



Nestlé

Good Food, Good Life

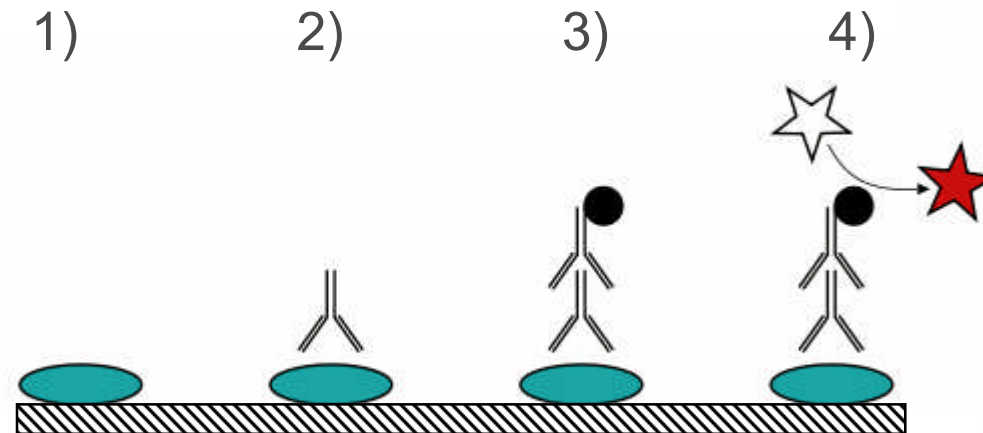
A Mixed Model for the Analysis of Enzyme Linked Immunosorbent Assay

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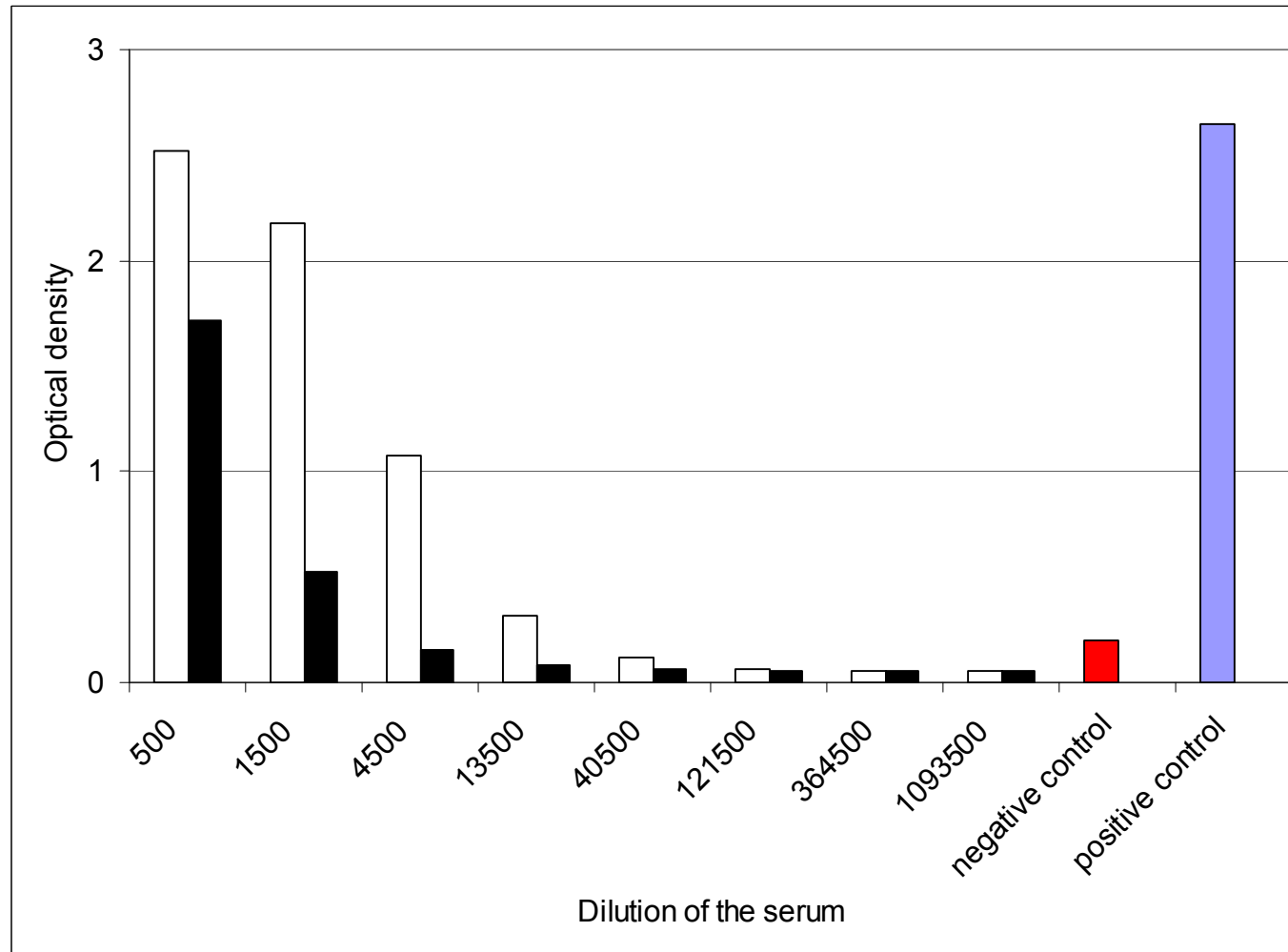
Enzyme Linked Immunosorbent Assay (ELISA)



Steps:

- (1) Plate is coated with a protein for capture.
- (2) Serum containing a mixture of antibodies is added. Antibodies specific for the capture protein will be bound.
- (3) A secondary antibody linked to an enzyme is added. It binds specifically to the first antibody.
- (4) Substrate is added, and is converted by enzyme to detectable form.

Cutoff analysis



Cutoff analysis Explanation



Why does it work?

Continuous inverse exists in
measurement range

$$\begin{aligned} OD_c &\cong f\left(\frac{1}{d_{j=c}} S_{ini}\right) \\ \Rightarrow \underbrace{f^{-1}(OD_c)}_{\text{constant}} &\cong \frac{1}{d_{j=c}} S_{ini} \\ \Rightarrow S_{ini} &\sim d_{j=c} \end{aligned}$$

Cutoff analysis Resume



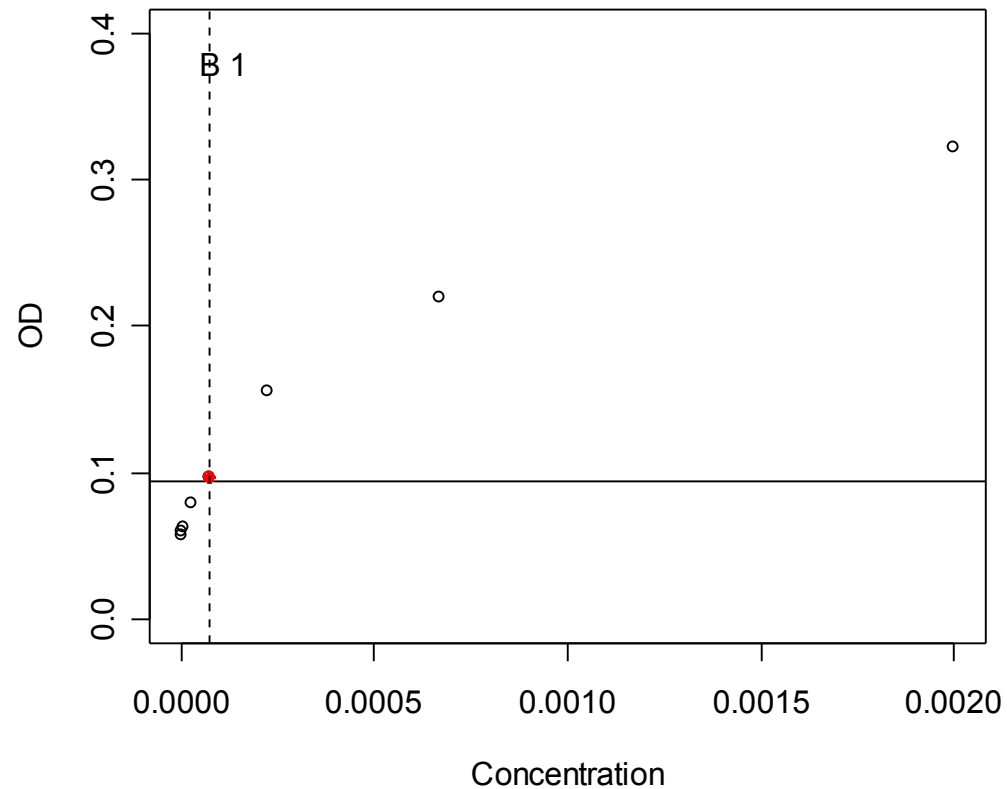
- Cutoff analysis is simple and robust
- No calibration necessary
- Producing ordered categorical data
- Wasting information
- Treatment effects in arbitrary units

Statistical analysis:

- Stage 1: Each subject has its own curve characteristic:
Value above the cutoff
- Stage 2: Characteristics is analyzed by conventional statistical techniques (e.g. Wilcoxon-test).



