



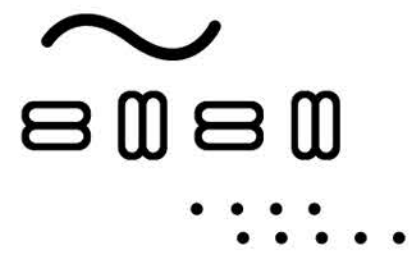
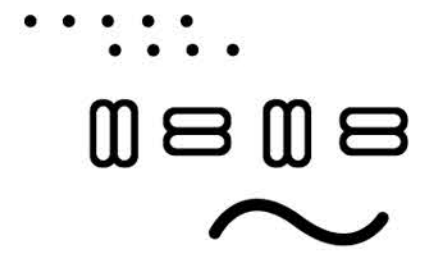
idorsia

Common concerns in visualization of pharmacometric data and models

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American Conference on Pharmacometrics (ACOP9)

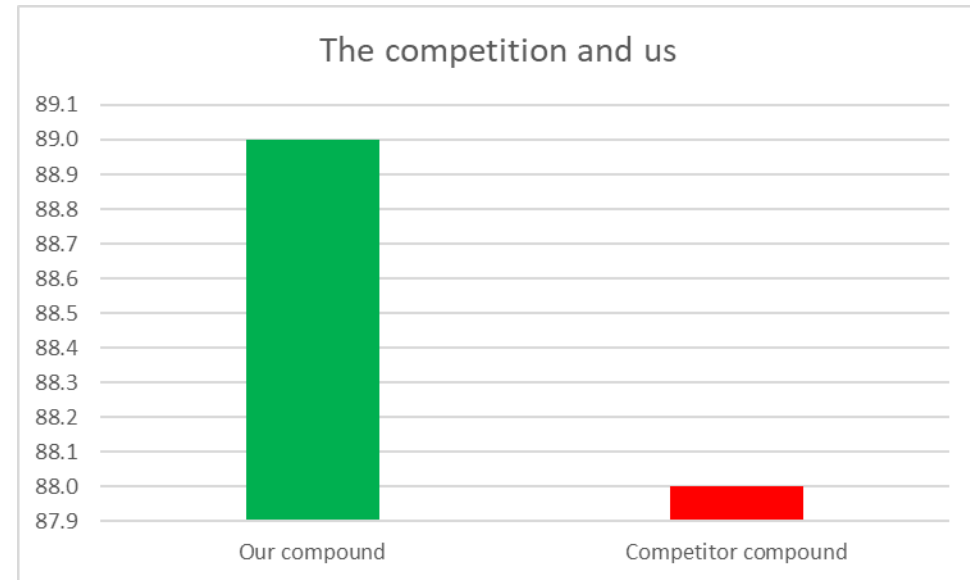
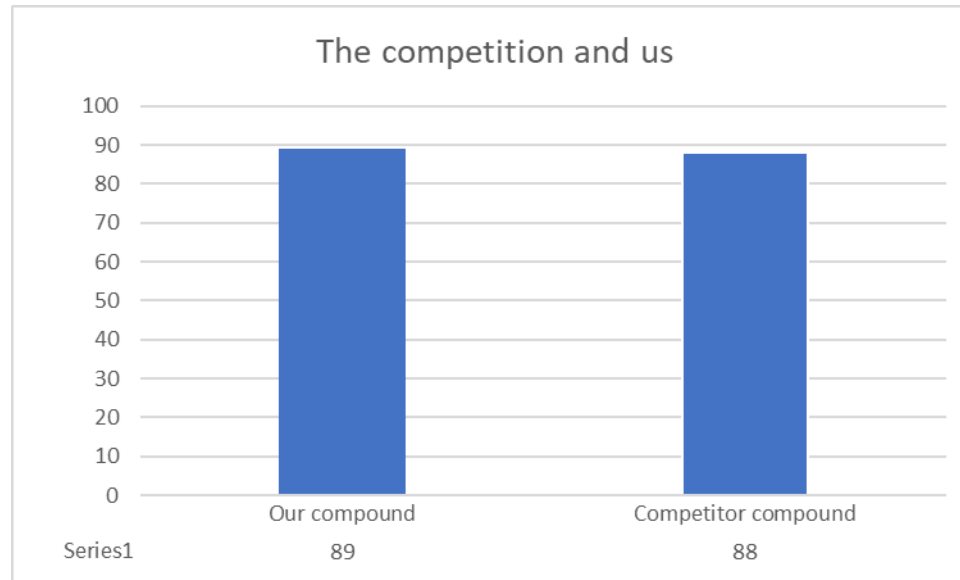
San Diego CA, October 2018



Bad intentions

Marketing Graph - A pictorial representation that uses 3 dimensions, 4 colors and 5 cartoons to show one fact that probably isn't true.

Source: The Devil's Drug Development Dictionaries. <http://www.senns.demon.co.uk/wdict.html>



Good intentions

The purpose of a visualization is to

- show features of the data or the model
- in a scientific manner
- with interpretation not dependent on how it is displayed

