

# Analyzing Outcome Scores

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May 25, 2022

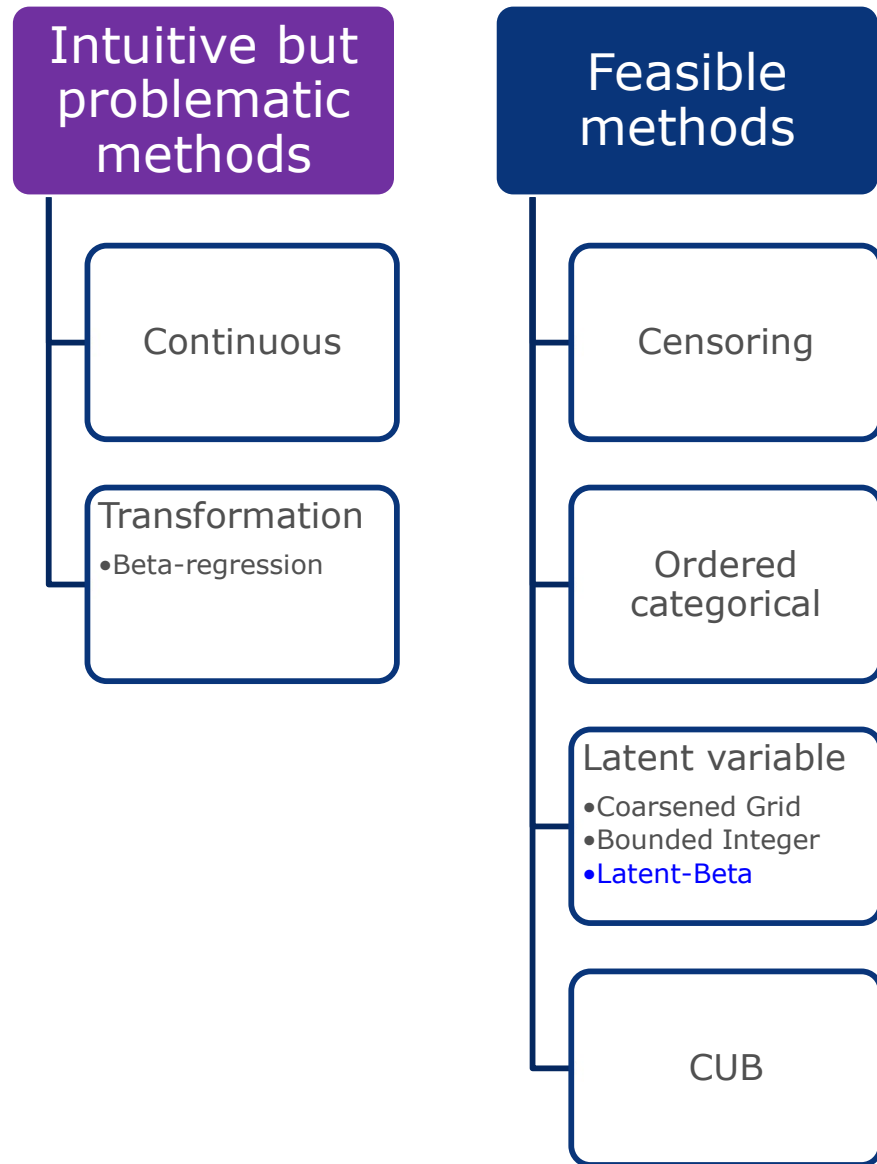


PHARMACEUTICAL COMPANIES  
OF *Johnson & Johnson*

Chuanpu Hu, PhD

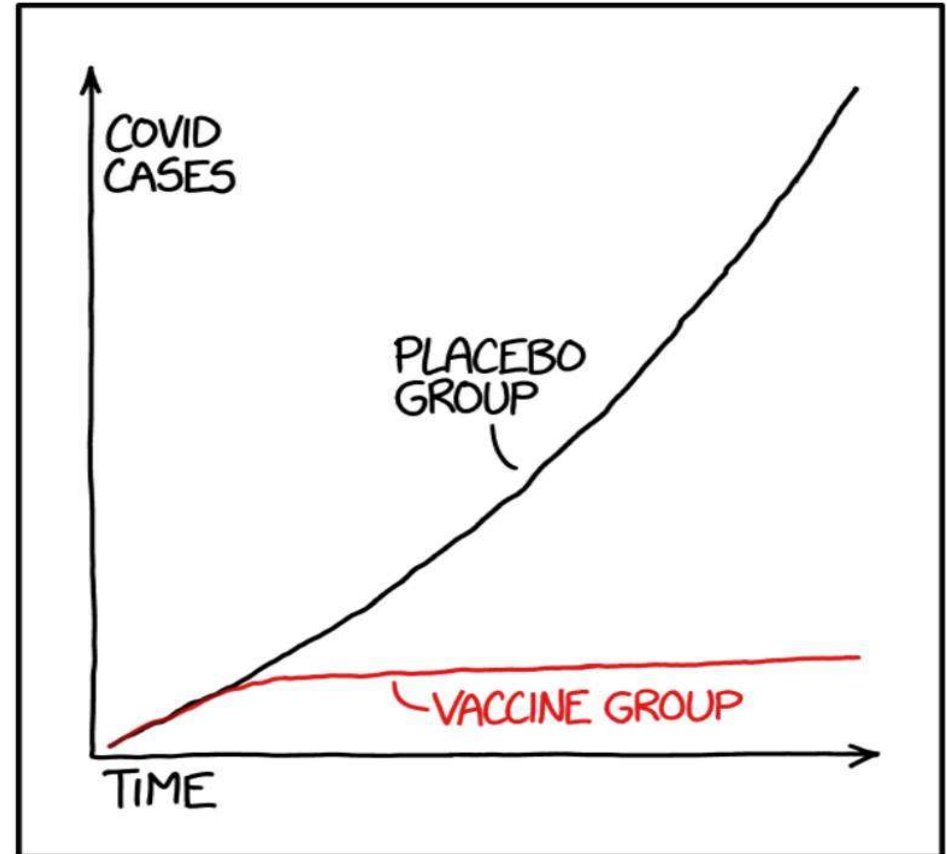
# Outline

- (Bounded) Outcome Scores (BOS)
  - What, why should you care?
- Analysis methods
  - Ideas
  - Confusions
- Practical recommendations



# Analyzing Data

- Often must make best use of data
  - Reduce bias
  - Increase efficiency
  - Smaller trials / better decisions
- A large class of data: (bounded) outcome scores
  - Emerging area in pharmacometrics, especially in past ~3 years



STATISTICS TIP: ALWAYS TRY TO GET DATA THAT'S GOOD ENOUGH THAT YOU DON'T NEED TO DO STATISTICS ON IT

# Bounded Outcome Scores (BOS)

- Take restricted values within boundary
- Composite scores measuring disease severity
  - Used in many disease areas – immunology, neuroscience, etc.
  - Primary clinical trial endpoints, or used to derive them
- Example:
  - Psoriasis Activity Severity Index (PASI) score: 0 – 72, with 0.1 increments
- For notation, may standardize data as integers 0, 1, 2, ..., n
  - Alternatively, onto **closed** interval  $[0,1]$ : for PASI score,  $[0, 1/721, 2/721, \dots, 1]$
- Ordered categorical endpoints in nature (with many categories)

# Derived Endpoints: Higher Bar for BOS

- Achieving a level, change from baseline, or combination of both (reaching certain threshold)
  - Often used as clinical trial primary endpoints
- Example:
  - Psoriasis: PASI 75/90/100: achieving 75, 90, or 100% improvement from baseline
    - Achieve PASI 100  $\Leftrightarrow$  PASI score = 0
- Model may describe often original scores but **rarely derived endpoints**
  - Describing derived endpoints requires that of the **distribution** of the original scores
    - Very difficult!

# Common (Folklore?) Thinking

- If small # of categories (e.g.,  $<6$ ), analyze as ordered categorical
- “Intermediate” (e.g.,  $>6$  but  $<10$ ) ??
- If “large” # of categories (e.g.,  $>10$ ), analyze as continuous
  - Problems:
    - Predicting data outside original range
    - Difficulty with skewed data distributions