Cutoff analysis Revisited



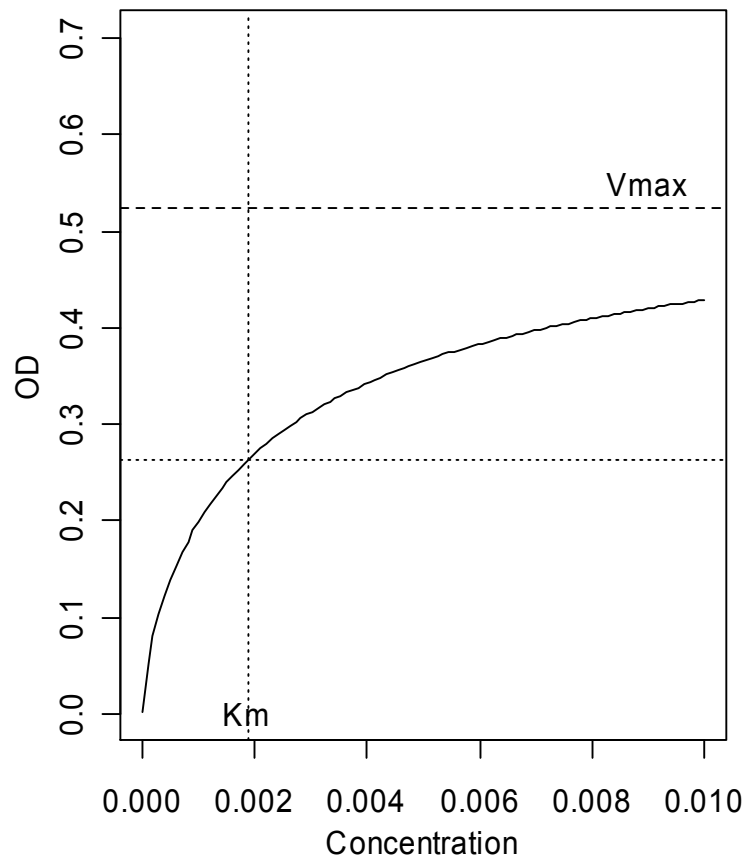
Measurements of optical density (OD) over concentration of mouse B1,
concentration is presented in arbitrary units: $\frac{1}{54675}, \frac{1}{18225}, \frac{1}{6075}, \frac{1}{2025}, \frac{1}{675}, \frac{1}{225}, \frac{1}{75}, \frac{1}{25}$

Michaelis-Menten model generalized Michaelis-Menten model

Leonor Michaelis 1875-1949
Maud Menten 1879-1960

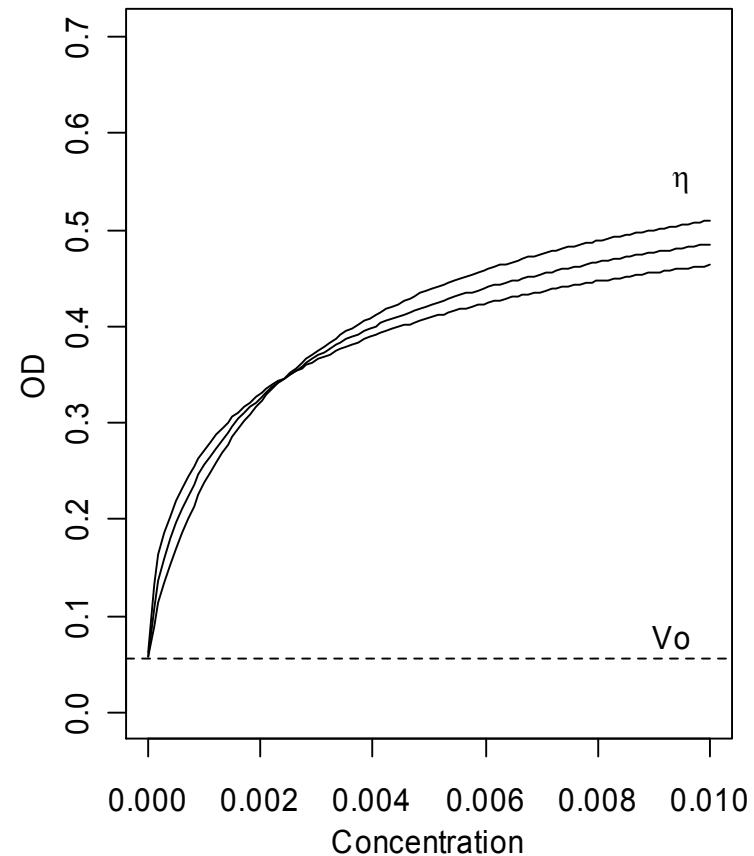
$$\mu = \frac{V_{\max} \cdot s}{K_m + s}$$

Michaelis-Menten model



$$\mu = V_0 + \frac{V'_{\max} \cdot s^{\eta}}{K_m + s^{\eta}}, \quad V'_{\max} = V_{\max} - V_0$$

generalized Michaelis-Menten model



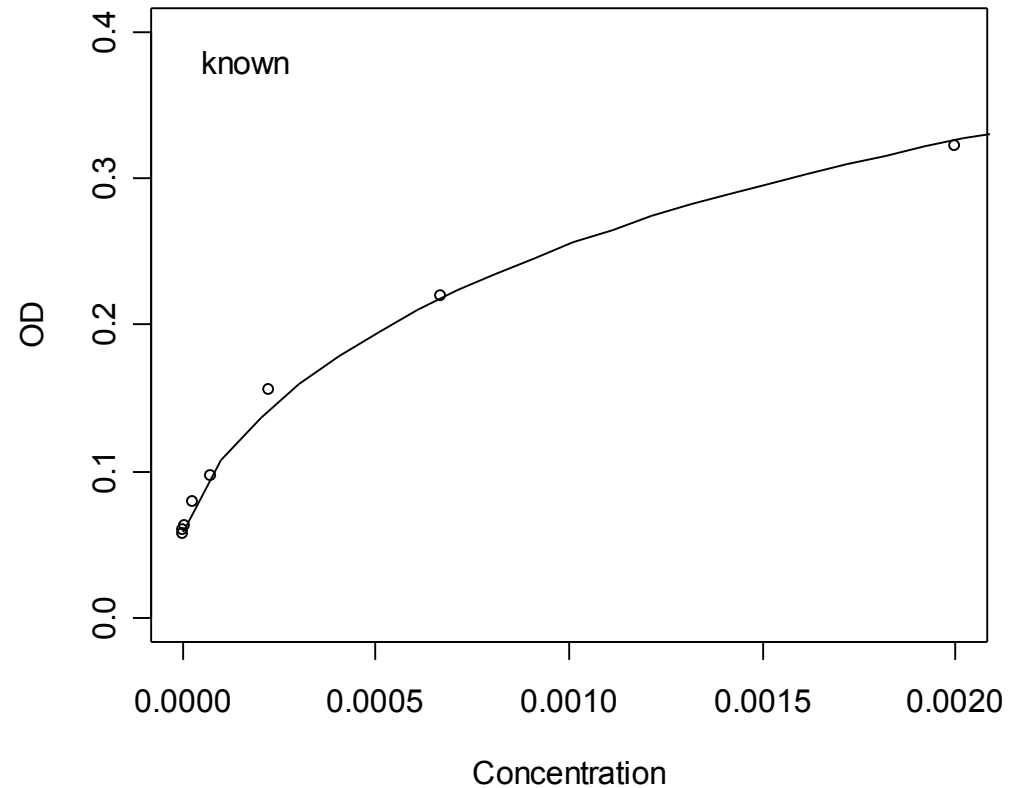
Nonlinear calibration

Calibrating step

$$\mu = V_0 + \frac{V'_{\max} \cdot \left(\frac{1}{d_j} S_{ini}^0\right)^\eta}{K_m + \left(\frac{1}{d_j} S_{ini}^0\right)^\eta}$$