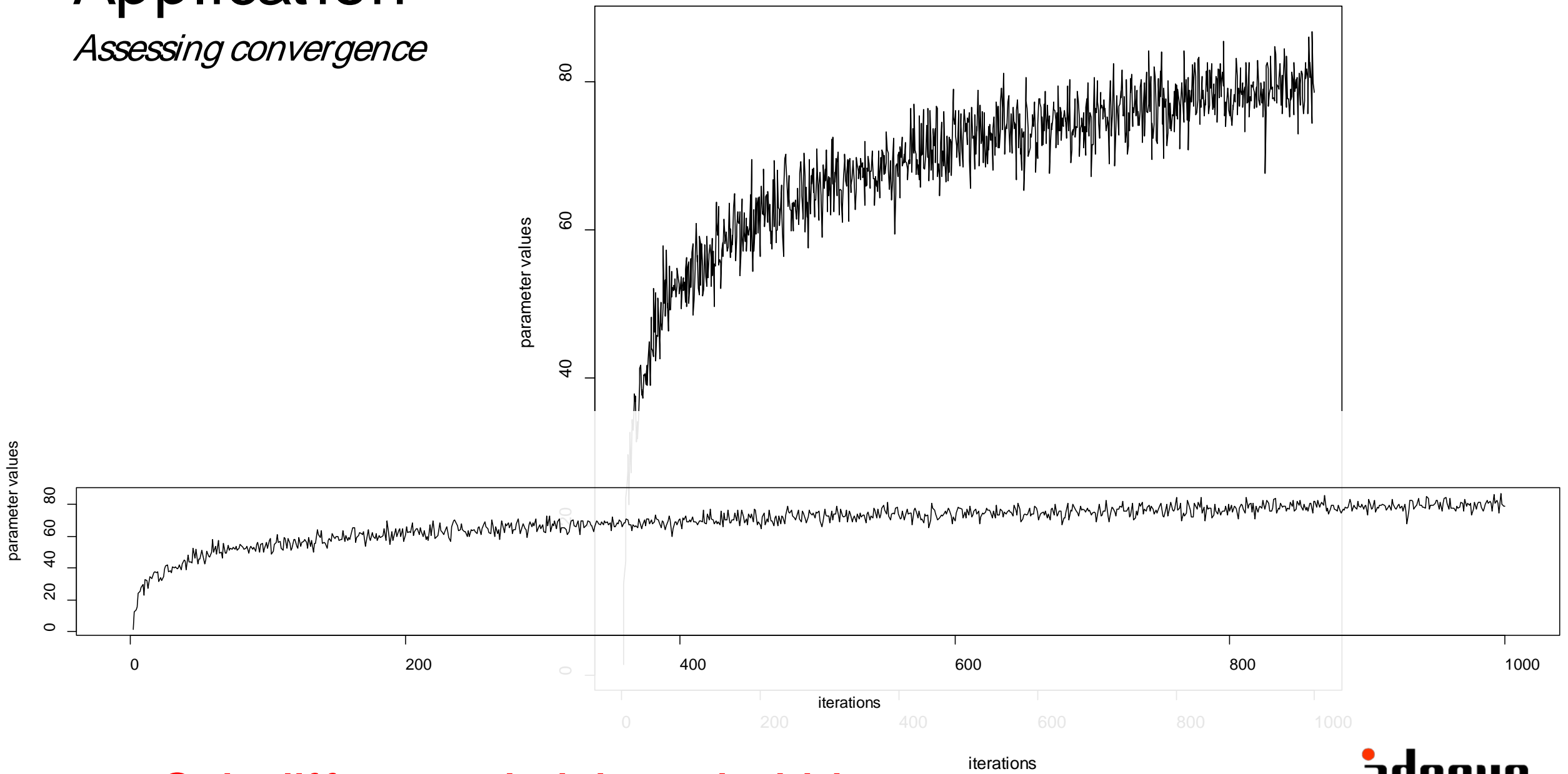
The visualization is

- accurate
- intuitive
- easy to interpret *correctly*



Application

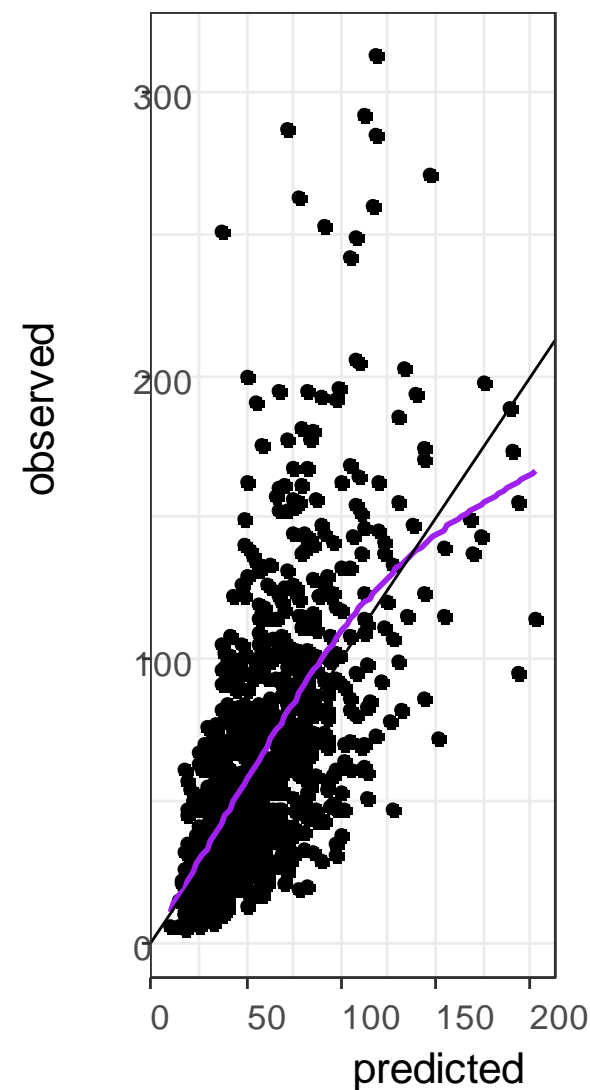
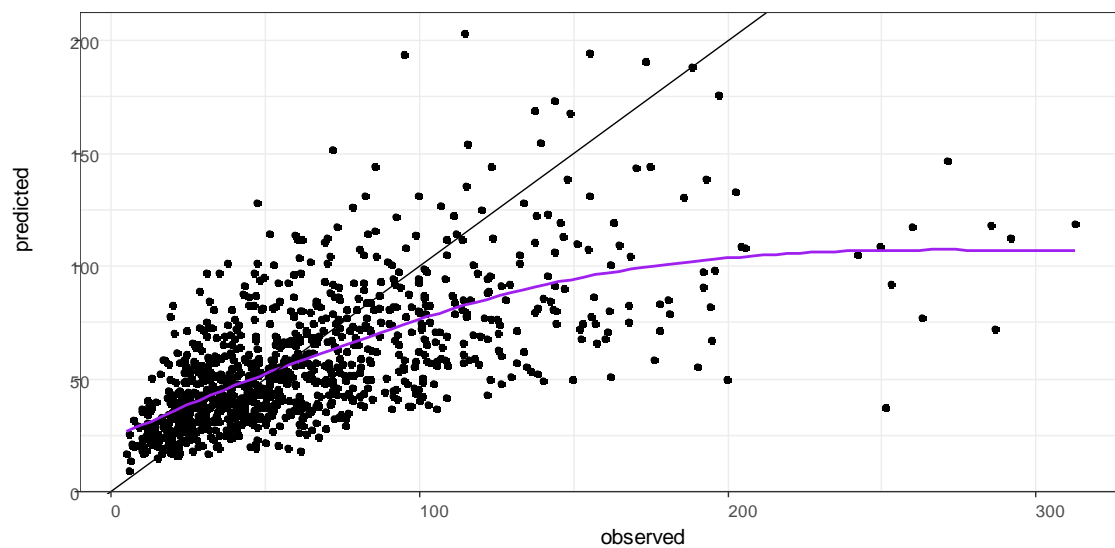
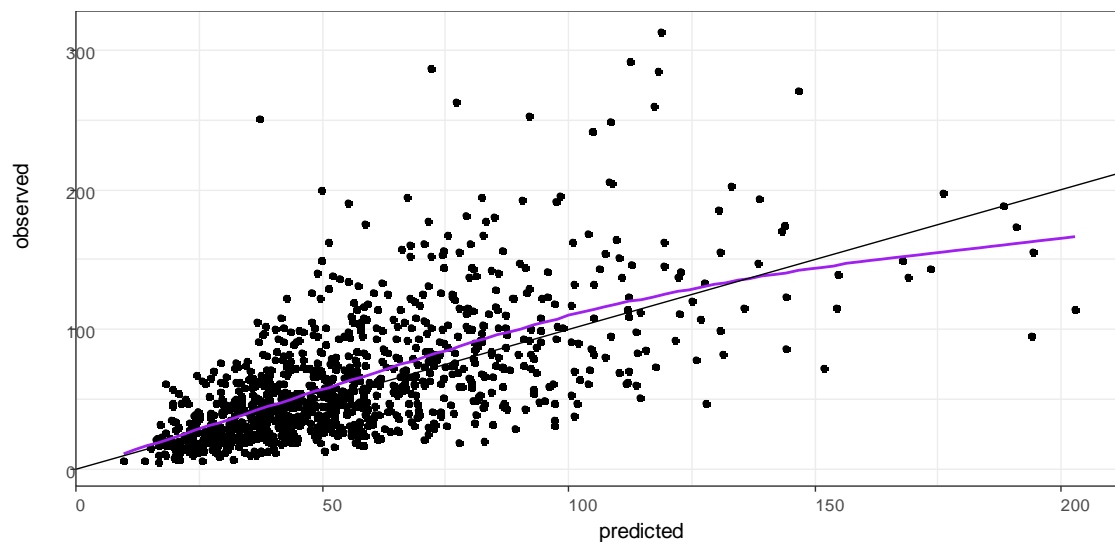
Assessing convergence



Only difference: height and width.

Application: Observed vs. predicted

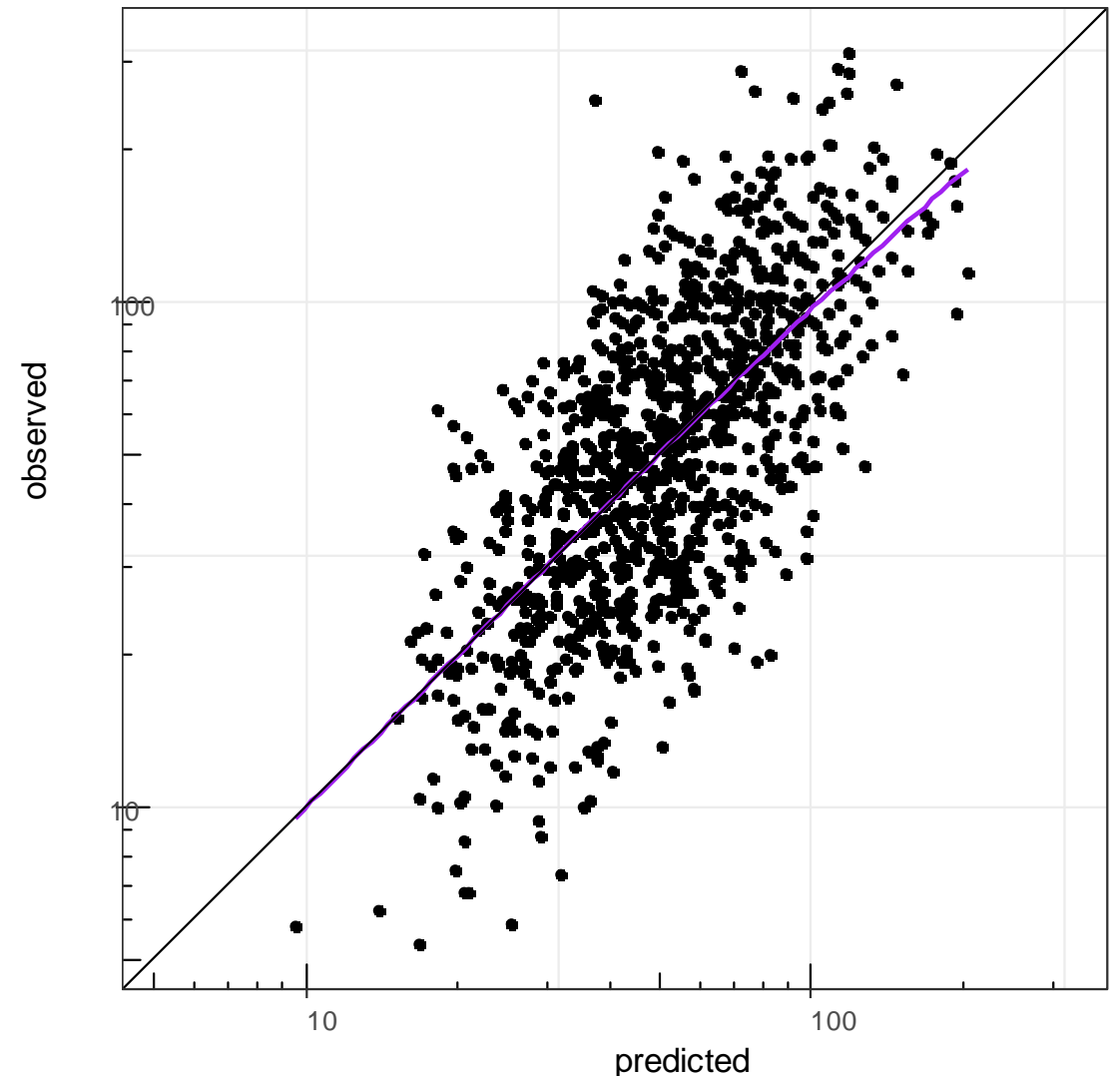
In search for an unbiased visual assessment



