

PREDICTION OF PRECISION OF INDIVIDUAL PARAMETER ESTIMATES AND OF SHRINKAGE VIA THE BAYESIAN FISHER INFORMATION MATRIX IN NON-LINEAR MIXED-EFFECTS MODELS WITH APPLICATION IN PHARMACOKINETICS

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CONTEXT

- Individual parameters in Non-Linear Mixed Effects Models (NLMEM)
 - Estimated by Bayesian methodology as Maximum *A Posteriori* (MAP)
 - Used to predict response, select covariates and draw diagnostic plots
 - Need high precision of estimation → smallest Standard Errors (SE) on parameters
- Optimal design
 - Evaluate the informativeness of the design and its influence on SE through the Fisher information Matrix
 - Prediction of SE:
 - * Individual fitting → Individual information Matrix of Fisher (IMF)
 - * Population fitting → Population information Matrix of Fisher (PMF) [1]
 - * Individual Bayes fitting → Bayesian information Matrix (BMF) [2]
 - IMF and PMF already implemented in various softwares (PFIM, PopDES, PopED,...)
- Shrinkage of Random Effects (RE)
 - Shrunk *a posteriori* distribution of estimated η towards the population mean
 - Occurs when few information is available for each patient
 - Problems in individual parameters used for modeling (toxicity, pharmacodynamics, ...) and therapeutic drug monitoring studies

OBJECTIVE

- Explore relationship between Bayesian information Matrix and shrinkage
- Evaluate by simulation prediction of individual parameters precision and shrinkage

MATERIALS AND METHODS

- Individual statistical model: $y = f(\theta, \xi) + \epsilon$, $\xi = \{t_1, \dots, t_n\}$, $f(\theta, \xi)$: model
 - $\theta = g(\mu, \eta)$: individual parameters $g(\mu, \eta) = \mu + \eta$ or $g(\mu, \eta) = \mu e^\eta$
 - Fixed effects $\mu = (\mu_1, \dots, \mu_p)$ $\epsilon \sim N(0, \Sigma(\theta, \xi))$: residual error
 - $\eta \sim N(0, \Omega)$, $\Omega = \text{diag}(\omega_1^2, \dots, \omega_p^2)$ $\Sigma(\theta, \xi) = \text{diag}(\sigma_{inter} + \sigma_{slope} f(\theta, \xi)^2)$
 - Design evaluation
 - Based on Rao-Cramer inequality: the inverse of the Fisher Information Matrix (MF^{-1}) is the lower bound of estimation variance
 - For individual fitting $IMF(\theta, \xi) = F(\theta, \xi)^T \Sigma(\theta, \xi) F(\theta, \xi)$ with $F(\theta, \xi) = \frac{\partial f(\theta, \xi)}{\partial \theta}$
 - Evaluation of Bayesian individual design

$$BMF(\xi) = -E_\eta \left(\frac{\partial^2 \log(p(\eta|y))}{\partial \eta \partial \eta^T} \right) = E_\eta (IMF(g(\mu, \eta), \xi)) + \Omega^{-1}$$
 $p(\eta|y)$ a posteriori distribution of η given y with known population parameters
 - Two methods to approximate BMF:
 - * Monte-Carlo (MC) simulation: simulation of η
 - * First-Order linearization (FO):

$$BMF(\xi) = M^T F(\mu, \xi)^T \Sigma(\mu, \xi) F(\mu, \xi) M + \Omega^{-1}$$
- $M = I$ for additive RE $M = \text{diag}(\mu_1, \dots, \mu_p)$ for exponential RE
- Prediction of shrinkage
 - For linear mixed effects models [3,4]: $\hat{\theta}_{MAP} = W(\xi)\mu + (I - W(\xi))\hat{\theta}_{ML}$
 - With:
 - * $W(\xi) = BMF(\xi)^{-1} \Omega^{-1} \hat{\theta}_{MAP}$ and $\hat{\theta}_{ML}$ Bayesian and Maximum Likelihood estimate respectively
 - * $W(\xi)$ quantifies the balance between prior and individual information → proposed as a measure of predicted shrinkage
 - Individual prediction: *IBMF* computed for one patient (with random effects η)

$$IBMF(\eta, \xi) = \Theta^T F(g(\mu, \eta), \xi)^T \Sigma(g(\mu, \eta), \xi) F(g(\mu, \eta), \xi) \Theta + \Omega^{-1}$$