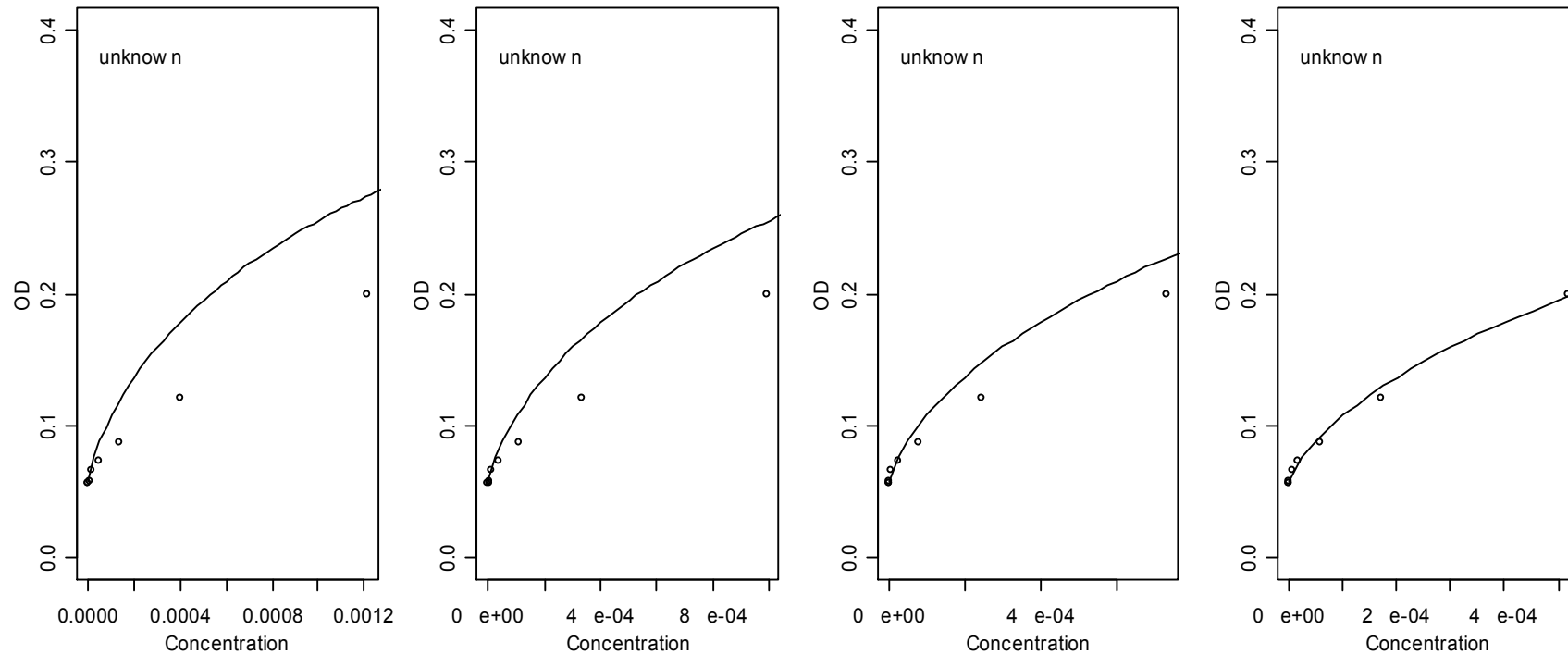
$$\text{known} : \frac{1}{d_j} S_{ini}^0$$

$$\text{fit} : V_0, V'_{\max}, K_m, \eta$$



Nonlinear calibration

Predicting step



$$V_0, V'_{\max}, K_m, \eta \text{ known} \Rightarrow \mu = V_0 + \frac{V'_{\max} \cdot \left(\frac{1}{d_j} \alpha \cdot s_{ini}^0\right)^\eta}{K_m + \left(\frac{1}{d_j} \alpha \cdot s_{ini}^0\right)^\eta} \Rightarrow s_{ini}^u = \alpha \cdot s_{ini}^0$$

Nonlinear calibration Resume



- Using all measurements
- Curve characteristics S_{ini}^0 is continuous
- Treatment effects in physical units
- Calibration sample necessary
- Needs nonlinear fitting software

Statistical analysis:

- Stage 1: Each subject has its curve characteristic: S_{ini}^u
 - Stage 2: Characteristics is analyzed by conventional statistical techniques (e.g. ANOVA).
-
- The parameters: V_0, V'_{max}, K_m, η are method characteristics, they can be determined by the laws of thermodynamics. They can be considered as **fixed effects!**
 - Biological variability is described in α , α will be considered as **random effect!**

Mean model

$$\mu_{ij} = V_0 + \frac{V'_{\max} \cdot s_{ij}^{\eta}}{K_m + s_{ij}^{\eta}} \quad \text{and} \quad s_{ij} = \frac{1}{d_j} \alpha_i \alpha_1^{trt_i} \overline{s^{init}}$$

$$\mu_{ij} = V_0 + \frac{V'_{\max}}{1 + \left[e^{(\beta_0 + b_i + \beta_1 \cdot trt_i)} \cdot \frac{1}{d_j} \right]^{\eta}}$$

with $e^{\beta_0} = e^{\frac{1}{-\eta} \log(K_m) \overline{s^{init}}}$, $e^{b_i} = \alpha_i$, $e^{\beta_1 trt_i} = \alpha_1^{trt_i}$

Error model

Autocorrelation $AR(1)$

Heteroscedasticity $Var(\varepsilon_{ij}) = (\mu_{ij})^{2\delta} \cdot \sigma^2$

Random effect $b_i \sim N(0, \sigma_b^2)$

Probability model *normal or log-normal*

n/group = 5, primary: IgE, secondary IgG1

B) Water (negative control)

E) Bacteria-DNA

F) Bacteria-DNAse

G) Calf-thymus-DNA (negative control)

Contrasts Expectation

E-B negative

F-B negative

G-B +/- zero

F-E ?