Application: Observed vs. predicted

Graphical settings

- **Same aspect ratio in x and y**
 - 1 observational unit (ng/mL, mmHg,...)
= same length on x- and y-axis
 - Same axis range
 - Symmetry between x and y
- **Logarithmic scales**
 - Log-normal distribution assumptions
 - This is the scale for optimization
 - Extreme values distract less (visually)
- **Observed = f(predicted)**
 - $\log(\text{obs.}) \sim N(\log(\text{pred.}), s) + e$
 - Observed on the y-axis



Observed vs. predicted: R code

R code: no excuses.

```
# Create a data set.
```

```
set.seed(348391)
```

```
df <- data.frame(predicted=exp(rnorm(1000, m=log(10), s=0.1)))
```

```
df$observed <- exp(rnorm(nrow(df), m=log(df$predicted), s=0.1))
```

```
library(ggplot2)
```

```
r <- range(c(df$observed, df$predicted))
```

```
ggplot(df, aes(x=predicted, y=observed)) +
```

```
  geom_point() +
```

```
  geom_smooth(col="pink") + theme_bw() +
```

```
  geom_abline(intercept=0, slope=1) +
```

```
  coord_fixed(ratio=1) +
```

```
  scale_x_log10(limits=r) + scale_y_log10(limits=r)
```

```
# range of obs. and pred.
```

```
# observed = f(predicted) + e
```

```
# diagonal y=x
```

```
# aspect ratio 1
```

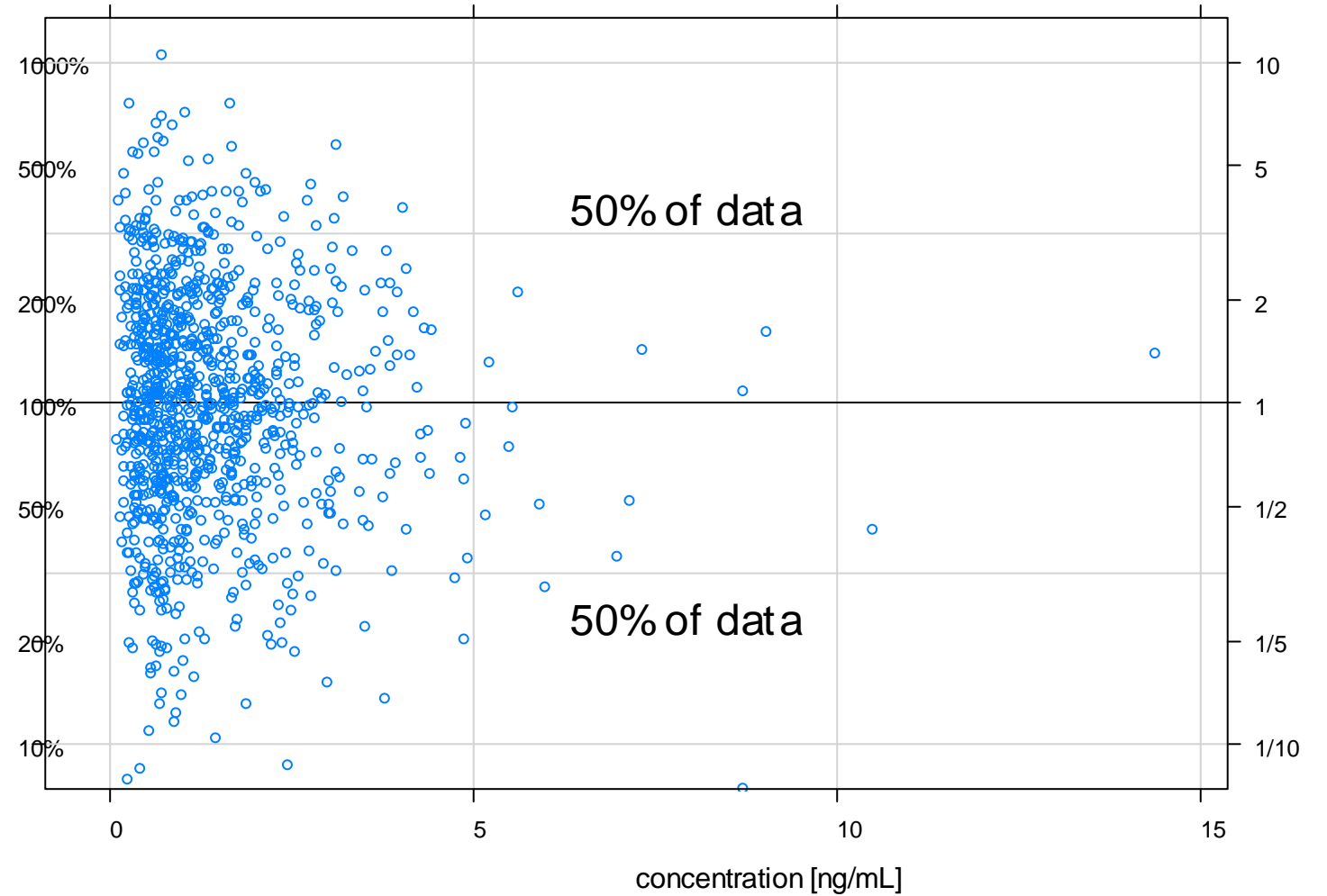
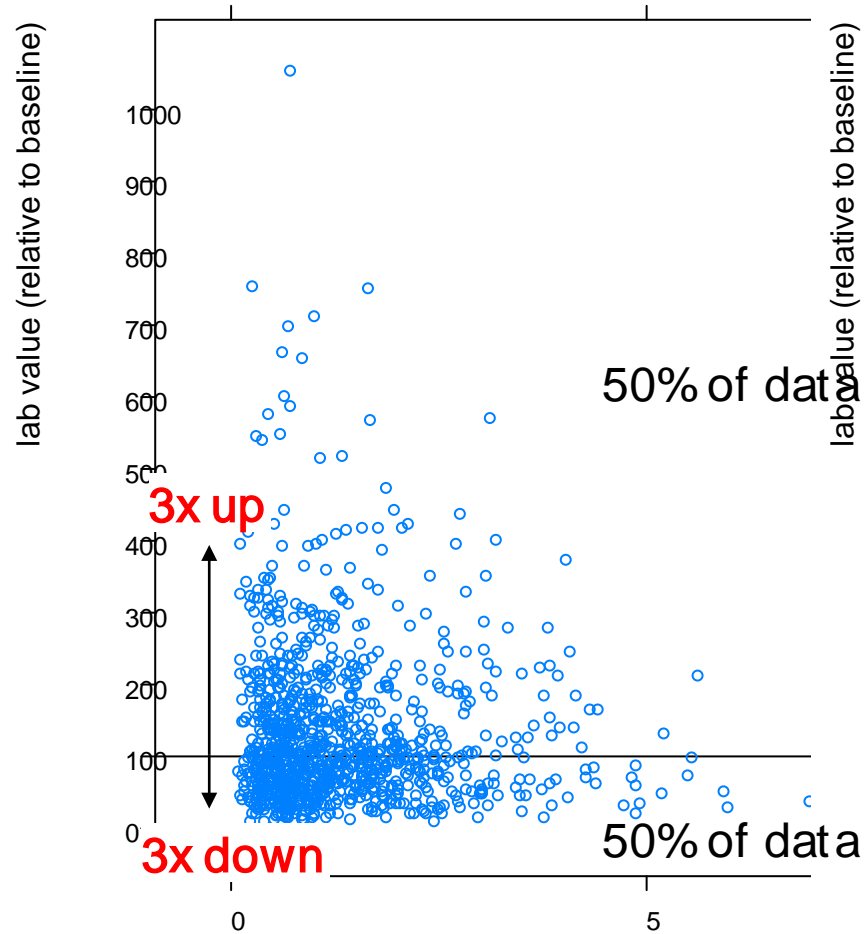
```
# log. axes, same range
```

Relative (fold) change

- **If the data scatter symmetrically around “no change”**
 - Half the data are above, half the data below “no change”
 - Show that.
 - Use a logarithmic scale:
 - 2-fold up and down have the same distance to “no change”.