# BOS May Have Skewed Distributions

The AAPS Journal (2020) 22:61  
DOI: 10.1208/s12248-020-00441-4

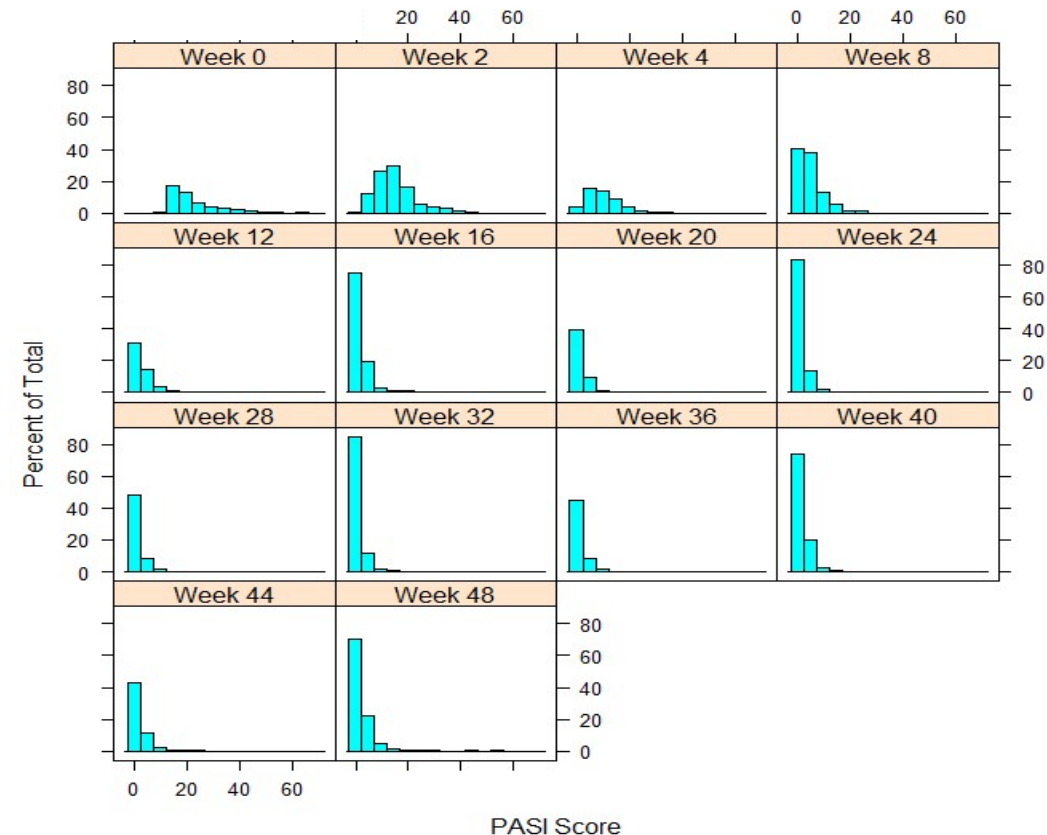


Research Article

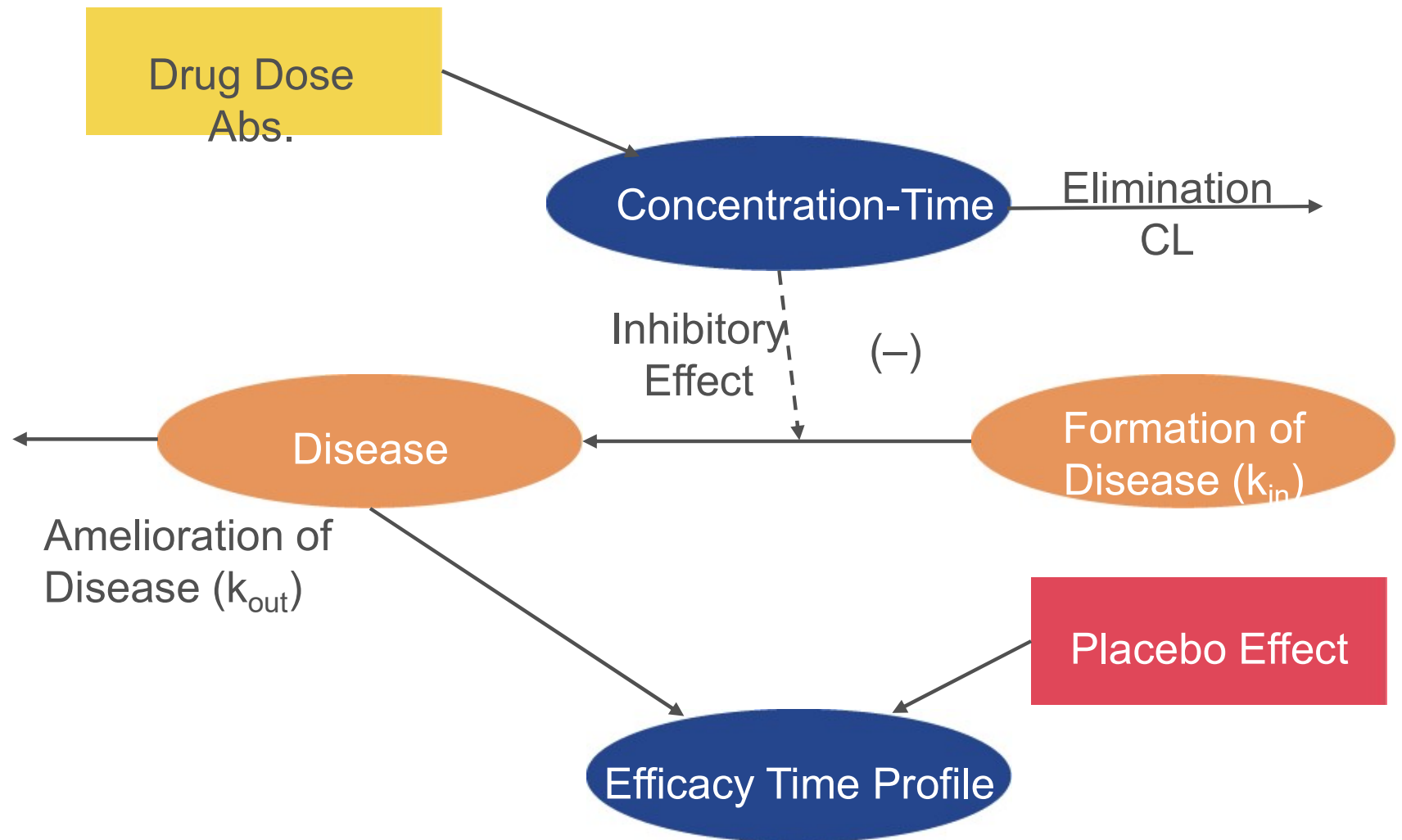
## Applying Beta Distribution in Analyzing Bounded Outcome Score Data

Chuanpu Hu,<sup>1,2</sup> Honghui Zhou,<sup>1</sup> and Amarnath Sharma<sup>1</sup>

- Data Example: guselkumab Psoriasis
  - 2 Phase 3 studies, placebo-controlled, 48 weeks
- PASI score histograms at all 14 visits skewed to left
  - More PASI score = 0 over time



# Longitudinal Model Diagram

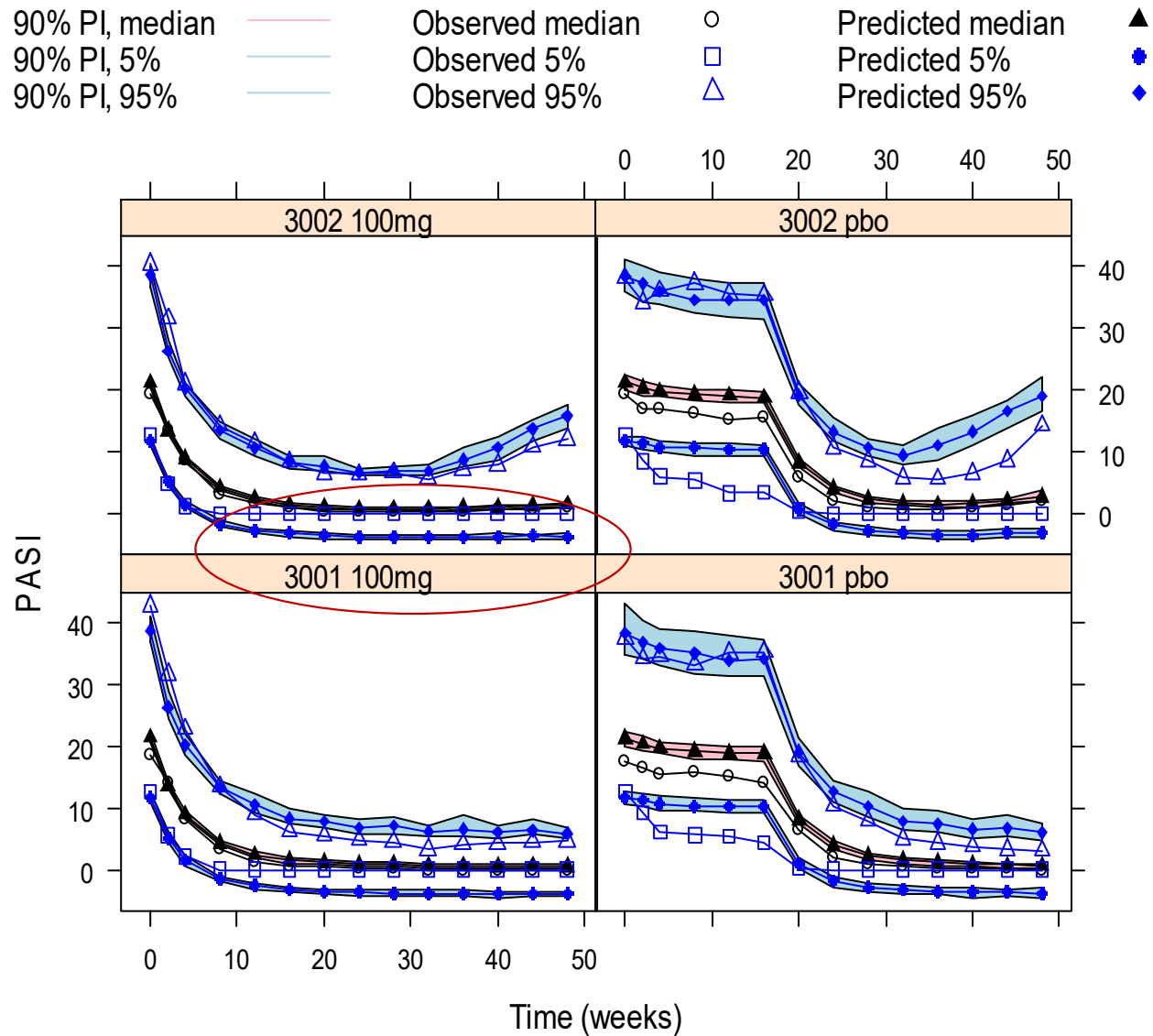


- Sufficient PK: sequential PK/PD analysis fixing individual Posthoc PK parameter estimates