Nonlinear mixed effect model

IgG1: Model selection, parameter estimates



Normal vs. log-normal

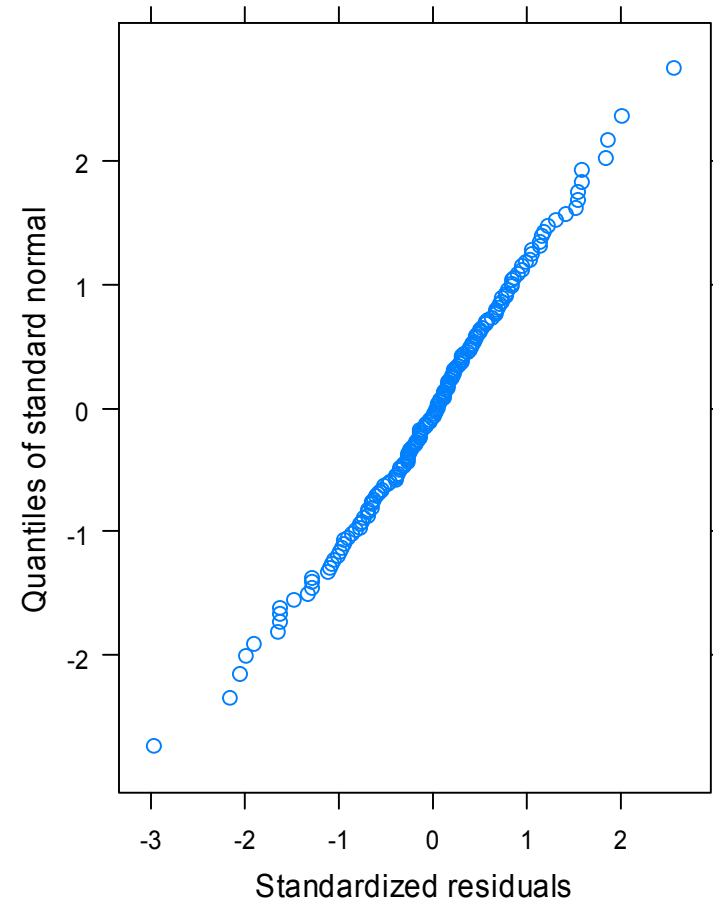
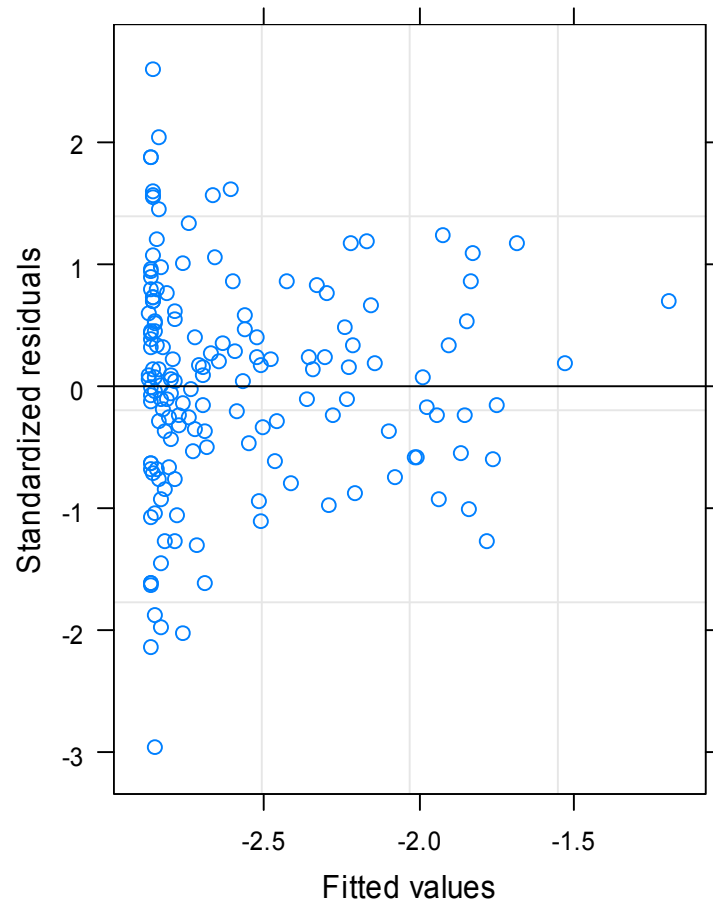
AIC(normal) = -1323.99

AIC(log-normal) = -1324.23

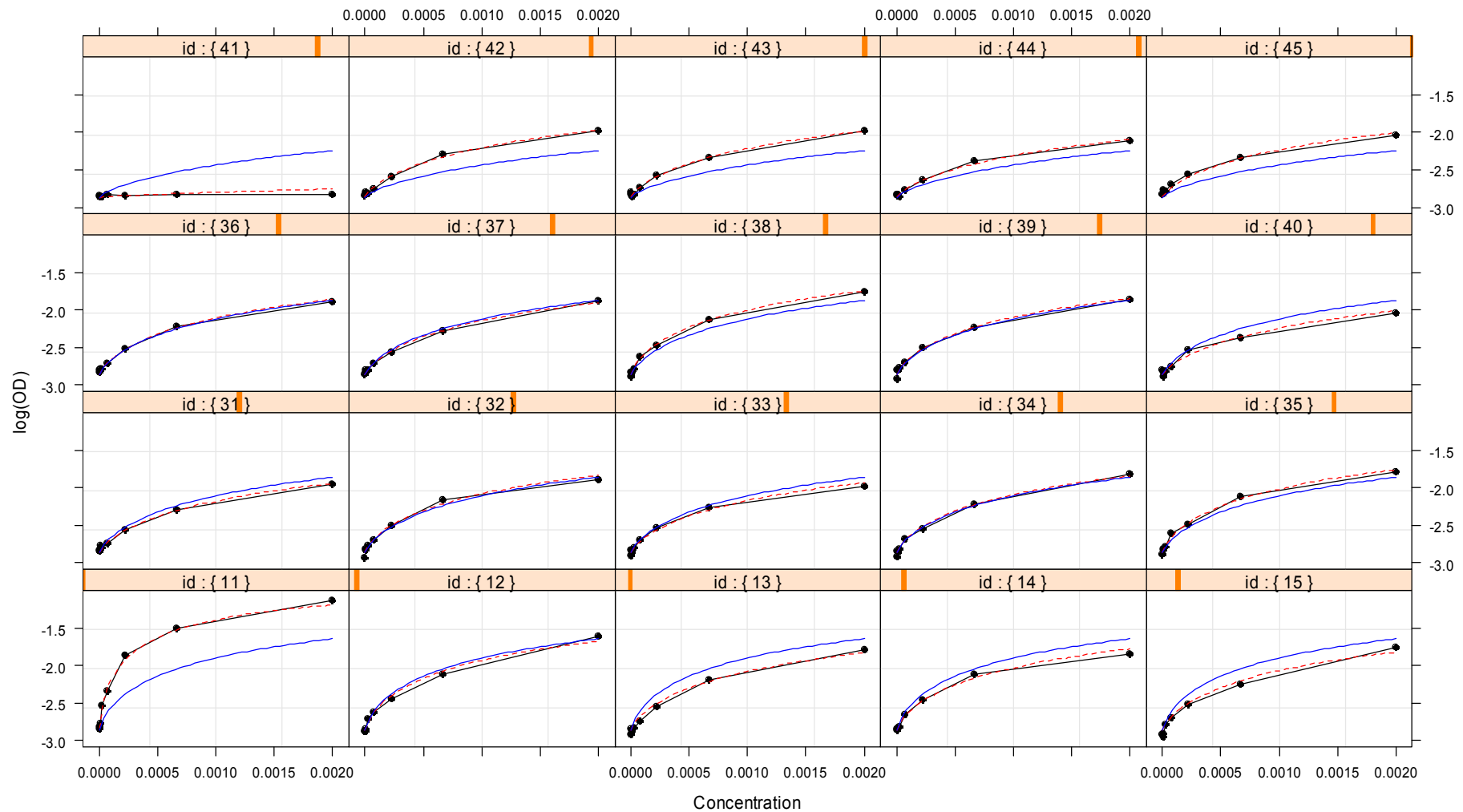
IgG1 analyzed by nonlinear mixed effect model,
parameter estimates and 95% confidence intervals

Description	Parameter	Lower	Estimate	Upper
background velocity	V_0	0.056	0.057	0.058
maximum velocity	V_{\max}	0.269	0.426	0.674
power trans. substrate	η	0.685	0.749	0.818
treatment effects	β_0^B	56.0	181.7	589.0
	β_1^E	0.198	0.554	1.551
	β_1^F	0.191	0.536	1.500
	β_1^G	0.064	0.181	0.514
random effect standard deviation	σ_b	0.555	0.815	1.198
autocorrelation parameter	ϕ	0.137	0.357	0.544
power of the variance function	δ	-1.881	-0.996	-0.110
residual standard deviation	σ	0.042	0.101	0.245