$\Theta = I$ for additive RE $\Theta = \text{diag}(\{\theta_1, \dots, \theta_p\})$ for exponential RE

THE SIMULATION STUDY

- Simple PK model** inspired from Mentré *et al* [5], describing a one compartment model ($V = 0.2$) with elimination ($CL = 0.5$), with $\sigma_{inter} = 0.15$ Simulation of 1000 patients following the same design (varying from 5 to 2 samples per patient) with R 2.14 under several scenarios: variation of variance of RE and residual error
- Illustration model** inspired from the structure of a published PK model of a real drug [6] with rounded fixed effect values and modified variabilities for simplification purposes Two-hours perfusions every 4 weeks at 8 mg/kg 2 compartments with linear and non-linear elimination and RE on CL , V_1 , V_2 and V_m Simulation of 1800 patients following the same design (varying from 10, 9, 4 or 2 samples per patient)

Scenario	aa	ac	ea	ec	Ea	Ec
Random effects						
Form	Add	Add	Exp	Exp	Exp	Exp
ω_V^2	0.0016	0.0016	0.04	0.04	0.25	0.25
ω_{CL}^2	0.01	0.01	0.04	0.04	0.25	0.25
Residual error						
σ_{slope}	0	0.15	0	0.15	0	0.15

Fixed effects	Random effects
CL (L/d)	0.3 ω^2 0.09
V_2 (L)	4 Residual error
Q (L/d)	0.15 σ_{inter} ($\mu\text{g}/\text{mL}$) 0.5
V_1 (L)	3 σ_{slope} (%) 0.3
V_m (mg/d)	6
K_m ($\mu\text{g}/\text{mL}$)	2

- Evaluation methods**
 - Individual parameters and their SE estimated with 2 softwares:
 - * NONMEM 7.0 with MAXEVAL = 0 and FOCEI
 - * MONOLIX 4.0 with population parameters fixed to their true values and SAEM algorithm
 - Observed shrinkage defined by Savic *et al* [7] on estimated $\hat{\eta}$:

$$Sh = 1 - \frac{\text{Var}(\hat{\eta}_i)}{\omega_i^2}, i = 1, \dots, N$$
 - Predicted shrinkage computed as $W(\xi)$ using *BMF* FO
 - Predicted SE computed with *IBMF* using simulated η

RESULTS

- Simple PK model** (Results for clearance only, similar for volume)