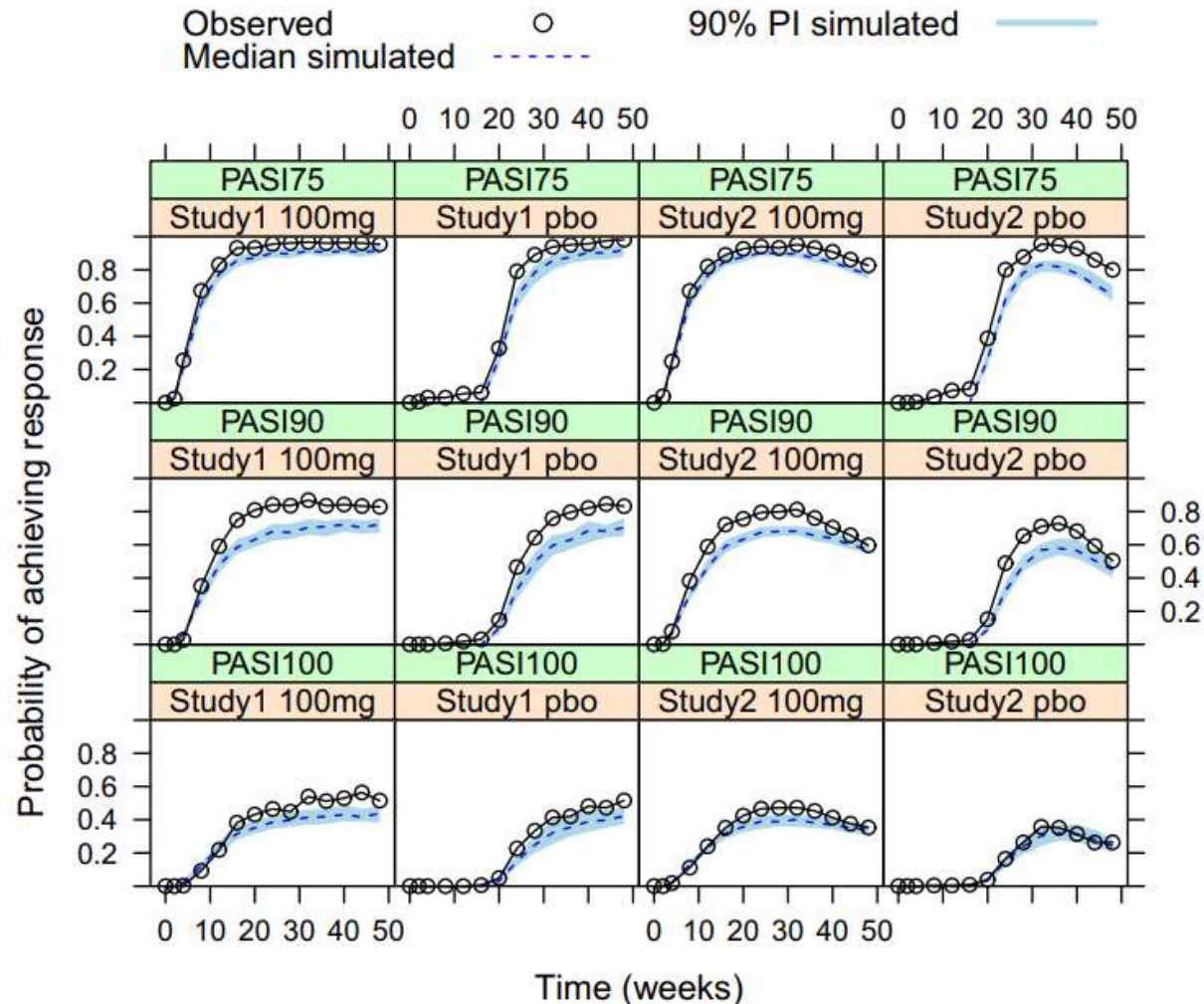
# Model Data as Continuous: VPC of PASI Score Biased at Low End

- As treatment progresses:
  - Observed median and 5% percentiles both become near 0
    - Cannot be achieved by continuous model predictions
  - Model predicted median is fine, but 5% percentile outside data range (<0)



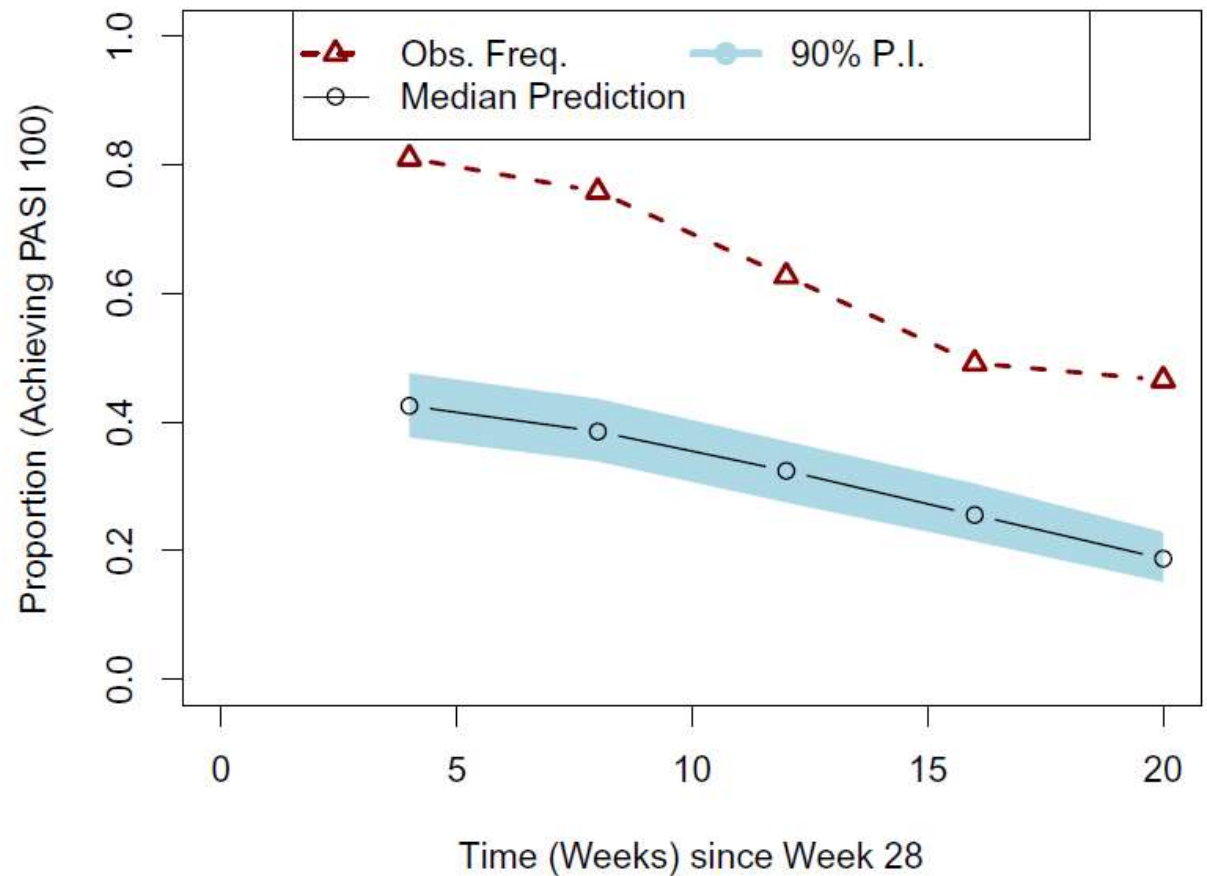
# VPC of Derived Endpoints: PASI 75/90/100

- Notably underpredicting PASI 90, among others



# More Biased VPC of A Derived Endpoint in a highly sensitive subpopulation

- Continuous model significantly underpredicted PASI 100 in a highly sensitive subpopulation
  - Achieved PASI 100 at Week 28, then taken off drug



**Fig. 3.** The continuous analysis model predicted and observed PASI 100 responder rates when active treatment was withdrawn after week 28

# Transformation and Related Approaches

- Common transformations, e.g., log or logit, cannot be directly applied
  - At boundary (0),  $\log(0) = \infty$

J Pharmacokinet Pharmacodyn (2017) 44:437–448  
DOI 10.1007/s10928-017-9531-3



ORIGINAL PAPER

## **Improvement in latent variable indirect response modeling of multiple categorical clinical endpoints: application to modeling of guselkumab treatment effects in psoriatic patients**