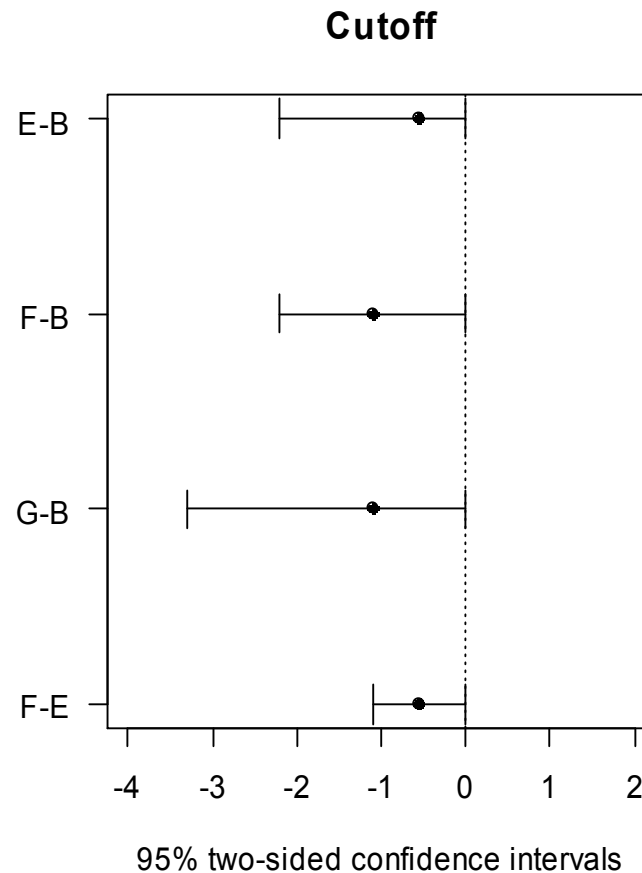
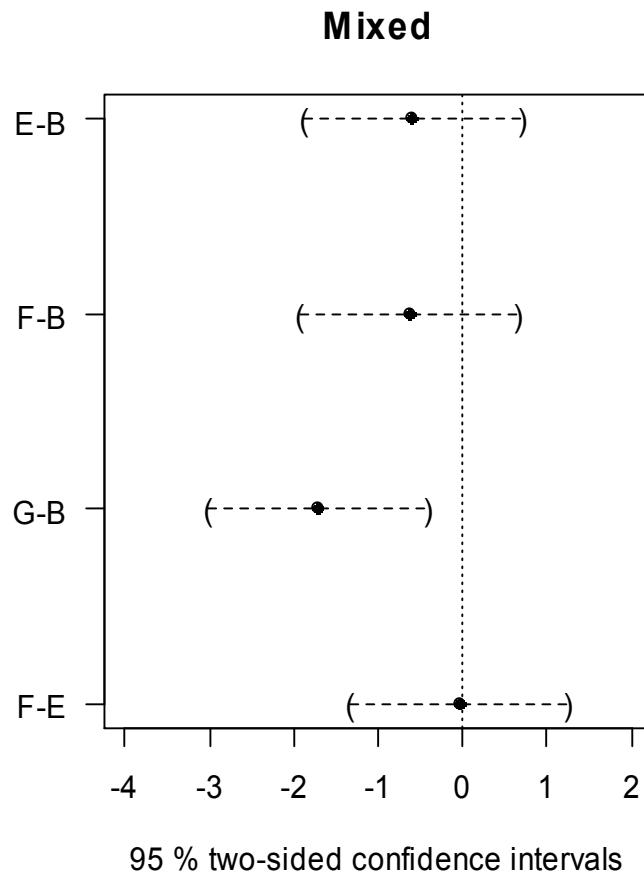
Nonlinear mixed effect model IgG1: Quality of the fit



Nonlinear mixed effect model IgG1: Prediction



Nonlinear mixed effect model, cutoff IgG1: Treatment differences



Nonlinear mixed effect model

IgE: Model selection, parameter estimates



Normal vs. log-normal

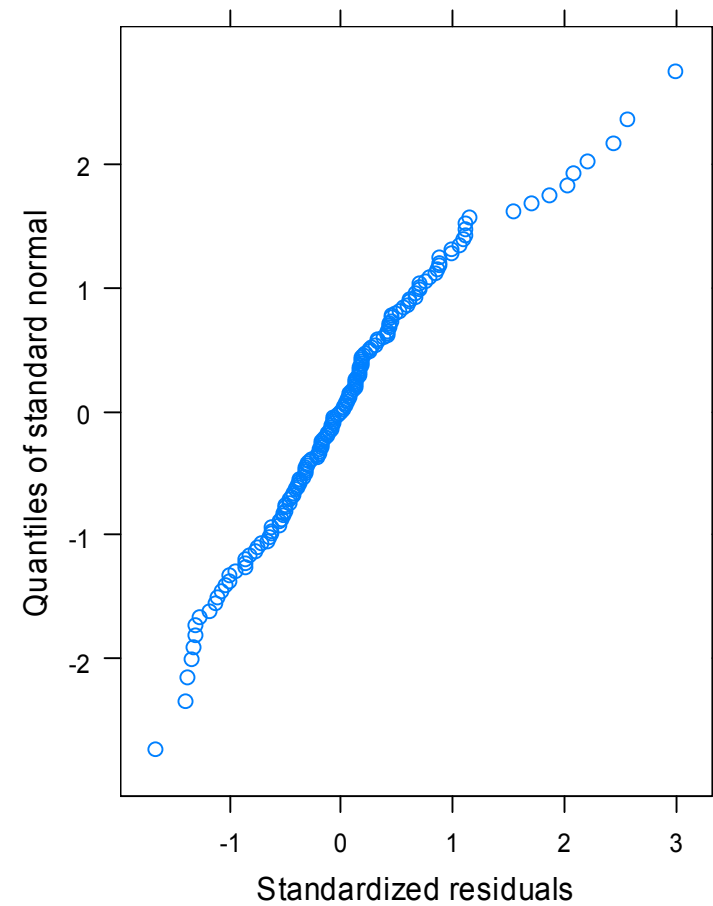
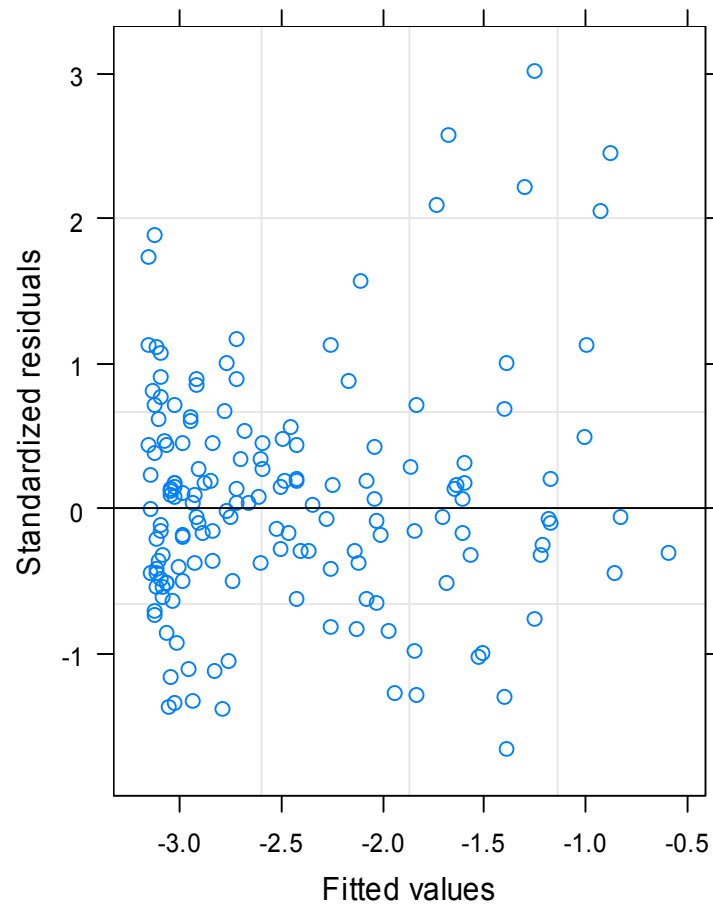
AIC(normal) = -1048.54