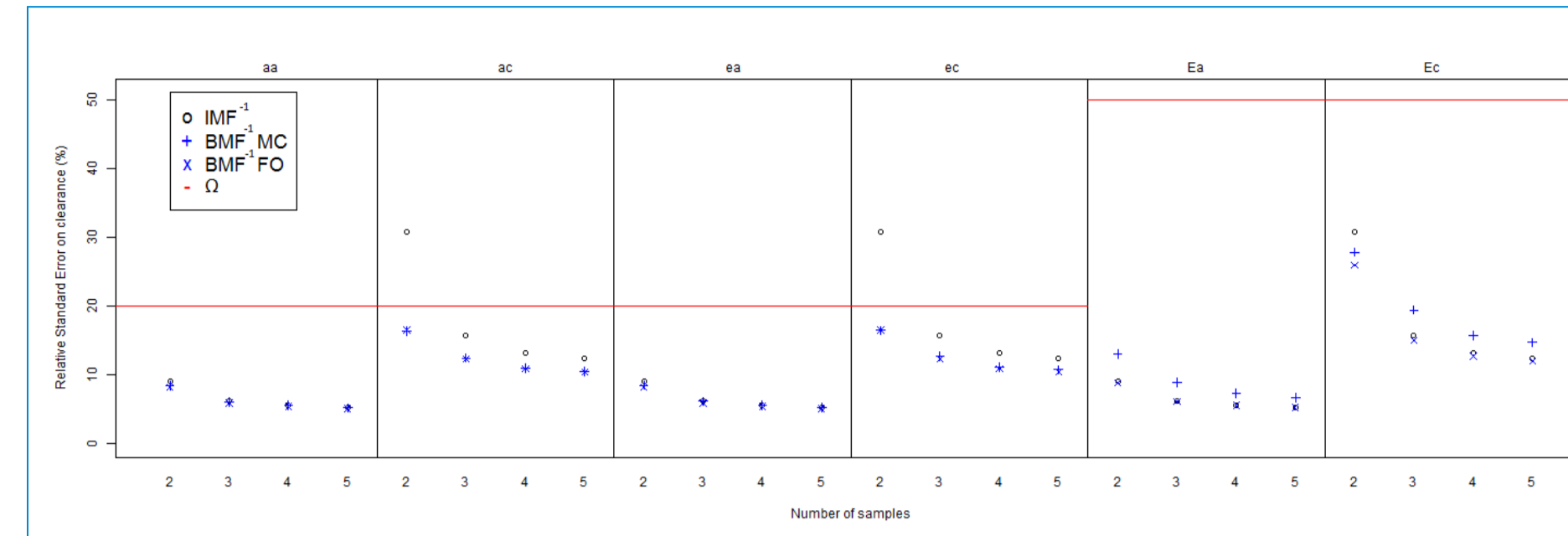


FIGURE 1: RSE for CL (%) predicted with IMF, BMF FO or BMF MC

- *BMF* FO close to *BMF* MC values
- RSE from *BMF* predictions below those from IMF or Ω
- Decrease of predicted RSE with increase of information