Chuanpu Hu<sup>1</sup> · Bruce Randazzo<sup>2</sup> · Amarnath Sharma<sup>1</sup> · Honghui Zhou<sup>1</sup>

- **Proportional/(additive + proportional) error model III-behaved**
  - At boundary (0), likelihood  $\rightarrow \infty$

# Transform Data to within Boundary?

## Beta-regression

Psychological Methods  
2006, Vol. 11, No. 1, 54–71

Copyright 2006 by the American Psychological Association  
1082-989X/06/\$12.00 DOI: 10.1037/1082-989X.11.1.54

### A Better Lemon Squeezer? Maximum-Likelihood Regression With Beta-Distributed Dependent Variables

Michael Smithson  
The Australian National University

Jay Verkuilen  
University of Illinois at Urbana–Champaign

- Originated from psychological literature
  - Spread to statistical literature (occasionally but not recently) and pharmacometrics
- Beta-distribution: on **open** interval  $(0,1)$ , with density:  $f(x) \sim x^a(1-x)^b$
- Linearly transform original score to  $(0,1)$ 
  - (Left) boundary must be transformed to some value:
  - Transform data to  $[\varepsilon, 1)$
  - Arbitrary **fudge factor**  $\varepsilon$ : often  $\varepsilon = 0.01$
- Intuition: small change does not matter

# Problem with Beta-regression

J Pharmacokinet Pharmacodyn (2017) 44:437–448  
DOI 10.1007/s10928-017-9531-3



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## Improvement in latent variable indirect response modeling of multiple categorical clinical endpoints: application to modeling of guselkumab treatment effects in psoriatic patients

Chuanpu Hu<sup>1</sup> · Bruce Randazzo<sup>2</sup> · Amarnath Sharma<sup>1</sup> · Honghui Zhou<sup>1</sup>

- Statistically ill-behaved
  - Boundary observations become arbitrarily influential with smaller  $\varepsilon$ , e.g.,  $10^{-6}$
- **Small change does matter at highly-sensitive location!**
  - “Butterfly effect”

# Censoring

- Motivated from modeling BQL PK
- Separate data on/within boundary:
  - Model data within boundary as continuous, with transformations to handle data skewness, if needed
  - Model boundary data as censored, like “BQL”
  - Need additional “LLOQ” parameters for boundary data
- Removes previous problems due to achieving boundary

## Estimating transformations for repeated measures modeling of continuous bounded outcome data

Matthew M. Hutmacher,<sup>a\*†</sup> Jonathan L. French,<sup>b</sup>  
Sriram Krishnaswami<sup>b</sup> and Sujatha Menon<sup>b</sup>

- Esthetics: boundary and within-bounds data have the same nature; why should they be treated differently (“BQL” vs continuous)?

# Ideally, Respect Data Nature

- BOS data are in fact ordered categorical
- Treating the data as such (using logit/probit regression) is superior, when can be done

Received: 31 October 2016 | Revised: 8 June 2017 | Accepted: 13 July 2017  
DOI: 10.1002/sim.7433

RESEARCH ARTICLE

WILEY **Statistics**  
in *Medicine*

## Modeling continuous response variables using ordinal regression


Qi Liu<sup>1</sup>  | Bryan E. Shepherd<sup>1</sup> | Chun Li<sup>2</sup> | Frank E. Harrell Jr.<sup>1</sup> 

Journal of Pharmacokinetics and Pharmacodynamics (2018) 45:803–816  
<https://doi.org/10.1007/s10928-018-9610-0>

ORIGINAL PAPER



Modeling near-continuous clinical endpoint as categorical: application to longitudinal exposure–response modeling of Mayo scores for golimumab in patients with ulcerative colitis

Chuanpu Hu<sup>1</sup>  · Omoniyi J. Adedokun<sup>1</sup> · Liping Zhang<sup>1</sup> · Amarnath Sharma<sup>1</sup> · Honghui Zhou<sup>1</sup>

- If **too many intercepts** to estimate: can they be “fixed”?



PHARMACEUTICAL COMPANIES  
OF *Johnson & Johnson*

Chuanpu Hu, PhD



# Recent Advances: Latent Variable Approaches

- Most natural
- Underlies standard categorical data analysis approaches of logit/probit regression
- Observed data occurs when underlying latent variable crosses certain thresholds
- The thresholds correspond to intercepts
- Idea:
  - Fix the thresholds “naturally”
  - Model latent variable with flexible distributions to handle skewness
    - Instead of transforming the original score

# Approach 1: Coarsened Grid

*Biostatistics* (2007), **8**, 1, pp. 72–85

doi:10.1093/biostatistics/kxj034

Advance Access publication on April 5, 2006

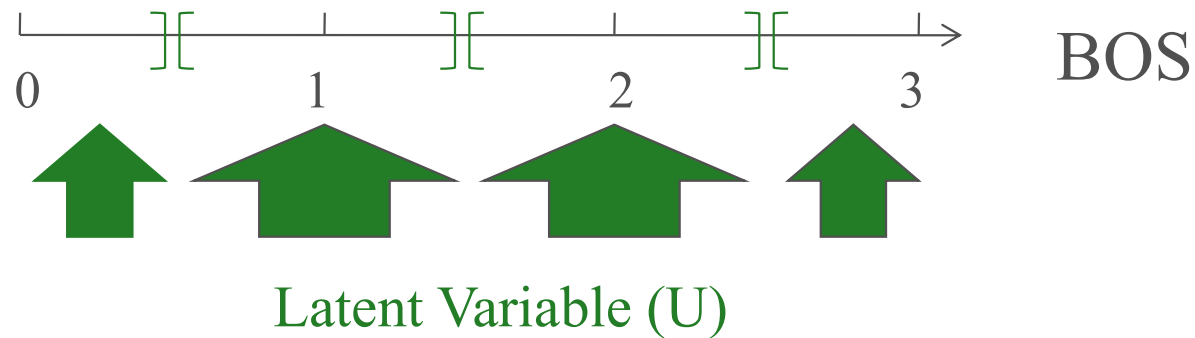
## The logistic transform for bounded outcome scores

EMMANUEL LESAFFRE\*, DIMITRIS RIZOPOULOS, ROULA TSONAKA

*Biostatistical Centre, Catholic University of Leuven,  
U.Z. St. Rafaël, Kapucijnenvoer 35, B-3000 Leuven, Belgium  
emmanuel.lesaffre@med.kuleuven.be*

- Established BOS concept

# Coarsened Grid Illustration



- Motivation: BOS value  $k = 0, 1, \dots, m$  occurred by **rounding of continuous latent variable  $U$**  on interval  $(0, m)$  to integer
  - Latent variable thresholds fixed at middle points: 0.5, 1.5, etc.
- Scale  $U$  to  $(0, 1)$ , then model with logit-normal distribution
  - **$\text{logit}(U) = \text{pred} + \varepsilon$** , with  $\varepsilon \sim N(0, \sigma^2)$

# Approach 2: Bounded Integer

- Motivated differently: Wellhagan et al, PAGE 2018

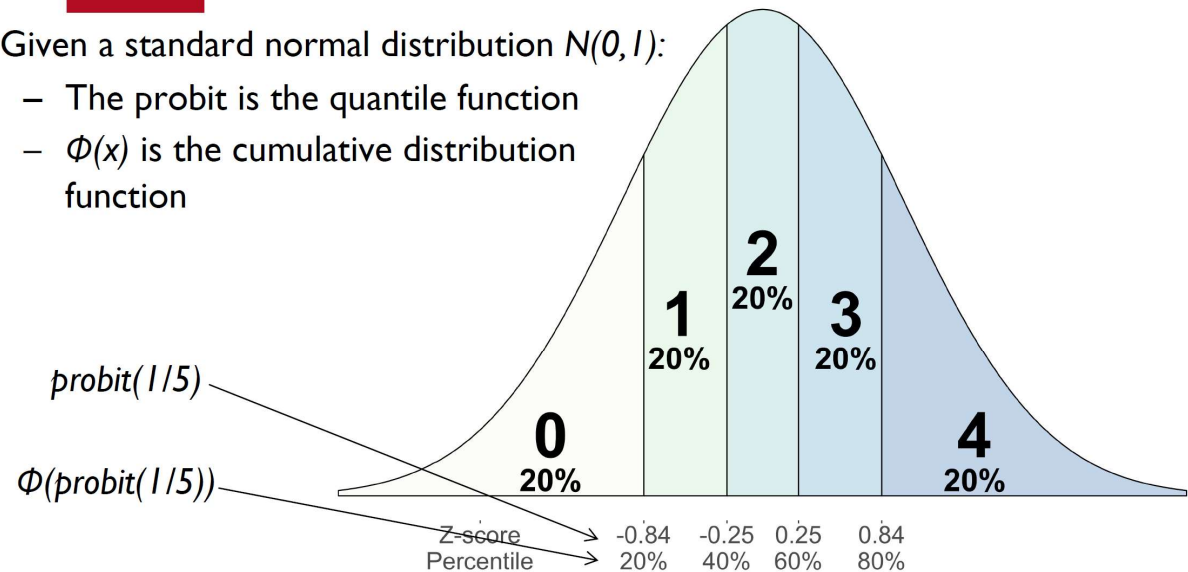
- Split a normal distribution
  - To # of intervals as BOS categories
  - With equal probability
- Model mean and sd