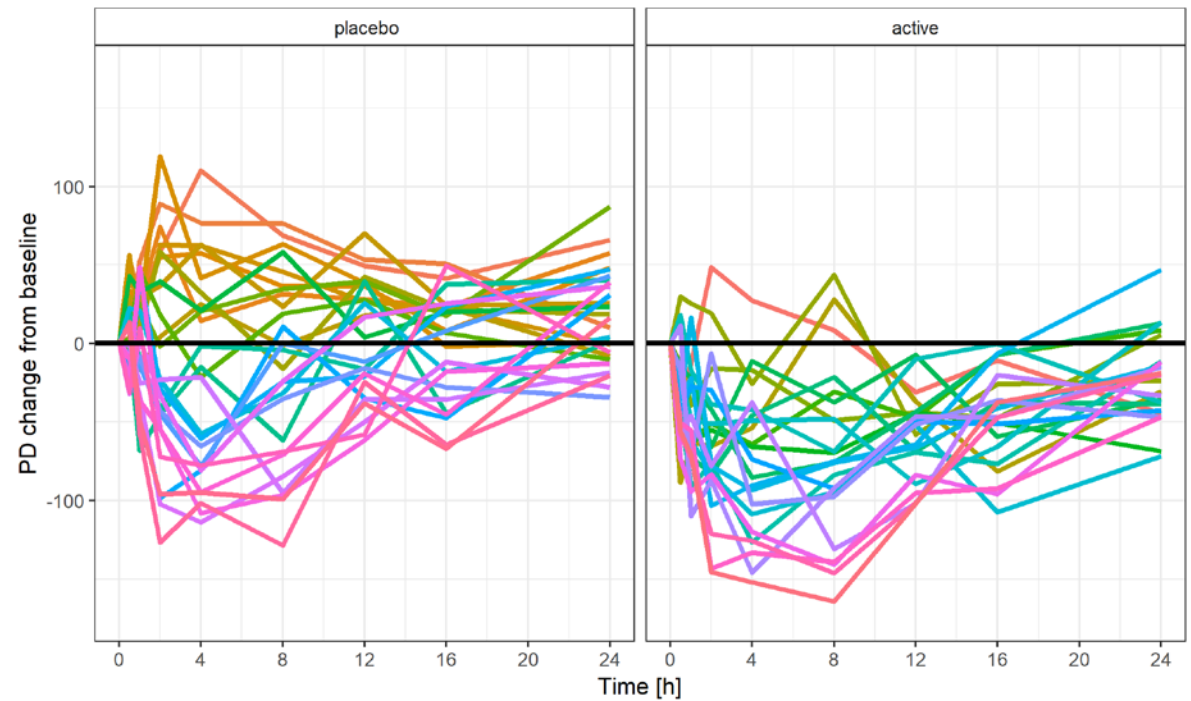
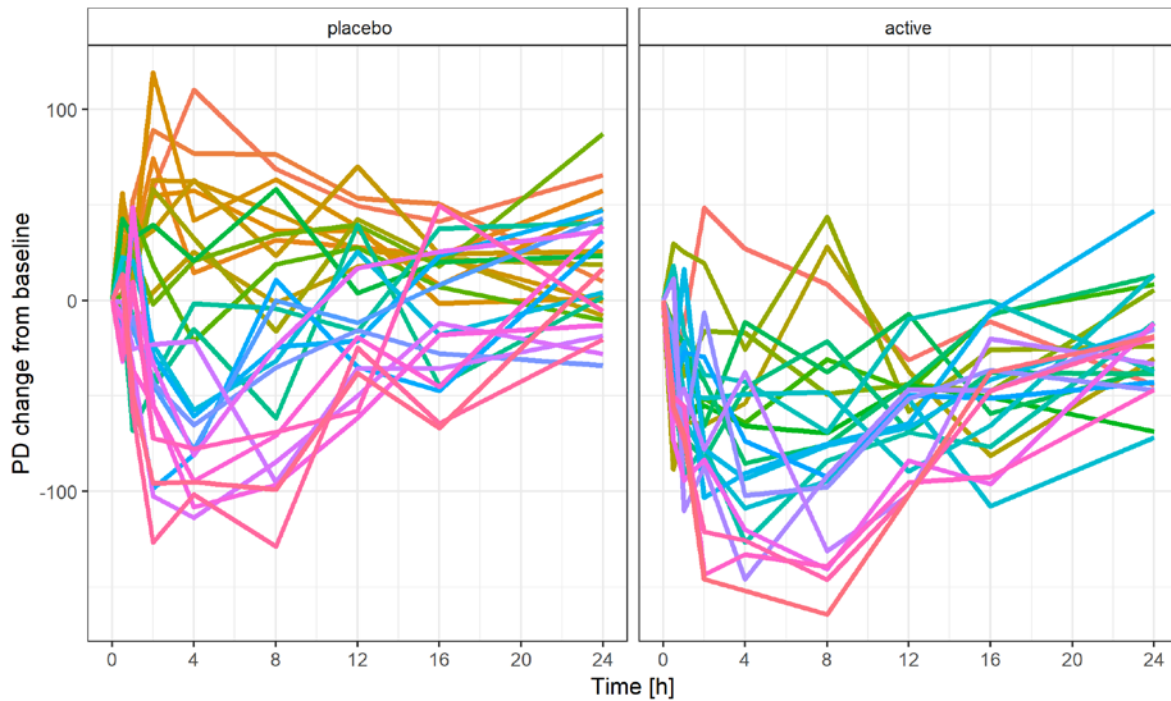
Relative (fold) change

Linear vs. logarithmic axis (when there is no change)



Change from baseline

Adding visual support



- Symmetric axis range
- Line of no change indicated

A modeler talks to an MD

- Modeler: So what is it you want to find out with your study?
- *MD:* *Whether the drug works or not.*
- Modeler: What does “works” mean?
- *MD:* *If the drug is better than placebo.*
- Modeler: What does “better” mean?
- *MD:* *Lower the blood pressure by more than 10 mmHg.*
- Modeler: On average, for 90% of the patients, or what else?
- *MD:* *For 80% of the patients.*
- Modeler: At steady state over 24 h, at trough, or what else?