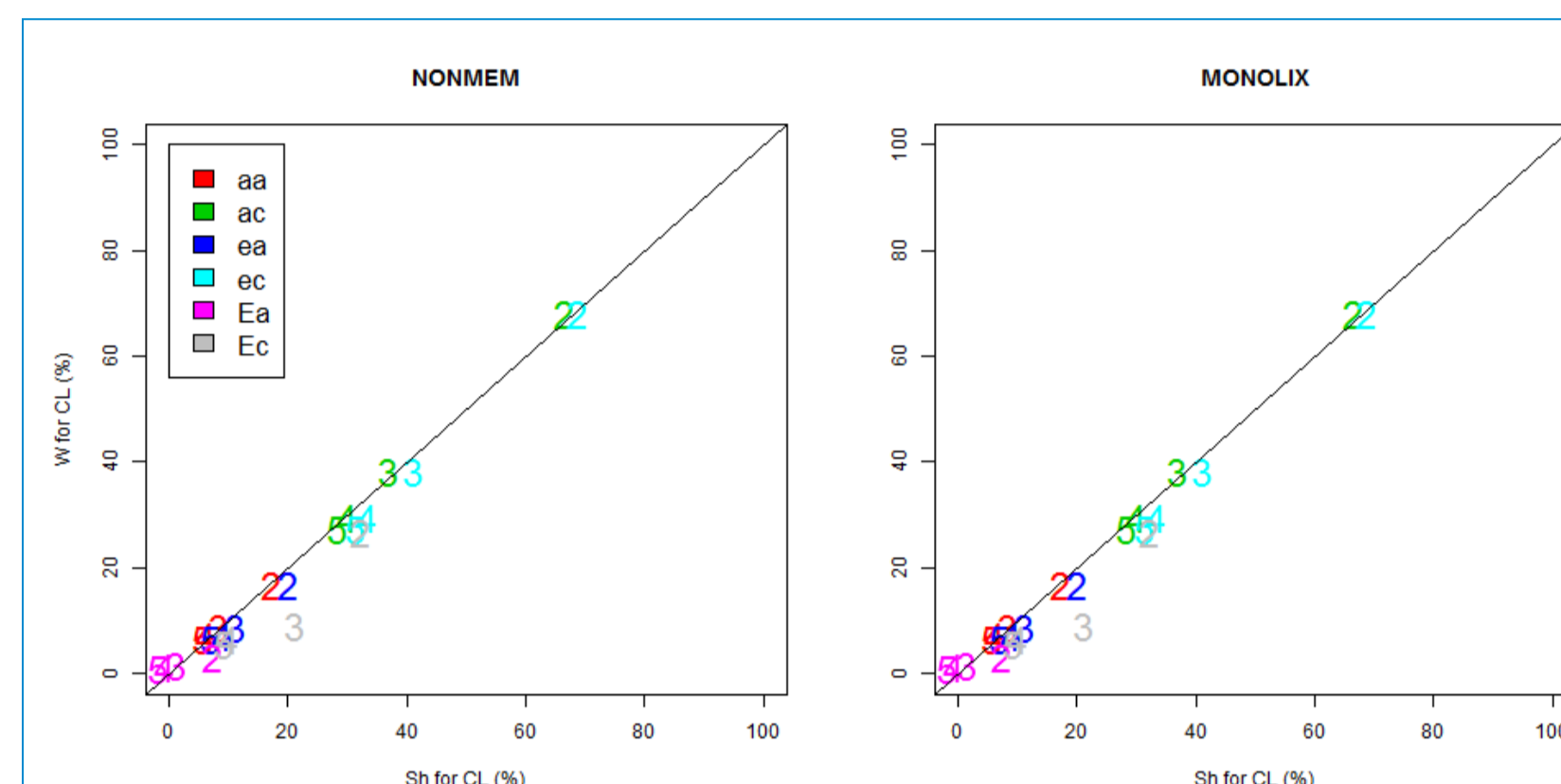


FIGURE 2: Expected (W) vs observed shrinkage (Sh) for CL (%), for each scenario and design Number stands for the design and color for the scenario

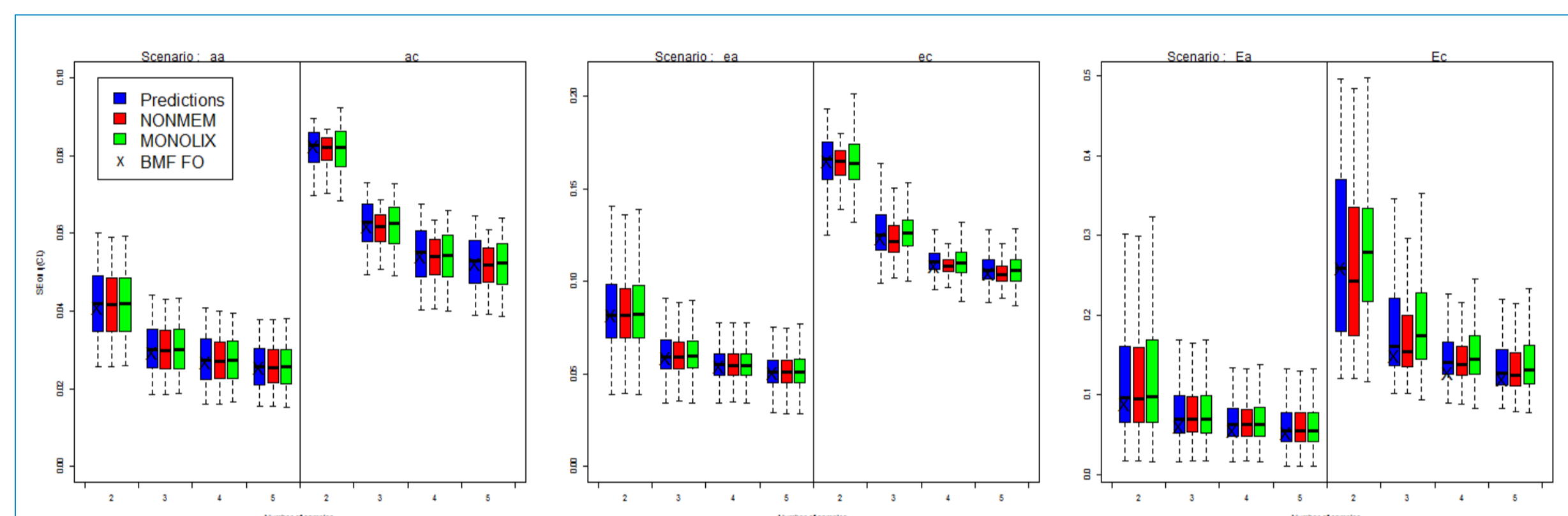


FIGURE 3: Predicted with *IBMF* and estimated SE

- Similar values of estimated SE with NONMEM and MONOLIX
- Predicted SE close to the estimated SE with some small differences with MONOLIX when high variance (CV 50%) of RE is used