## A scale with 5 categories

Given a standard normal distribution  $N(0, 1)$ :

- The probit is the quantile function
- $\Phi(x)$  is the cumulative distribution function



14

- Should be close to Coarsened Grid, especially if # of category is large

# More on Coarsened Grid and Bounded Integer

*The AAPS Journal* (2019) 21:74  
DOI: 10.1208/s12248-019-0343-9



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*Research Article*

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## **A Bounded Integer Model for Rating and Composite Scale Data**

Gustaf J. Wellhagen,<sup>1</sup> Maria C. Kjellsson,<sup>1</sup> and Mats O. Karlsson<sup>1,2</sup>

*The AAPS Journal* (2019) 21:102  
DOI: 10.1208/s12248-019-0370-6



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*Commentary*

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## **On the Comparison of Methods in Analyzing Bounded Outcome Score Data**

Chuanpu Hu<sup>1,2</sup>

- Both approaches may have **difficulties with skewness** with underlying normal distribution

# Approach 3: Latent-beta

Article

## **A new parsimonious model for ordinal longitudinal data with application to subjective evaluations of a gastrointestinal disease**

**Moreno Ursino<sup>1,2</sup> and Mauro Gasparini<sup>1</sup>**

- The newest and brightest



Statistical Methods in Medical Research  
2018, Vol. 27(5) 1376–1393

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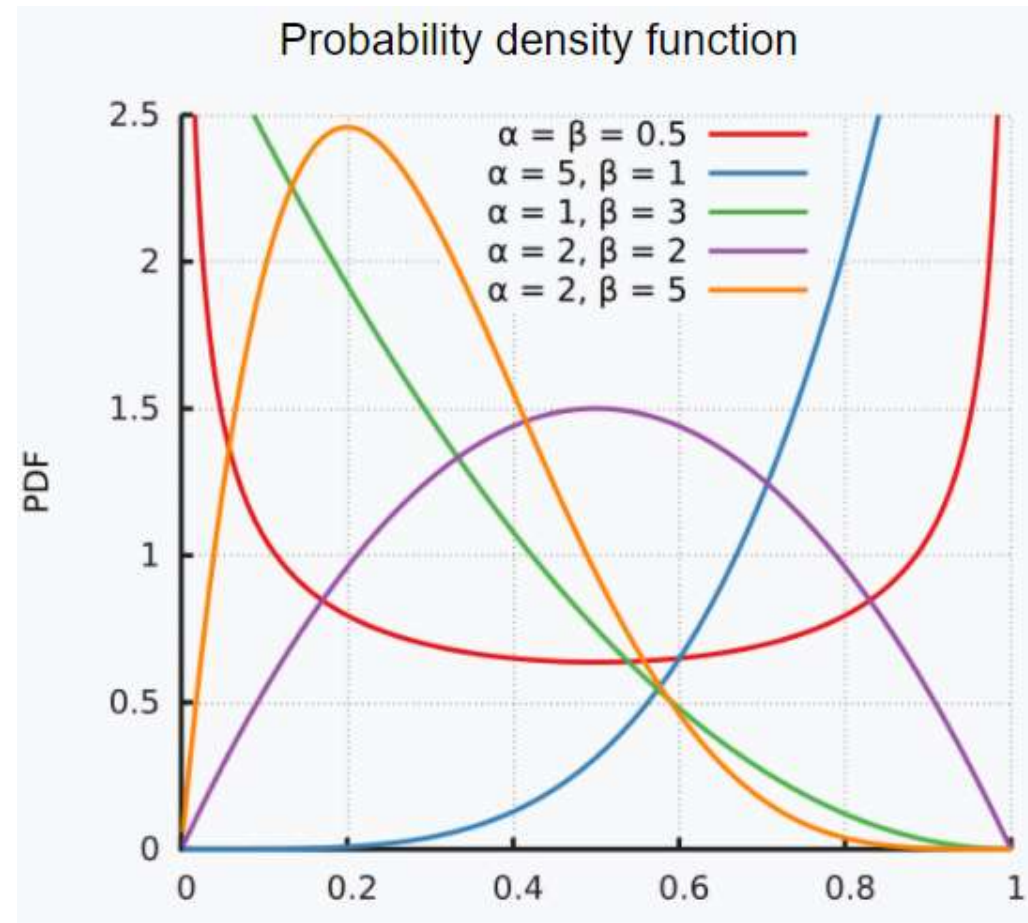
DOI: 10.1177/0962280216661370

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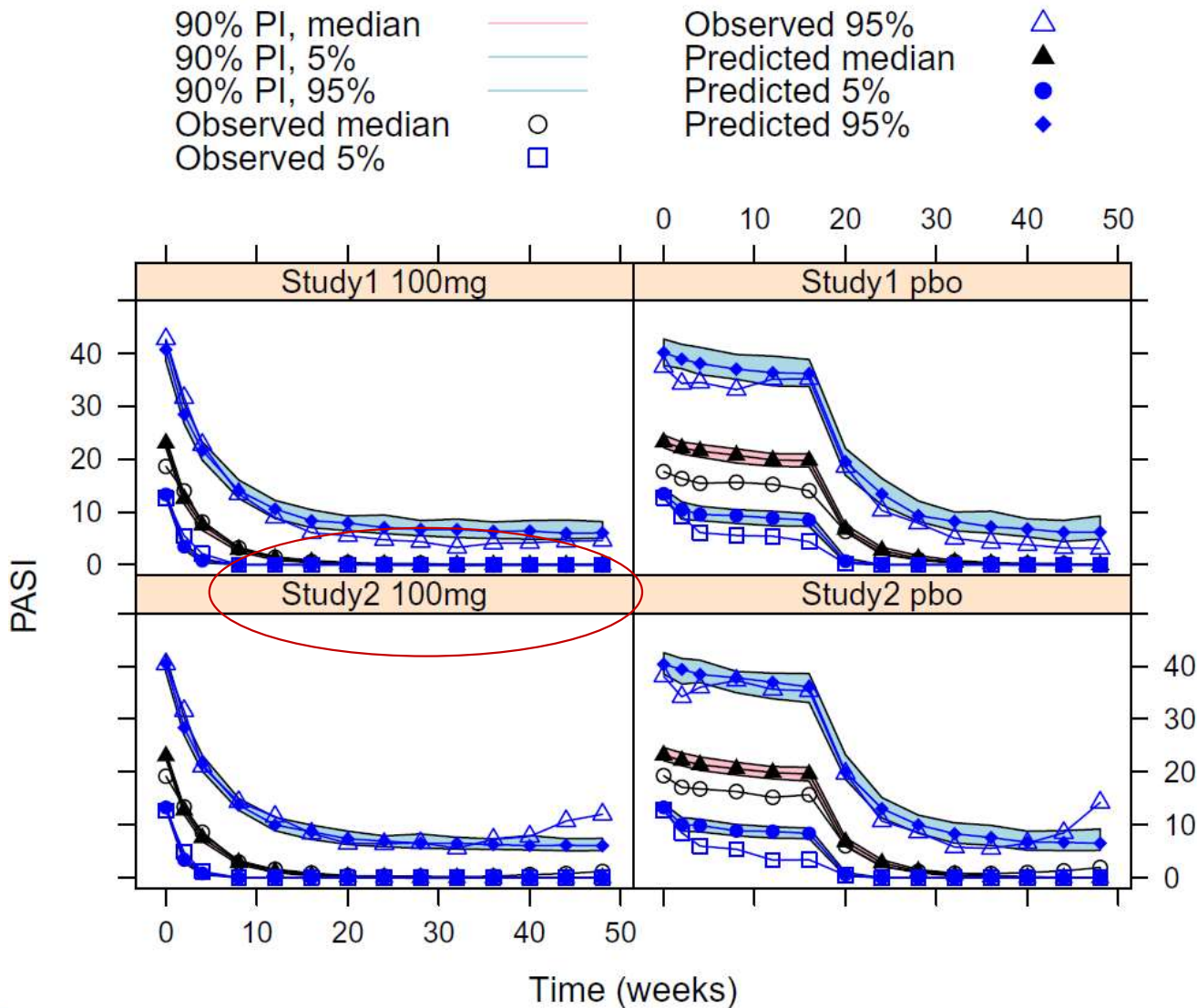
# Latent-beta

- Use beta distribution instead of (logit)normal
- Wikipedia:
  - Beta distribution shapes
- High flexibility to model skewed distributions
- Resolves all previous issues with other approaches