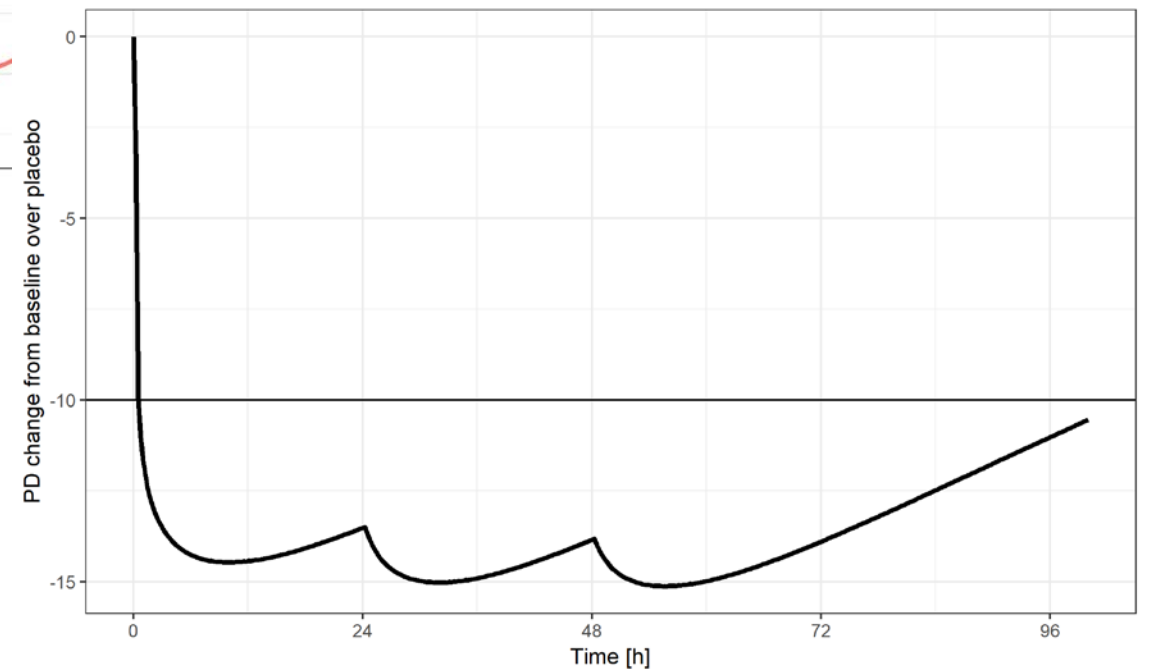
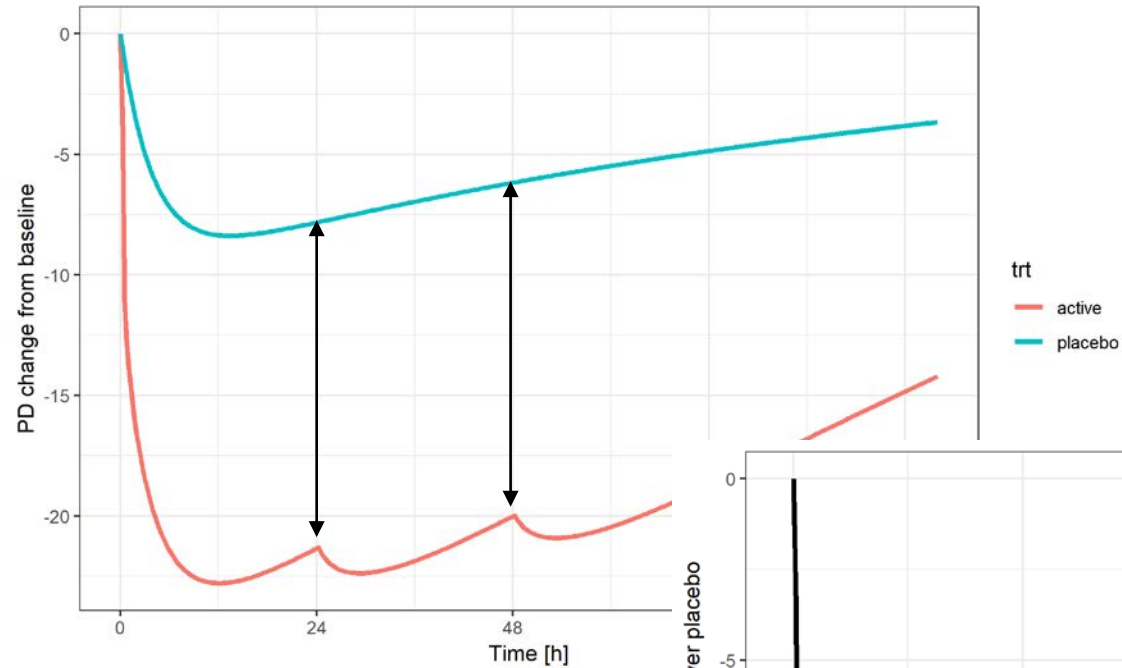
etc. with improving precision over time, occasionally in circles.

Show the quantity of interest

Here: the placebo-corrected change from baseline

The quantity of interest is *not* shown here:

the difference between active and placebo



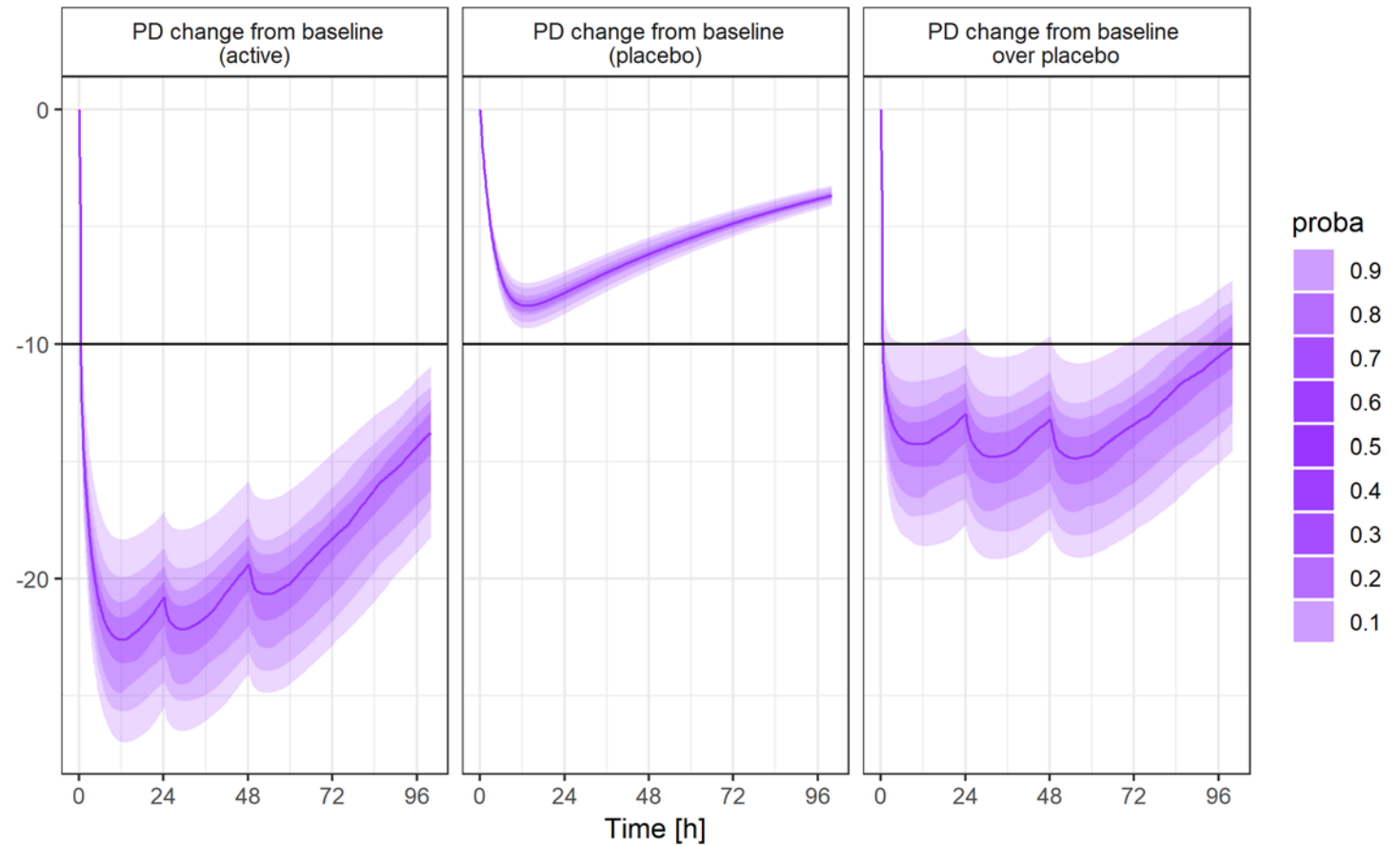
Show the quantity of interest

Here: the placebo-corrected change from baseline

- **Distribution of response**

- Bands indicate quantiles (10-90%)