- Illustration model**

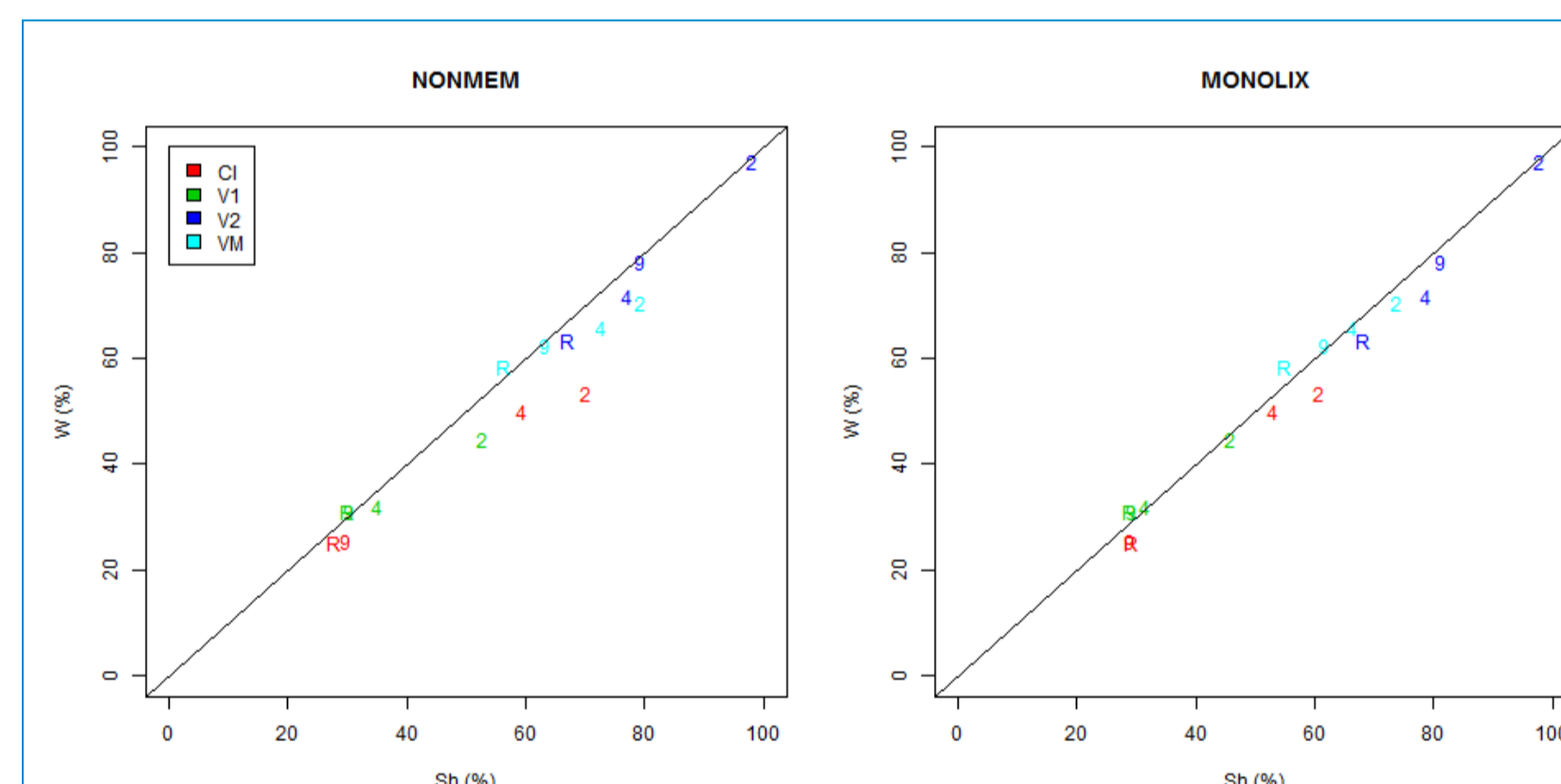


FIGURE 4: Expected (W) vs observed shrinkage (Sh)

Number stands for the design (R = 10 samples per patient) and color for the parameter

- Similar values of observed shrinkage with NONMEM and MONOLIX
- W and observed shrinkage scatterplot close to the identity line
- Highest discrepancy on CL with 17% of difference between W and observed shrinkage for 2 samples per patient