AIC(log-normal) = -1073.40

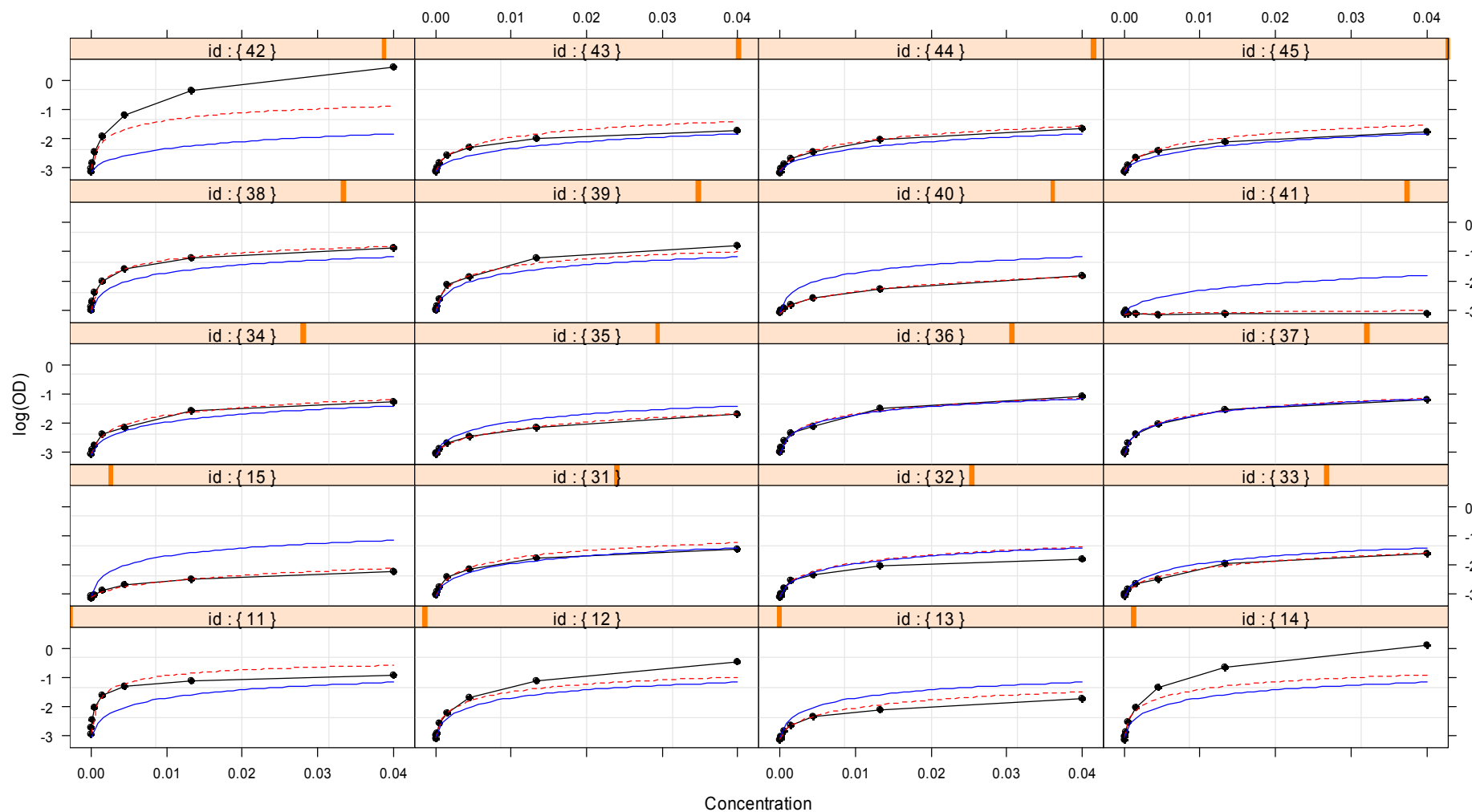
IgE analyzed by nonlinear mixed effect model,
parameter estimates and 95% confidence intervals

Description	Parameter	Lower	Estimate	Upper
background velocity	V_0	0.041	0.043	0.044
maximum velocity	V_{\max}	0.326	0.762	1.777
power trans. substrate	η	0.579	0.646	0.721
treatment effects	β_0^B	1.012	9.773	94.417
	β_1^E	0.064	0.504	4.002
	β_1^F	0.121	0.960	7.615
	β_1^G	0.023	0.189	1.533
random effect standard deviation	σ_b	1.137	1.628	2.333
autocorrelation parameter	ϕ	0.623	0.775	0.871
power of the variance function	δ	-2.020	-1.653	-1.286
residual standard deviation	σ	0.317	0.440	0.612

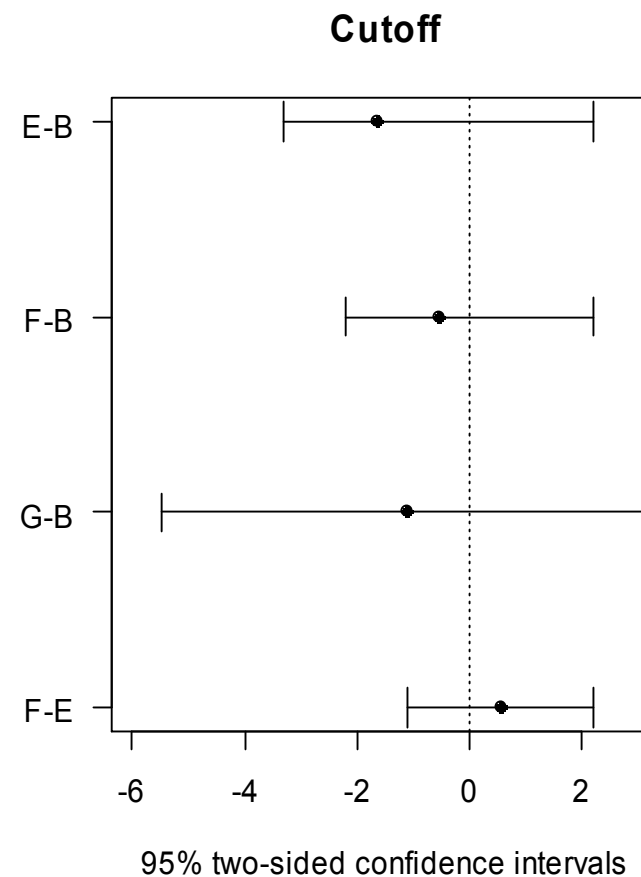
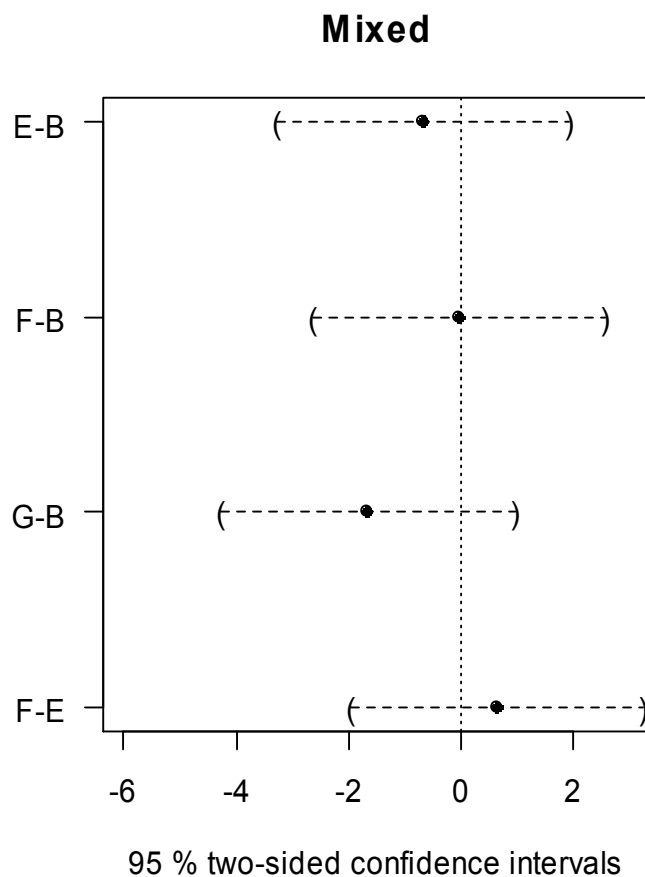
Nonlinear mixed effect model IgE: Quality of the fit