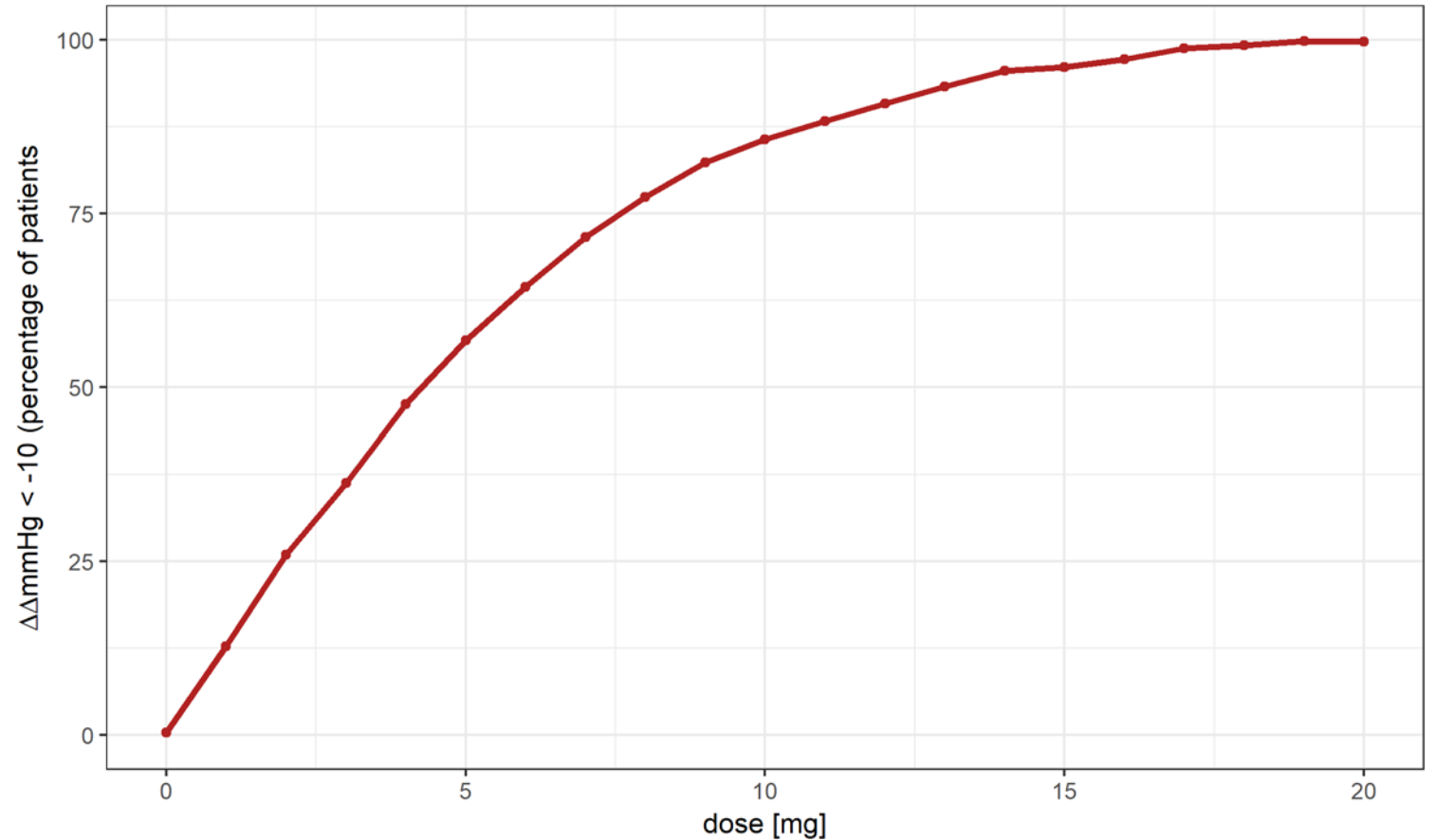
- Clinical threshold indicated ($y=-10$)



Show the quantity of interest

Here: the placebo-corrected change from baseline

- Percentage of patients predicted to reach clinical response
 - for a set of doses



Covariate selection: differences btw. patients

Fixed-effects quantification

- **Statistically significant differences**
 - Age, sex, body weight, race, baseline, disease status, etc.
 - Driven by parameter estimate and precision (variability and n)
- **Clinical relevance**
 - For a clinical audience

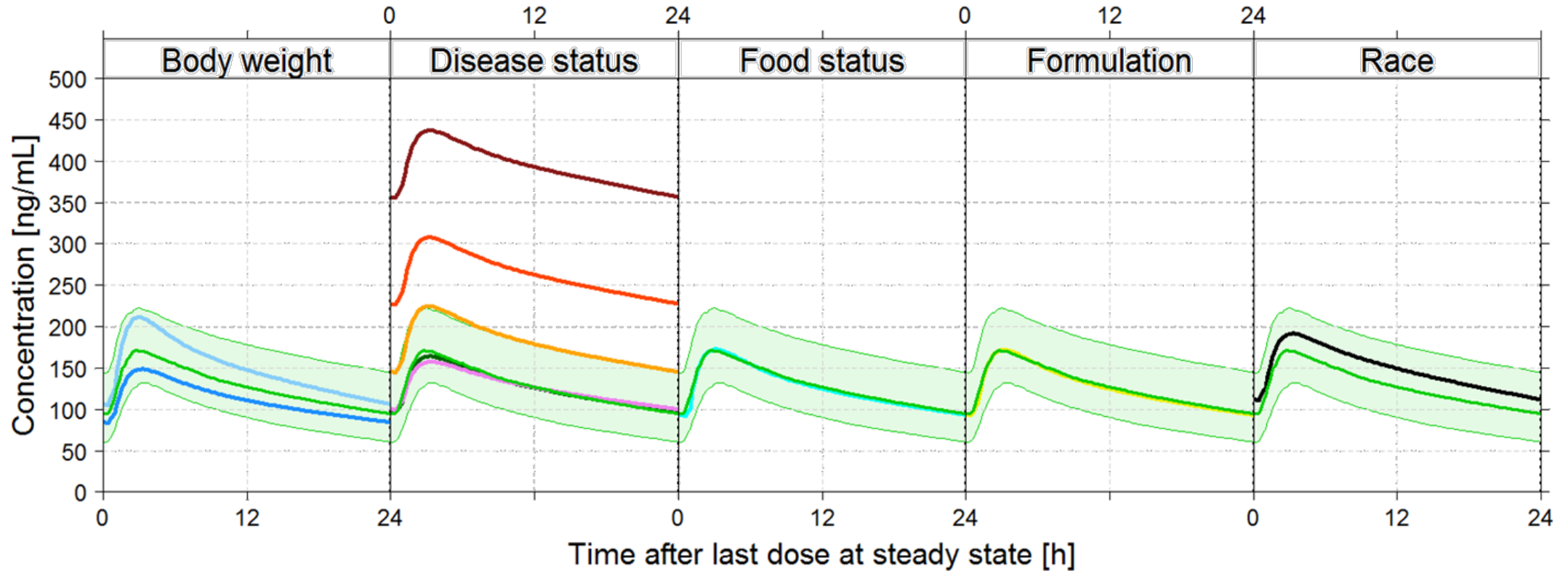
Covariate selection: Modeler's answer

Of no relevance to the MD, probably not even understood. Kills any interest quickly.

Parameter	Description	Estimate (r.s.e.%)	IIV, %CV (r.s.e.%)	Shrinkage
T_{lag} (h)	Absorption lag time (ref)	0.40 (6)	43 (8)	6%
T_{lag} (h)	T_{lag} with capsule C	0.59 (5)		
T_{lag} (h)	T_{lag} with the intake of food	0.64 (13)		
TK_0 (h)	Duration of the zero-order absorption process	0.58 (5)	56 (8)	1%
Fr	Fraction absorbed via zero order	0.15 (8)	62 (10)	3%
k_a (1/h)	Absorption rate constant	0.93 (7)	61 (6)	2%
V_c/F (L)	Apparent central volume of distribution (ref))	165 (2)	22 (6)	8%
V_c/F (L)	V_c for a subject with psoriasis	239 (12)		
V_c/F (L)	V_c for a subject with MS	200 (4)		
Body weight on V_c	Covariate effect of body weight on V_c	0.85 (4)		
V_p/F (L)	Apparent peripheral volume of distribution (ref)	107 (4)	29 (9)	5%
V_p/F (L)	V_p for a subject of race Black	67 (11)		
Body weight on V_p	Covariate effect of body weight on V_p	0.69 (21)		
Q/F (L/h)	Apparent inter-compartmental flow	21 (11)	10 (244)	6%
CL/F (L/h)	Apparent clearance (ref)	6.64 (1)	26 (3)	5%
CL/F (L/h)	CL for a subject of race Black	5.65 (4)		
CL/F (L/h)	CL for a subject with mild HI	4.66 (9)		
CL/F (L/h)	CL for a subject with moderate HI	3.18 (8)		
CL/F (L/h)	CL for a subject with severe HI	2.13 (9)		
Body weight on CL	Covariate effect of body weight on CL	0.42 (10)		
Residual error terms				
a	Additive error	0.006 (28)		
b	Proportional error	0.21 (1)		

Covariate selection: Clinical answer

This is what it means



50 kg body weight
100 kg body weight

Mild hepatic impairment
Moderate hepatic impairment
Severe hepatic impairment
Psoriasis
Multiple sclerosis