# Applying Latent-beta to Guselkumab Psoriasis

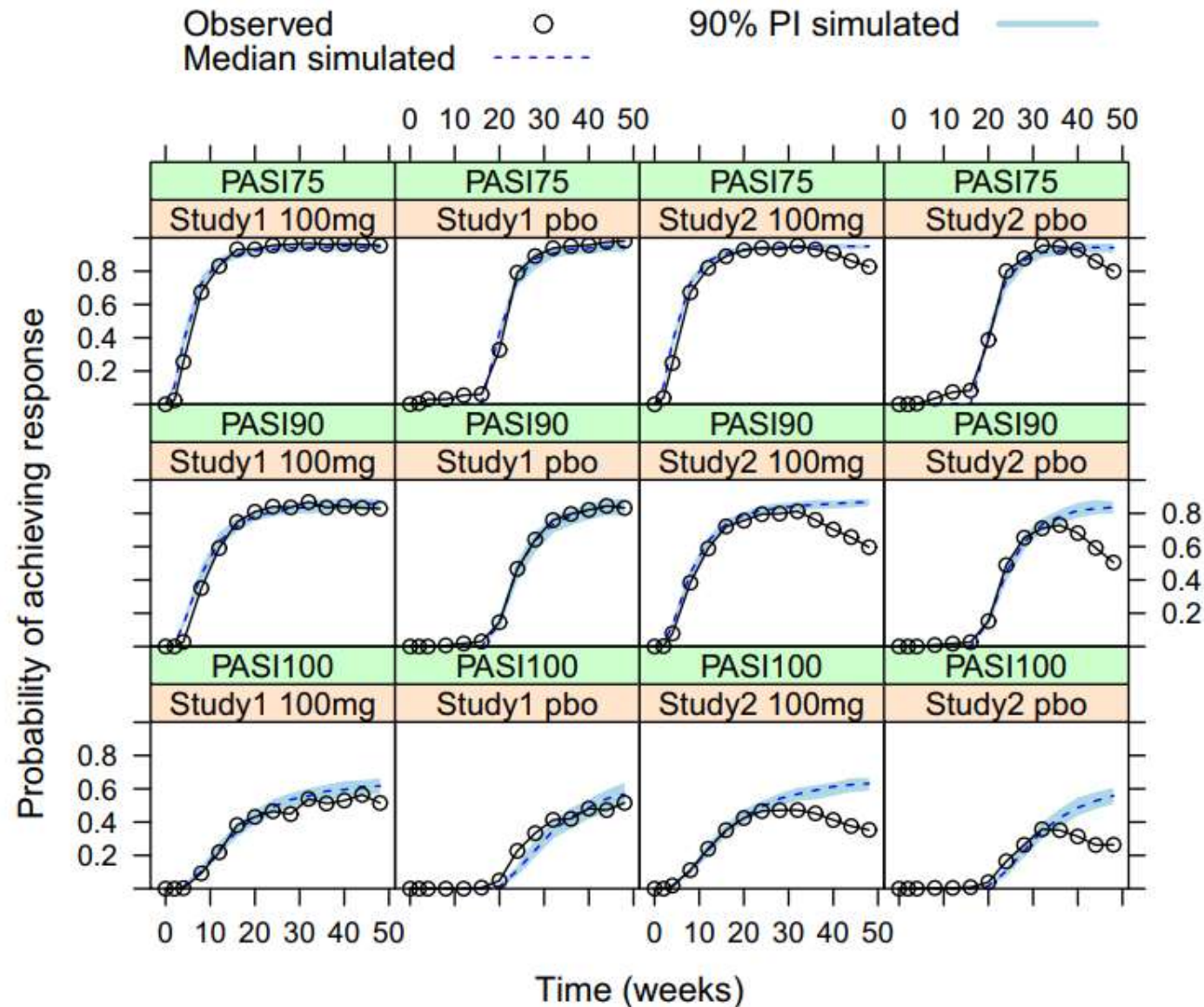
- Model reasonably predicted observed PASI scores
  - Minor problem remained at baseline median
    - Baseline distribution appeared more skewed
  - Reasonable prediction of treatment effect





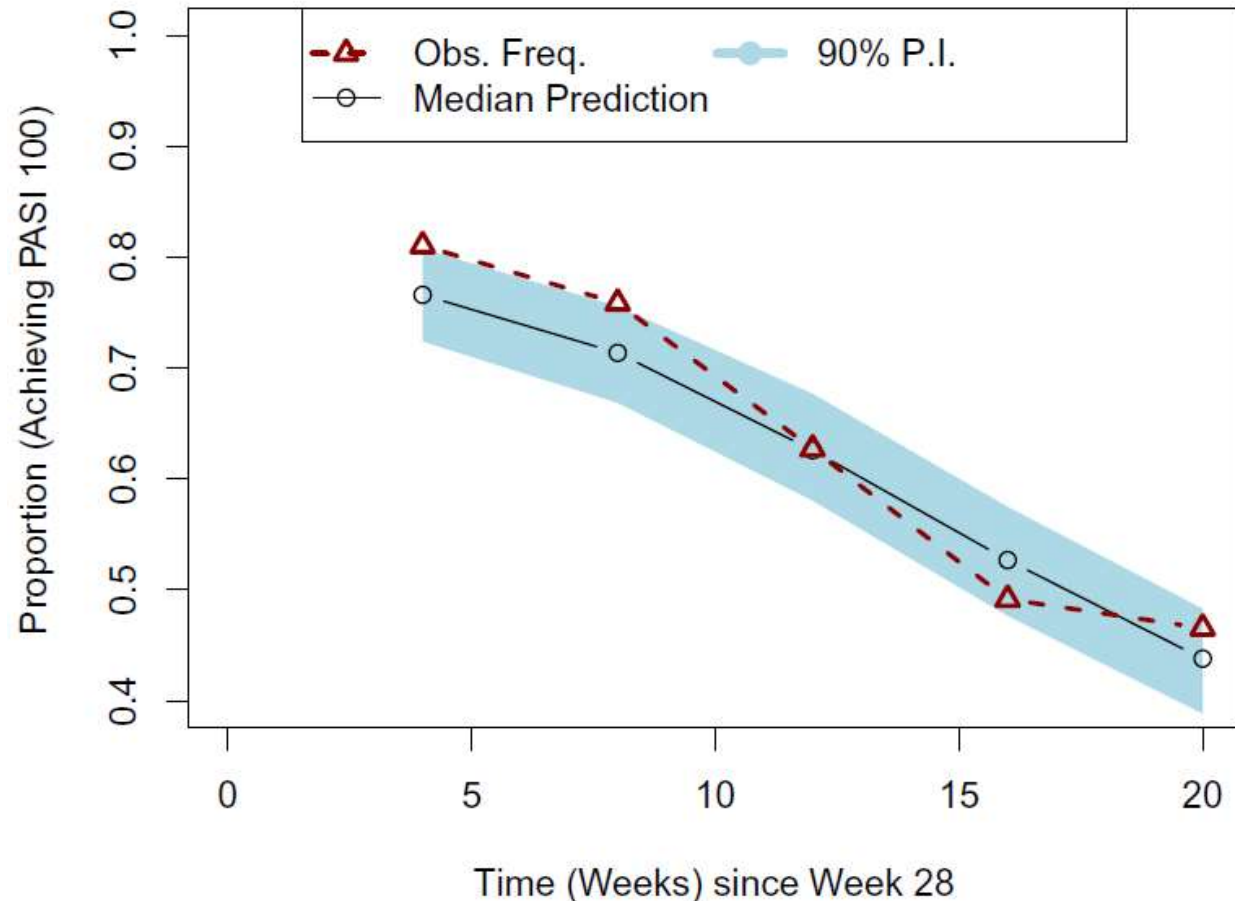
# Latent-beta VPC of Derived Endpoints: PASI 75/90/100

- Model reasonably described data
- Later time points of Study 2 are nuanced due to treatment optimization
- Much improved from the continuous approach



# Reasonable VPC of Derived Endpoint

- Latent-beta model **reasonably predicted PASI 100** in a highly sensitive subpopulation
  - Achieved PASI 100 at Week 28, then taken off drug
- Much improved from the continuous model



**Fig. 6.** The BOS analysis model predicted and observed PASI 100 responder rates when active treatment was withdrawn after week 28

# Complexities of Describing Derived Endpoints in Skewed Distributions:

- Brief History of PASI Score Modeling
  - Few publications pre 2020 – suggesting its difficulty
- Unpublished (Hutmacher ~2016): Censoring described PASI scores and PASI 75, but biased in PASI 90/100
- Success in describing PASI scores and PASI 75/90/100 not achieved until 2020, with Latent-beta
  - Even in a highly sensitive subpopulation!
- 2021: latent-beta success in PASI score and PASI 75/90/100 repeated, and another method applied
- 2022: latent-beta success repeated in a highly sensitive subpopulation

# Complexities of Describing Responses in Highly Sensitive Subpopulations

- Response-adaptive study designs
  - Induction-maintenance paradigm:
    - Responders to initial treatment re-randomized to different “maintenance” treatments
- Few successes in modeling “maintenance” data

Journal of Pharmacokinetics and Pharmacodynamics (2022) 49:283–291  
<https://doi.org/10.1007/s10928-021-09796-3>

ORIGINAL PAPER

## Improving categorical endpoint longitudinal exposure–response modeling through the joint modeling with a related endpoint