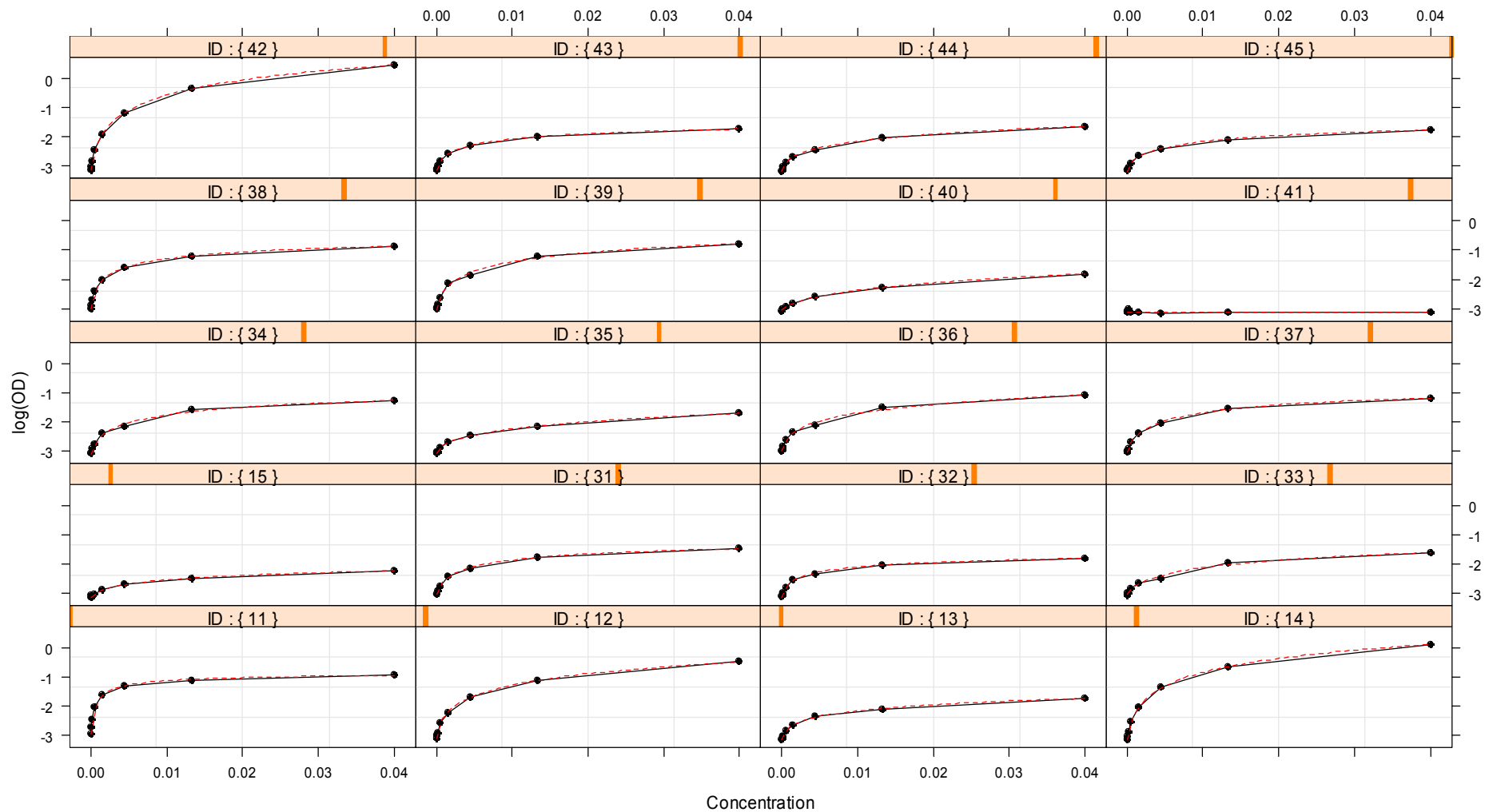
Nonlinear mixed effect model IgE: Prediction



Nonlinear mixed effect model, cutoff IgE: Treatment differences



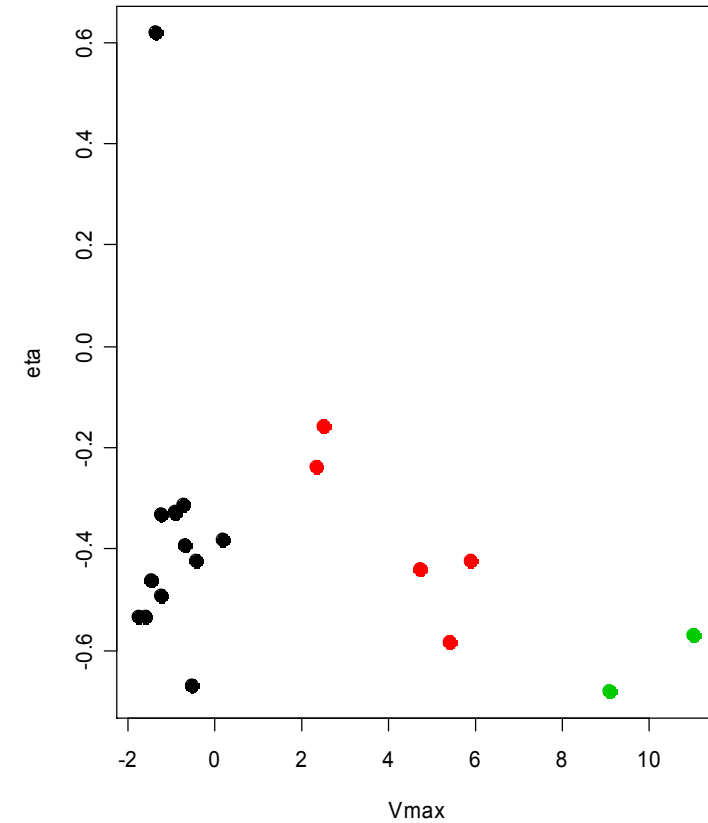
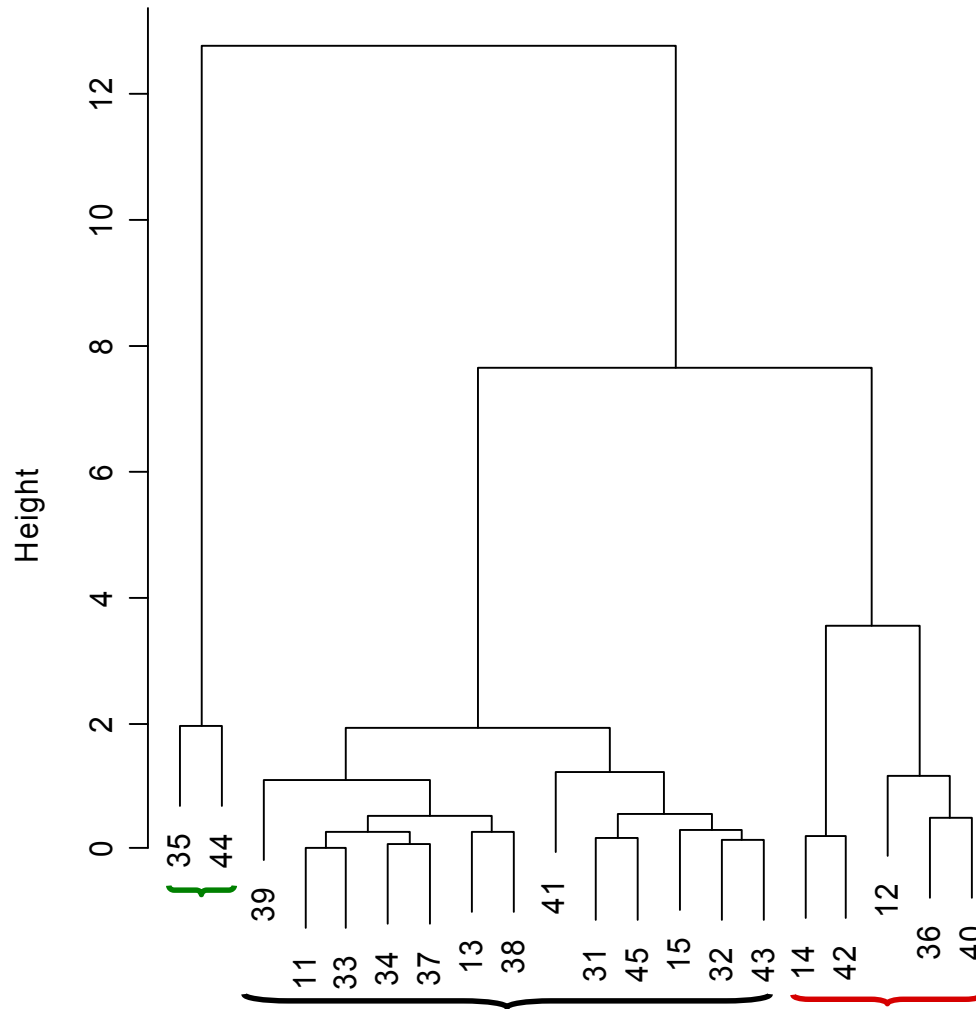
Nonlinear model, IgE: All parameters free