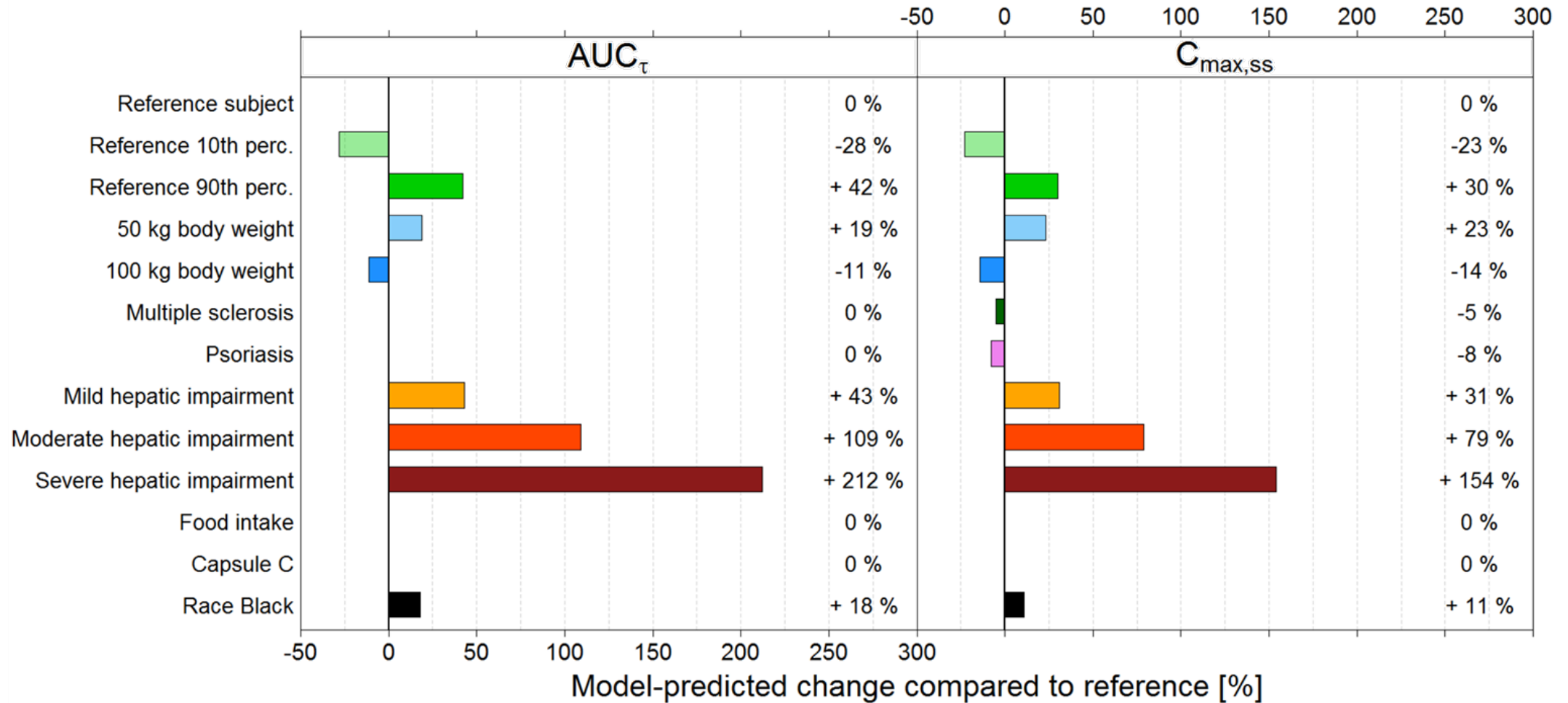
Food intake

Capsule C

Race black

Covariate selection: Clinical answer

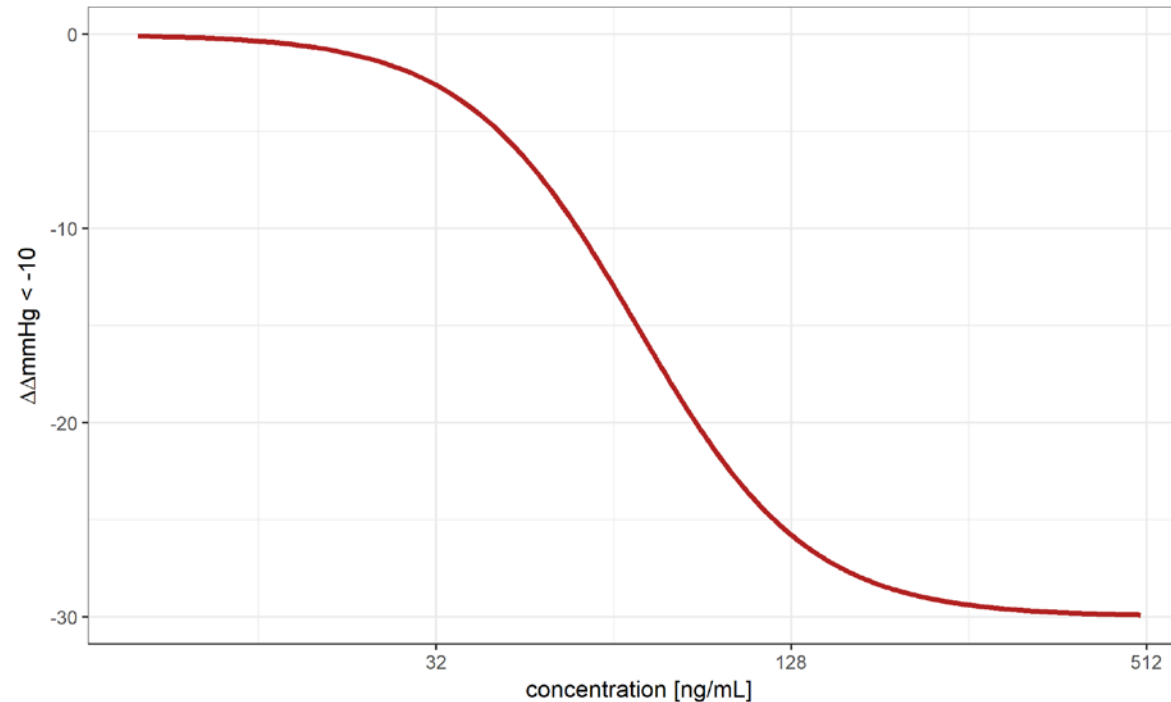
This is what it means



Covariate effect: Clinical answer

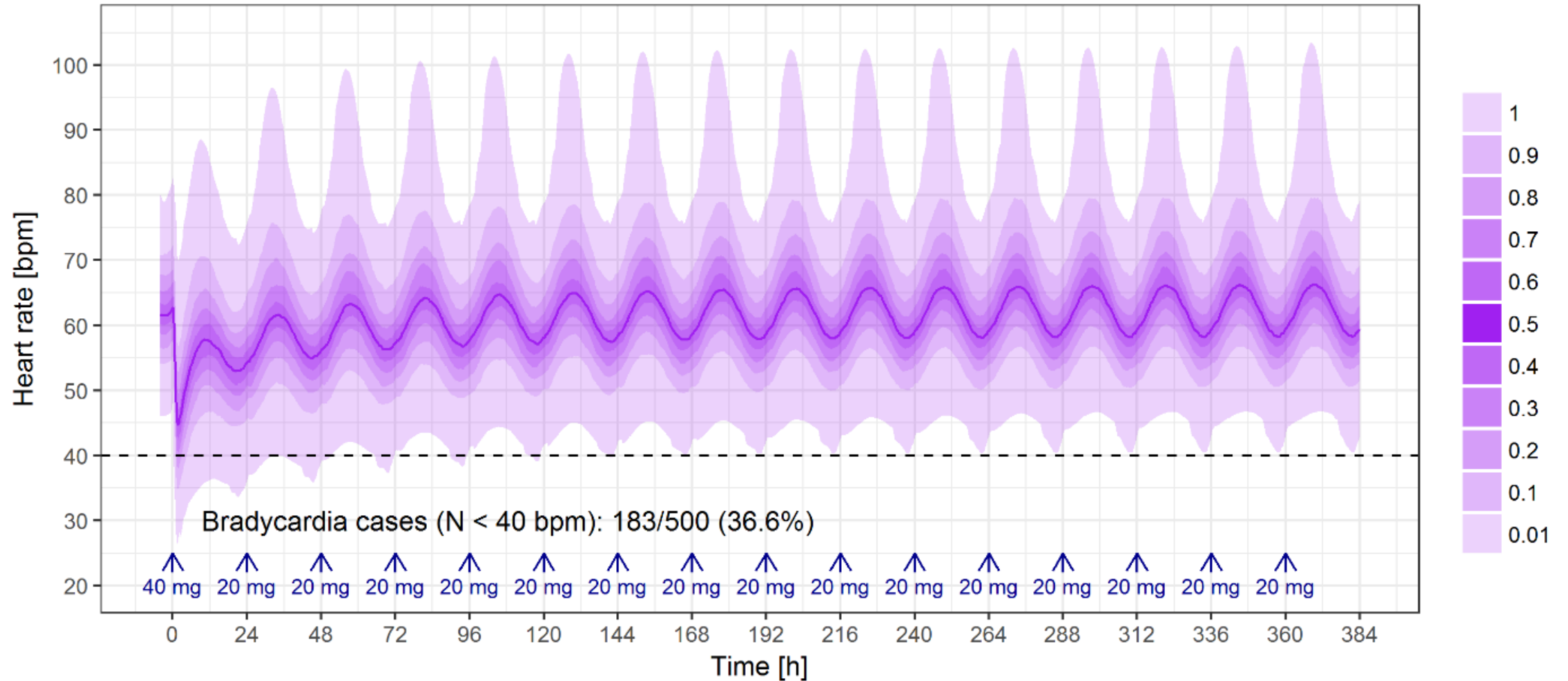
Translation of double (half) the exposure into clinical effect