Chuanpu Hu<sup>1</sup>  · Honghui Zhou<sup>1</sup>

- Requires getting between-subject variabilities right

# Another Family of Models: CUB

*International Statistical Review* (2018), 0, 0, 1–30 doi:10.1111/insr.12282

## **Cumulative and CUB Models for Rating Data: A Comparative Analysis**

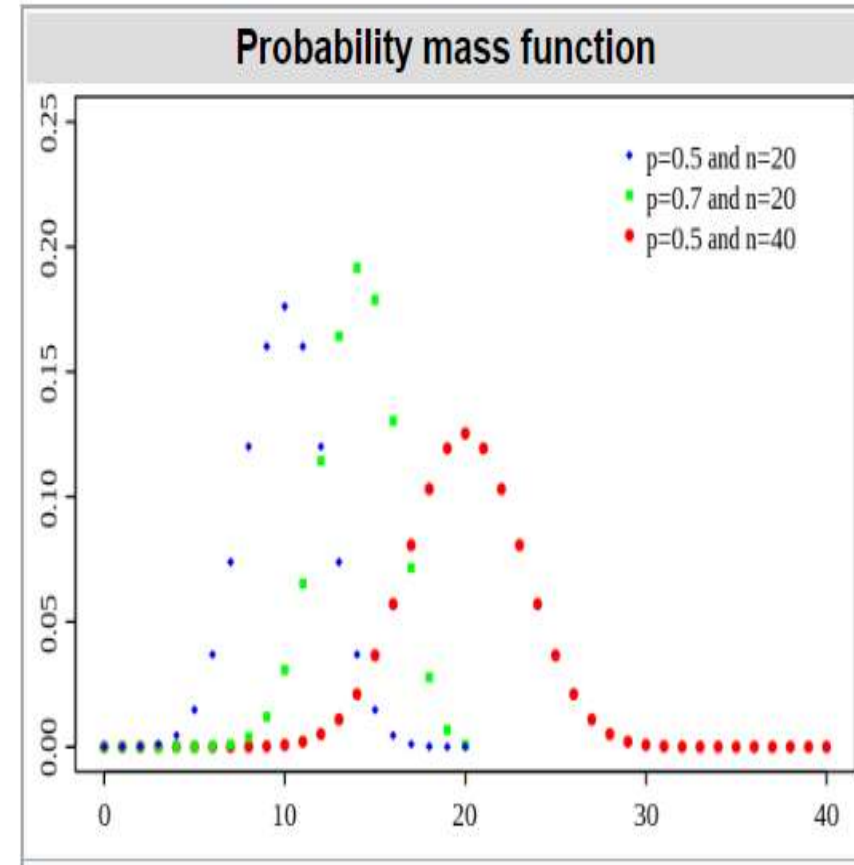
**Domenico Piccolo** , **Rosaria Simone** and **Maria Iannario**

- Popular in psychological rating data analysis
- Motivated from the **Binomial** distribution
  - Not a latent variable approach
  - But still respect data nature

# CUB: Details

- **Binomial** distribution with total level = n:
  - Prob(score = k) =  $\binom{n}{k} p^k (1-p)^{n-k}$
  - Distribution skewed (left, right) when p (<, >) 0.5
- Random noise, i.e., **Uniform**:
  - Prob(score = k) = 1/n
- Combine the distributions, with mixture probability  $\pi$ :
  - **Combined Uniform Binomial (CUB)**
    - Prob(score = k) =  $\pi \binom{n}{k} p^k (1-p)^{n-k} + (1-\pi) / n$

## Binomial distribution



# Latent-beta vs CUB

*The AAPS Journal* (2020) 22:95  
DOI: 10.1208/s12248-020-00478-5



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*Research Article*

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## **Application of Beta-Distribution and Combined Uniform and Binomial Methods in Longitudinal Modeling of Bounded Outcome Score Data**

Chuanpu Hu,<sup>1,2</sup> Honghui Zhou,<sup>1</sup> and Amarnath Sharma<sup>1</sup>

- Data: ustekinumab psoriasis Phase 2
- 320 patients randomized to receive SC injection in 5 arms:
  - PBO (till Week 20), 45 mg, 90 mg, (45 mg weekly x4), (90 mg weekly x4)
- Data collected ~q4w during Weeks 0-32

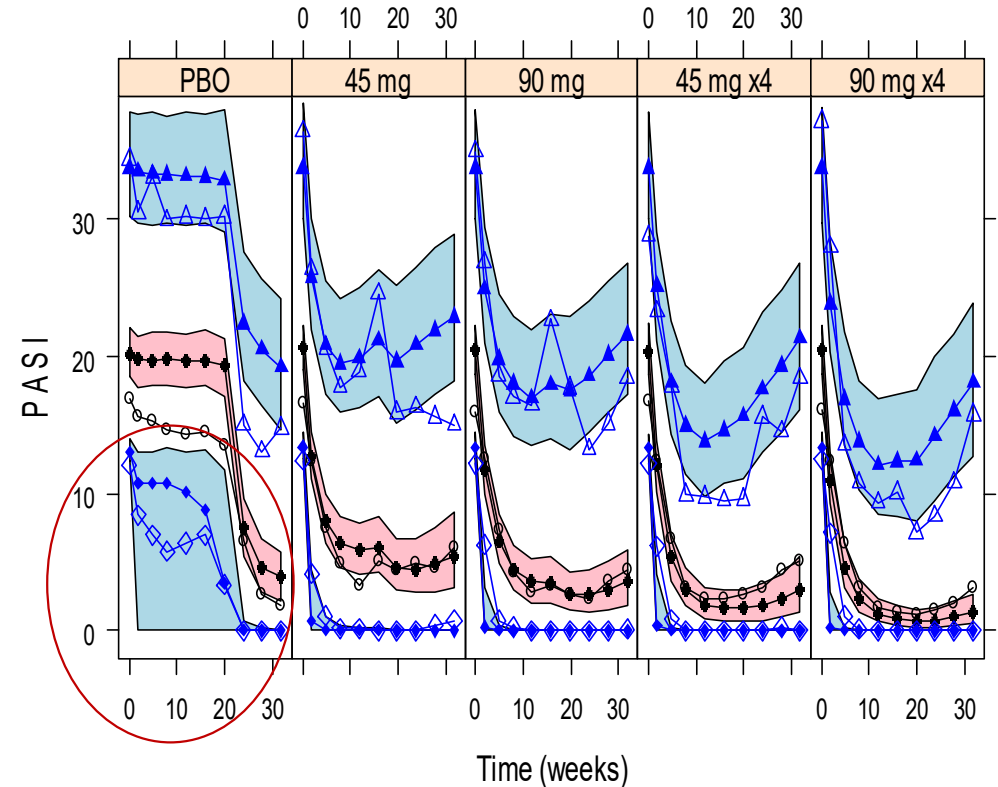
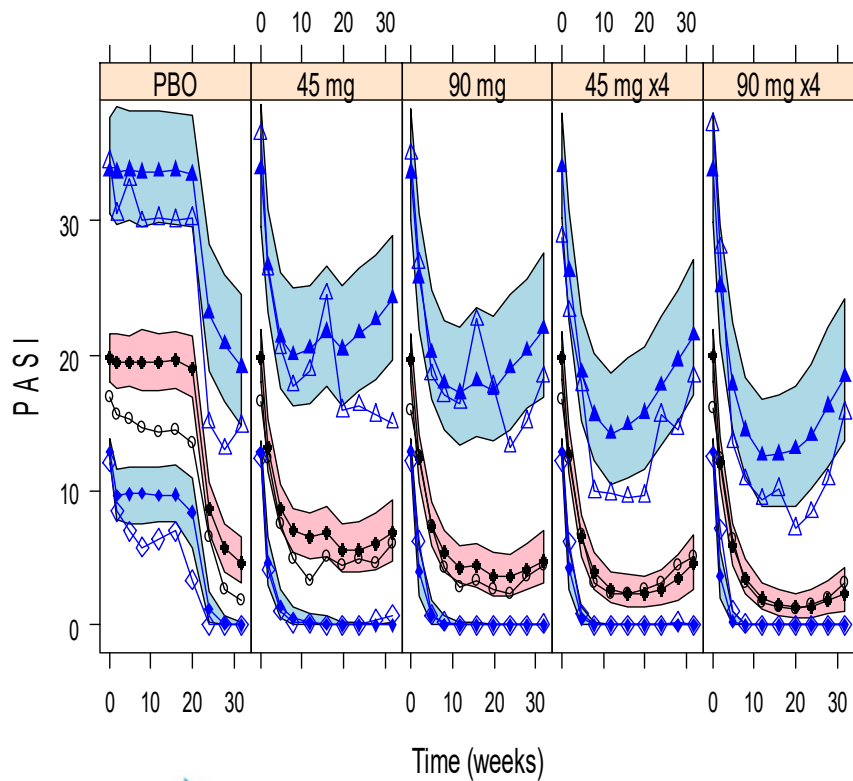
# PASI Score VPC: CUB Somewhat Nuanced

## • Latent-beta

## • CUB

90% PI, median — 90% PI, 5% — 90% PI, 95% —  
 Observed median ○ Observed 5% ◇ Observed 95% △  
 Predicted median ● Predicted 5% ◆ Predicted 95% ▲

90% PI, median — 90% PI, 5% — 90% PI, 95% —  
 Observed median ○ Observed 5% ◇ Observed 95% △  
 Predicted median ● Predicted 5% ◆ Predicted 95% ▲



