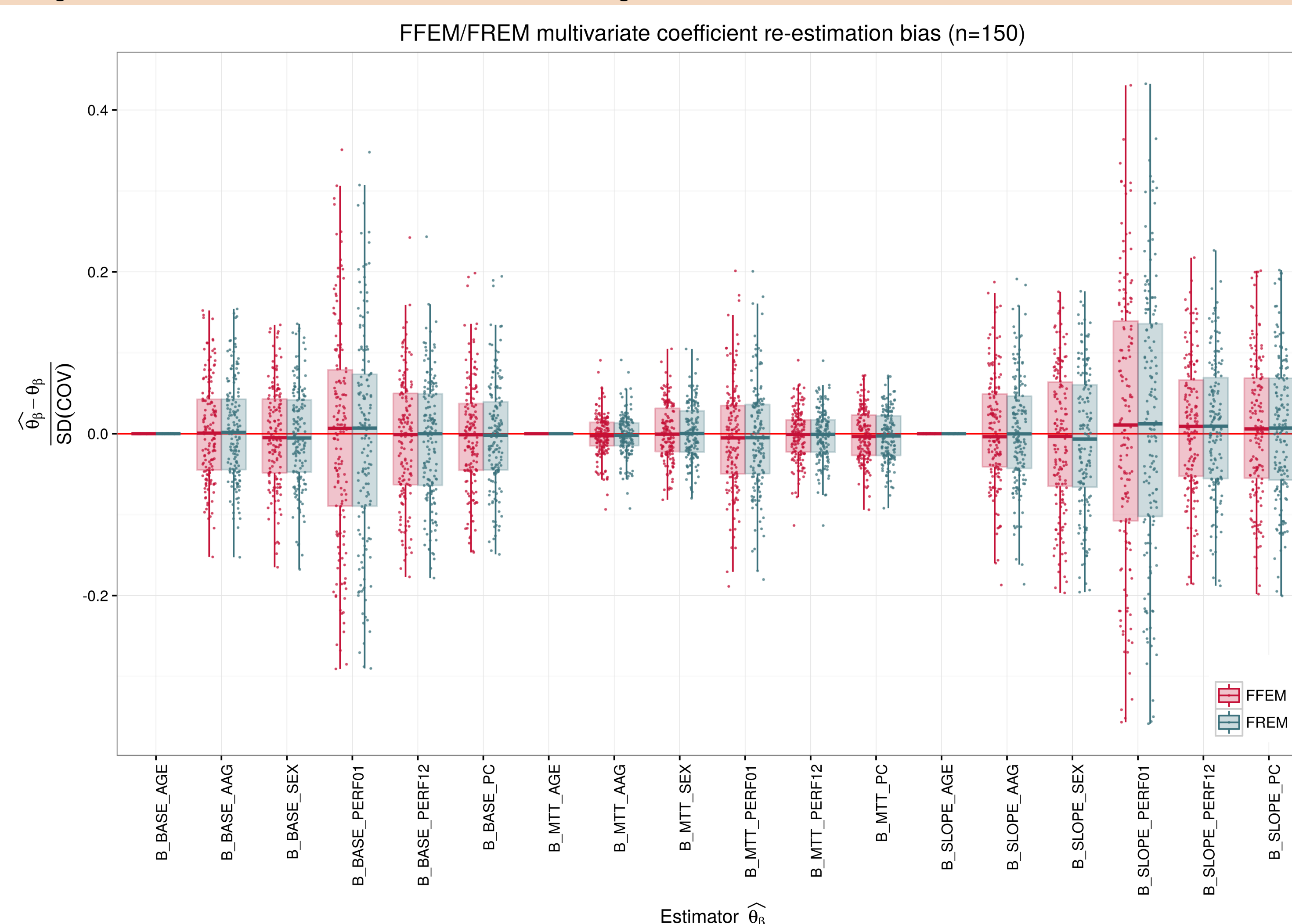


Figure 3. Estimation bias (absolute bias normalized by covariate standard deviation) of FFEM and FREM coefficients (multivariate; conditional on all) in simulation (n=150) of 6 covariates and 3 parameters, utilizing IMPMap in NONMEM 7.3 to re-estimate both FFEM and FREM.

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