- **Where are we on the concentration-effect range**
 - Flat part (limited clinical relevance) or
 - Steep part (possibly clinically relevant)



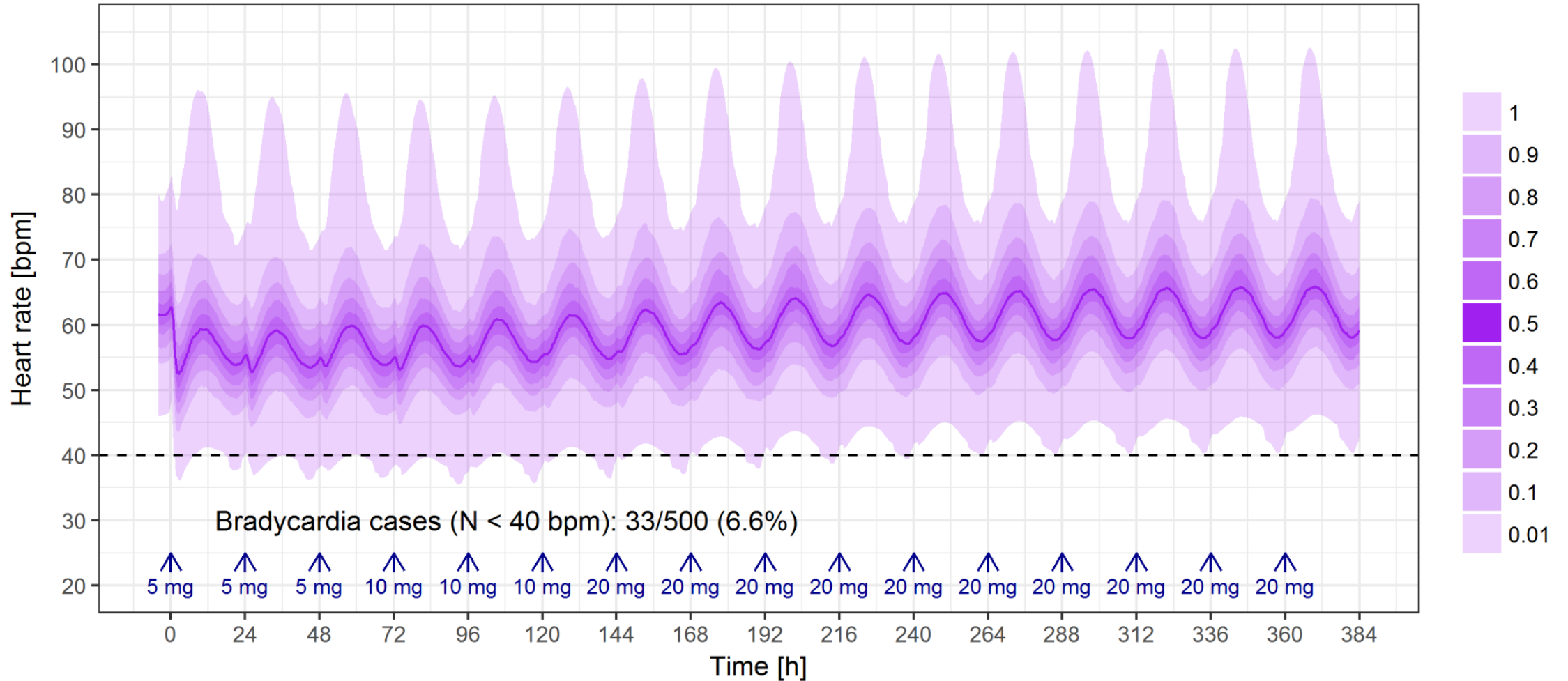
Covariate effect: clinical impact

Tolerance with up-titration



Covariate effect: clinical impact

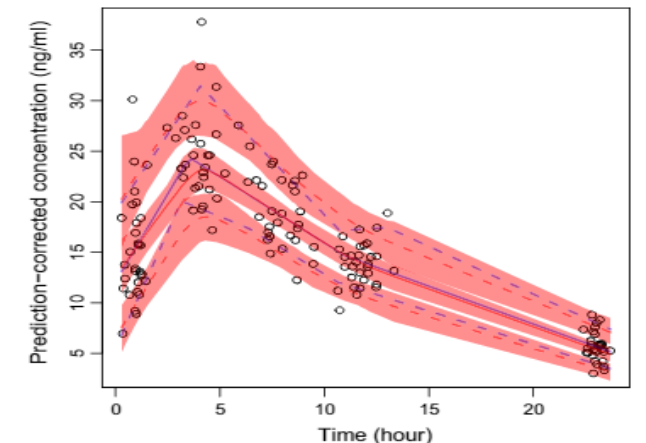
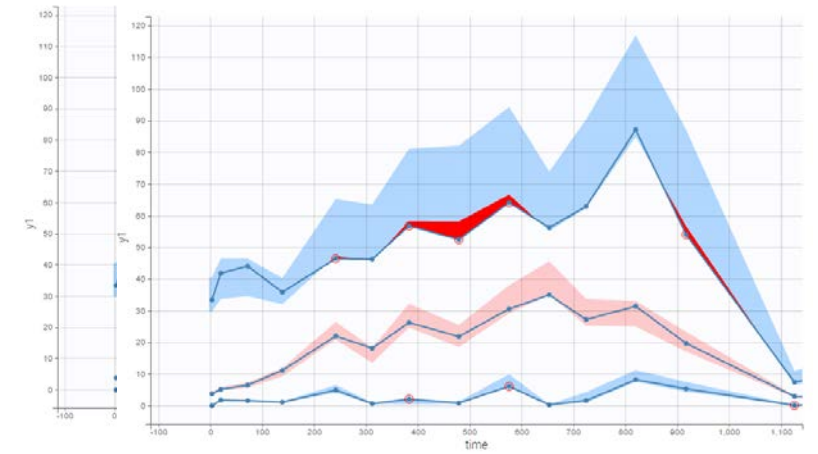
Tolerance with up-titration



VPC: visual judgment

Possible distortions

- Options
 - Bins: same width, same no. of obs., other
 - Quantiles to show: 80%, 90%, etc.
 - Intervals: blocks, interconnected lines
 - Model shortcomings: red areas, white
 - Subsets: Stratification, pcVPC
- Visual impression and judgment depends on the type of graphic chosen
 - Bins: Lavielle JPKPD 2011
 - Jansen et al., CPT:PSP 2018: quantile regression



Summary (1)

Visualization topics in pharmacometrics and statistics

- **Visualization**
 - intuitive, easy to grasp, accurate (by the audience!)
- **Data**
 - Appropriate scale (logarithmic or linear)
 - Comparison must be facilitated
- **Models and simulations**
 - What is the question again?
 - Show the quantity of interest
- **Clarity on what is shown (axis labels, intervals with SD or CI, ...)**
- **Get the message across to the decision maker**

Summary (2)

Potential collaborative work between statistics and pharmacometrics (SIG SxP)

- **Goodness of fit: observed vs predicted**
 - Is a smoother appropriate that minimizes in the y-direction only?
 - Alternative: errors-in-variables regression (errors in x and y)
 - A statistic to summarize an obs-vs-pred plot (beyond R^2)?
- **VPC**
 - Log-likelihood (OFV, AIC), Shrinkage are established
 - How about a statistic to summarize a VPC? (qq-plot idea?)
 - Can a fit be “too good to be true” (100% of data stats inside 80% VPC band)?

Indonesia

Thank you for
your attention.