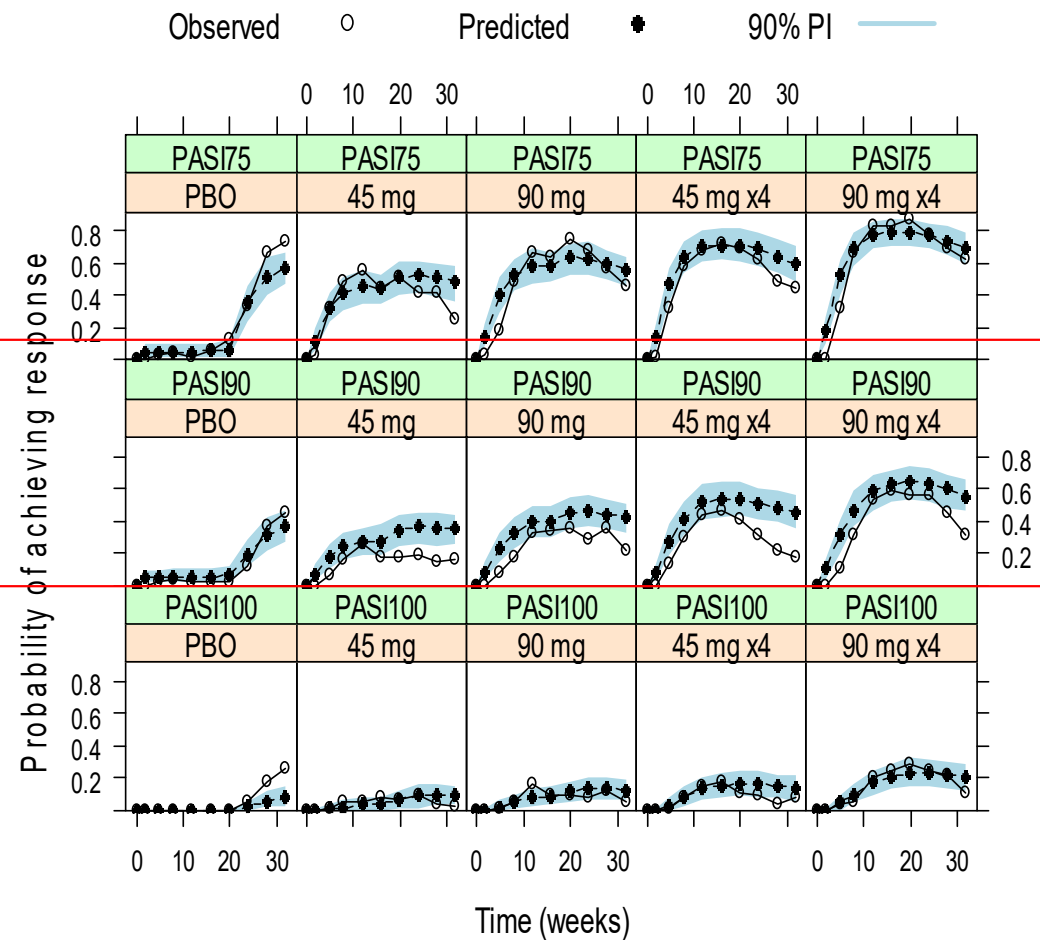
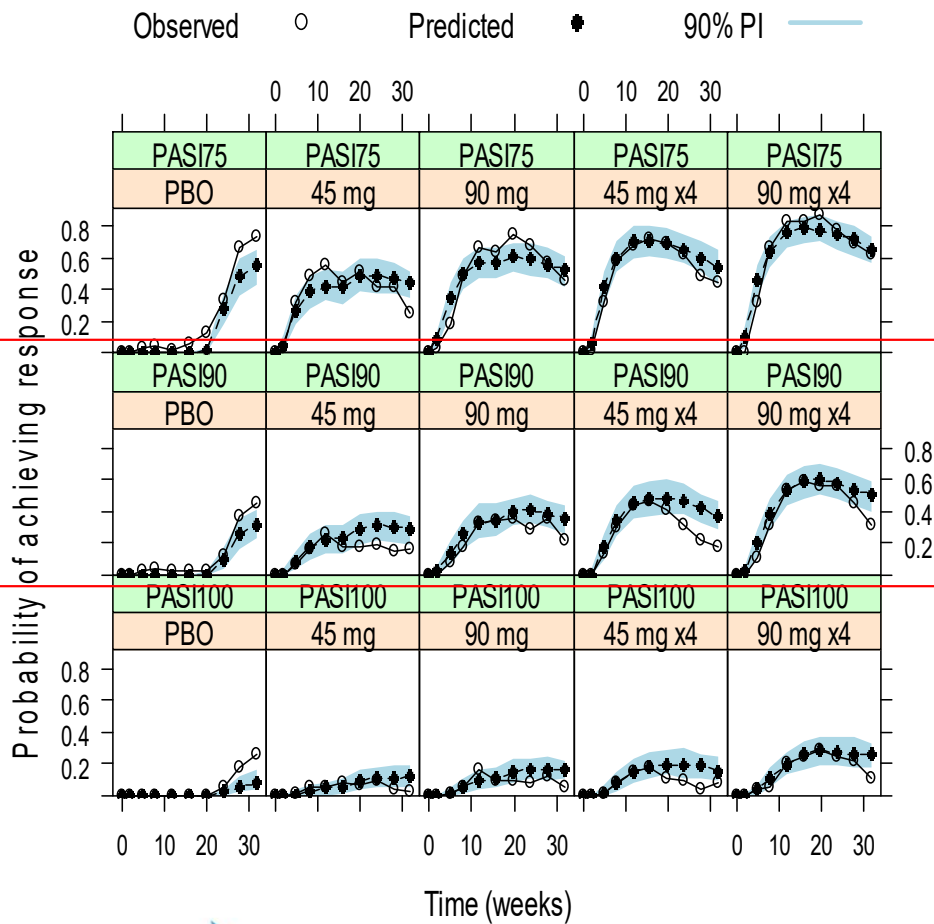


# PASI 75/90/100 VPC: Latent-beta

## Somewhat better in PASI 90

- Latent-beta

- CUB



# More Details

- Overall, VPC of latent-beta slightly better than CUB
  - In both PASI scores and PASI 75/90/100
- Latent-beta also has much better NONMEM OFV
  - Improvement >400 over CUB
- **Uniform distribution in CUB too noisy?**
  - May need future verification
- NONMEM implementation of latent-beta:

*The AAPS Journal* (2020) 22:61  
DOI: 10.1208/s12248-020-00441-4



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*Research Article*

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## **Applying Beta Distribution in Analyzing Bounded Outcome Score Data**

Chuanpu Hu,<sup>1,2</sup> Honghui Zhou,<sup>1</sup> and Amarnath Sharma<sup>1</sup>

# Model Parameters - Complexity

- Continuous: (mean, sd)
- Censoring: (mean, sd, censoring limits at boundary) – 2 extra parameters
- Ordered categorical: (intercepts) – many parameters!
- Coarsened Grid: (mean, sd)
- Bounded Integer: (mean, sd)
- Latent-beta: (mean, precision)
- CUB: ( $p$ ,  $\pi$ )

# Which parameter to model?

- Modeling is typically done on the mean parameter
  - As function of dose/exposure, etc.
- How about the variance/precision parameter, e.g., should it be modeled as a function of the mean?
  - Like “proportional error” in pharmacokinetics
  - Used in BOS literature, though no clear evidence of need
- To avoid overfitting, likely best to keep variance/precision as a constant parameter for BOS, unless clear reasons supporting otherwise

# Comparing the Methods: Confusion with AIC for Pharmacometricians

*The AAPS Journal* (2019) 21:102  
DOI: 10.1208/s12248-019-0370-6



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*Commentary*

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## On the Comparison of Methods in Analyzing Bounded Outcome Score Data

Chuanpu Hu<sup>1,2</sup>

- AIC/BIC cannot be used to compare Continuous with Censoring or categorical approaches
  - “Likelihood” not comparable with censored data
  - Same when **treating data differently** (numerical vs. categorical)!
    - Category levels have no numerical meaning: cannot calculate “Low” + “Mild”
    - Read Akaike (1974)
  - Confusion in pharmacometrics literature even to-date

# Appropriate Method Comparisons

- Use AIC/BIC to compare only categorical approaches
  - i.e., latent variable approaches, and CUB
- To compare approaches treating data differently, e.g., continuous vs. categorical: Use VPC
  - In abstract:
    - Continuous scale will favor the continuous approach
    - Categorical scale (proportion of achieving category) will favor the Categorical approach
  - (Another indication that Continuous/Categorical approaches are not formally comparable)
  - Choose the quantity/scale of practical interest

# Summary: Which Method to Use, When?

- Use **Ordered Categorical** when possible, even if  $>10$  categories
- If not (i.e., too many intercepts to estimate):
  - OK to use **Continuous**, if
    - Symmetric data
    - Tight timelines
  - OK to use **Censoring**, if
    - Skewed data
    - Do not care about esthetics, or predicting outside data range
  - Can use **Coarsened Grid / Bounded Integer**, if
    - Near-symmetric data
  - **(Should?) use Latent-beta**
    - The only method shown to describe derived endpoints, in a highly sensitive subpopulation
  - Might consider **CUB**

# References: See within

*The AAPS Journal* (2019) 21:102  
DOI: 10.1208/s12248-019-0370-6



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## *Commentary*

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### **On the Comparison of Methods in Analyzing Bounded Outcome Score Data**

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*The AAPS Journal* (2020) 22:95  
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## *Research Article*

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