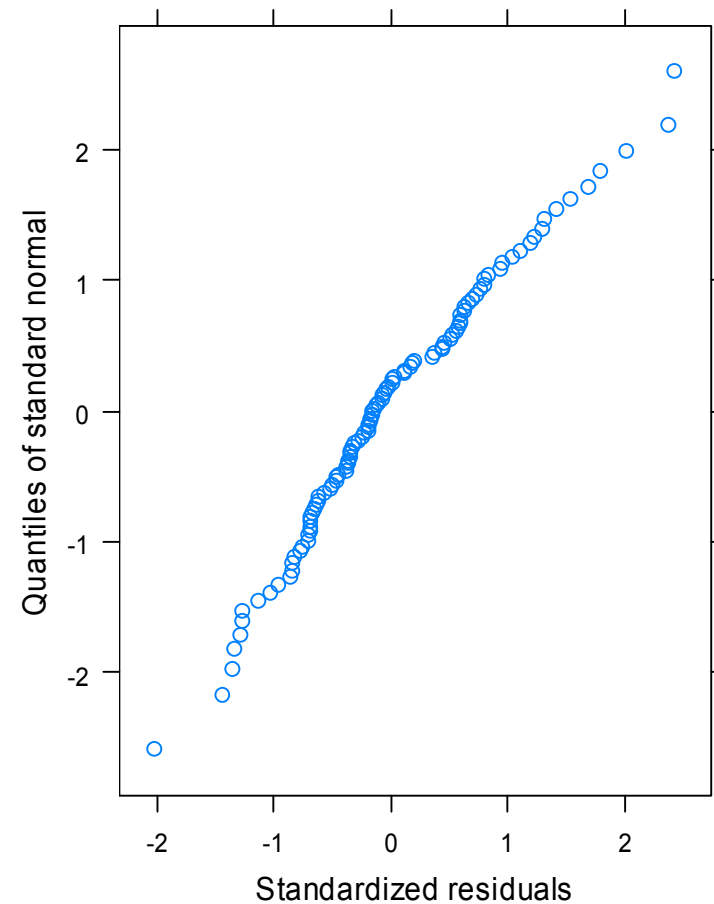
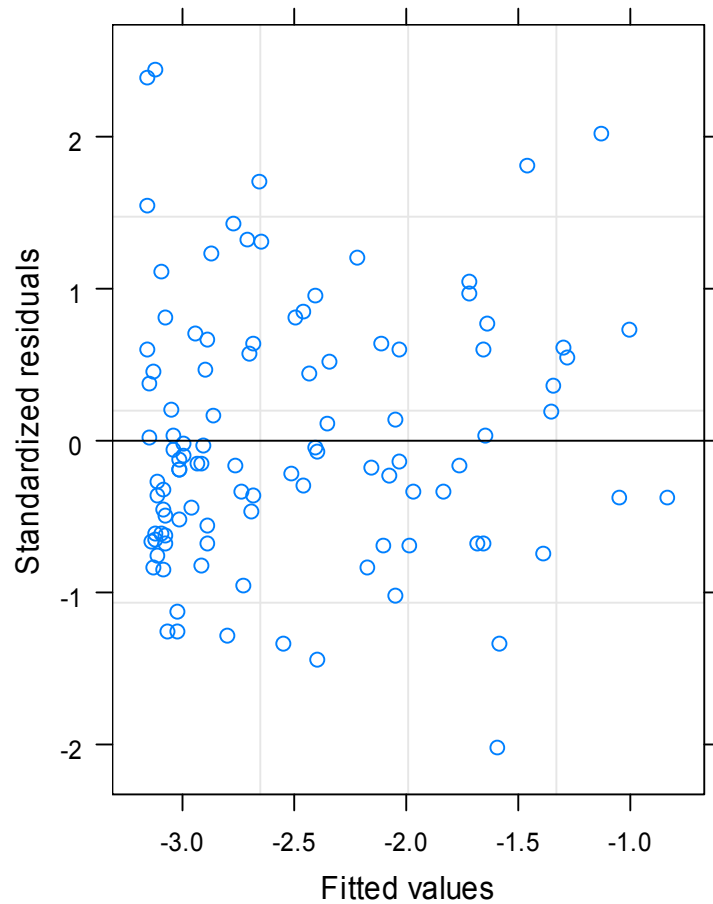
Parameter estimates

ID	V0	Vmax	eta	beta	sigma
11	-3.17	-0.92	-0.33	5.80	0.021
12	-3.22	4.75	-0.44	-5.01	0.023
13	-3.25	-0.52	-0.67	0.85	0.028
14	-3.21	2.35	-0.24	0.48	0.016
15	-3.19	-1.74	-0.53	2.30	0.024
31	-3.10	-1.22	-0.33	3.86	0.022
32	-3.22	-1.57	-0.53	3.83	0.020
33	-3.08	-0.90	-0.33	2.50	0.053
34	-3.17	-0.67	-0.39	2.99	0.044
35	-3.13	11.03	-0.57	-19.85	0.017
36	-3.11	5.43	-0.58	-8.72	0.042
37	-3.09	-0.71	-0.31	3.34	0.017
38	-3.15	-0.41	-0.42	3.66	0.008
39	-3.13	0.19	-0.38	2.25	0.054
40	-3.09	5.90	-0.42	-9.07	0.010
41	-3.12	-1.35	0.62	-6.86	0.038
42	-3.18	2.52	-0.16	0.95	0.014
43	-3.21	-1.44	-0.46	3.72	0.012
44	-3.25	9.08	-0.68	-18.40	0.013
45	-3.22	-1.22	-0.49	2.89	0.025

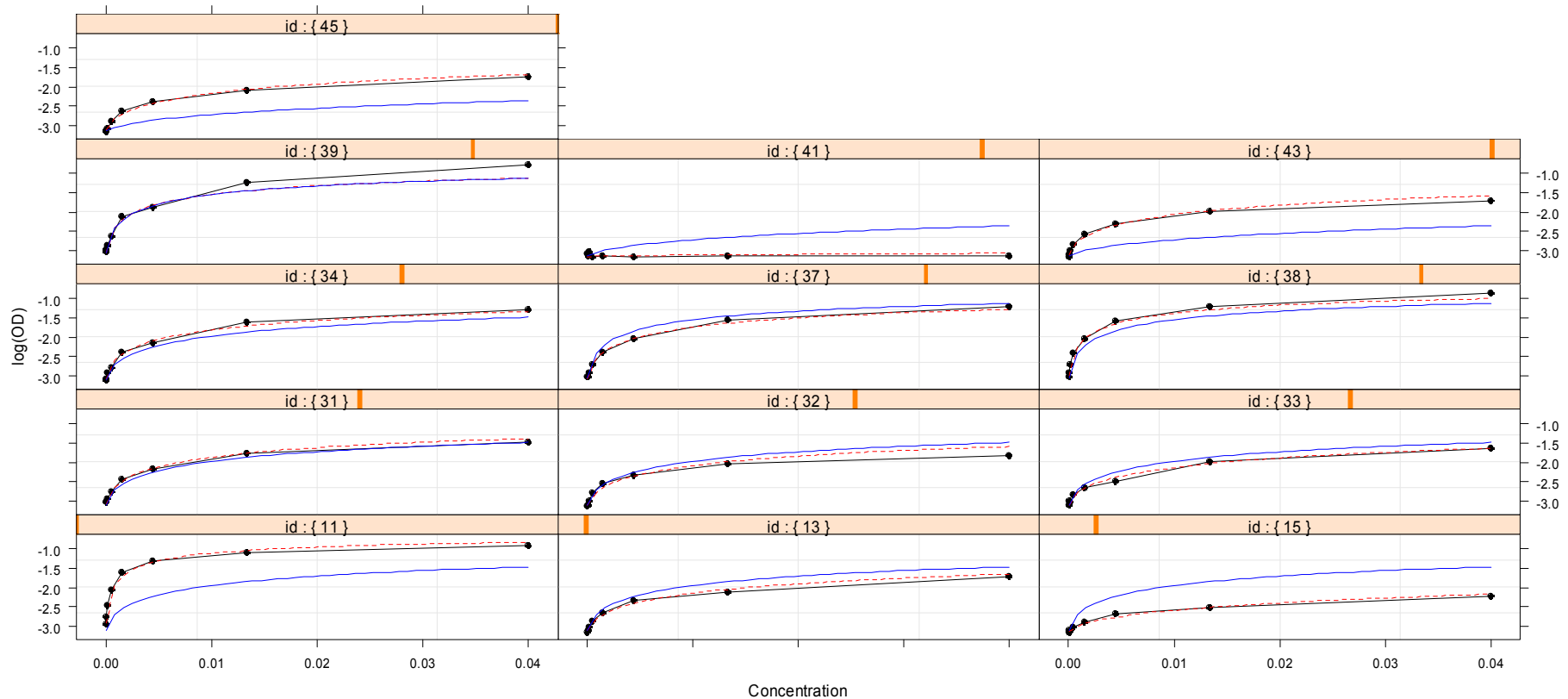
Identifying stable subpopulation



Nonlinear mixed effect model On “stable” subpopulation (quality)



Nonlinear mixed effect model On “stable” subpopulation (prediction)



- Mechanistic model with clear interpretation of parameters
- Enables to identify cross reactions
- Enhance power of analysis by using all measurements
- No calibration necessary
- Treatment effects in arbitrary units
- Needs nonlinear fitting software

Statistical analysis:

- Stage 1 and Stage 2 are merged together.
The calibration step is done “en passant”.