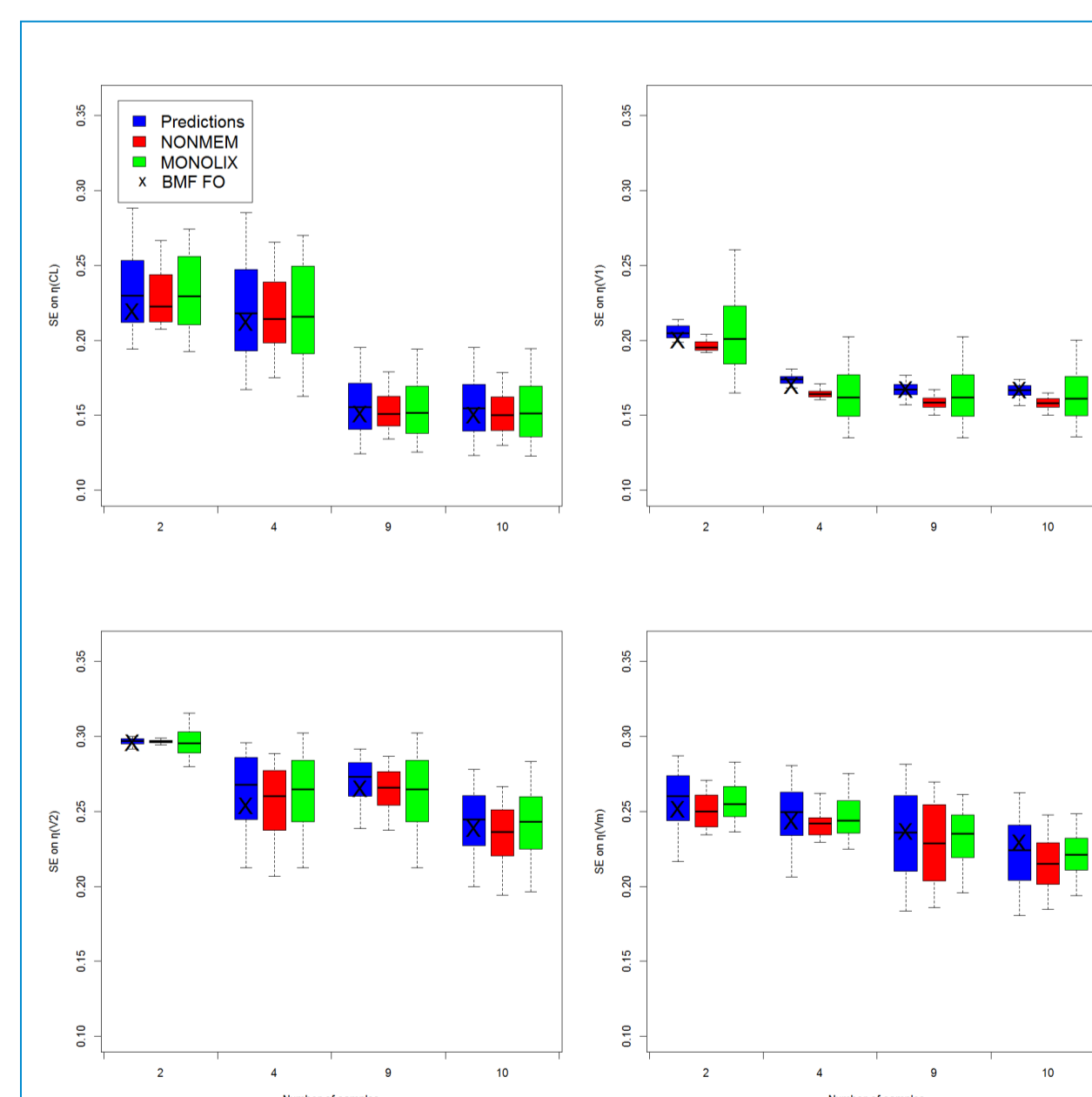


FIGURE 5: Predicted and estimated SE along with SE with *BMF* FO

- Predictions close to estimations
- Similar values of SE with NONMEM and MONOLIX
- Higher distribution for SE on V_1 with MONOLIX

DISCUSSION

- FO computation of *BMF* adequate
- Development of new formula to predict shrinkage ($W = BMF^{-1} \Omega^{-1}$)
- Further explorations needed on more "extreme" models with high variances of RE or of residual error
- Perspectives:
 - Impact of precision of estimates on covariate determination
 - Link between shrinkage and power of test



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During this work, François Combes was supported by a grant from the Roche Pharma Research & Early Development group and the French government.

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