



Product Quality Research Institute

Alternative Statistical Approaches to Shelf Life Estimation

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About the Working Group

- Formed in 2006 with the mandate to investigate current statistical methods for estimating shelf life and, if possible, to develop improved method(s)
- Composed of pharmaceutical, regulatory, and statistical scientists from industry, government, and academia

ICH Harmonised Tripartite Guideline

❑ Stability Testing of New Drug Substances and Products Q1A(R2) (2003)

Shelf life (also referred to as expiration dating period): The time period during which a drug product is expected to remain within the approved shelf life specification, provided that it is stored under the conditions defined on the container label.

❑ Evaluation for Stability Data Q1E (2003)

The purpose of a stability study is to establish, **based on testing a minimum of three batches** of the drug substance or product, a retest period or shelf life and label storage instructions **applicable to all future batches** manufactured and packaged under similar circumstances.

In this talk

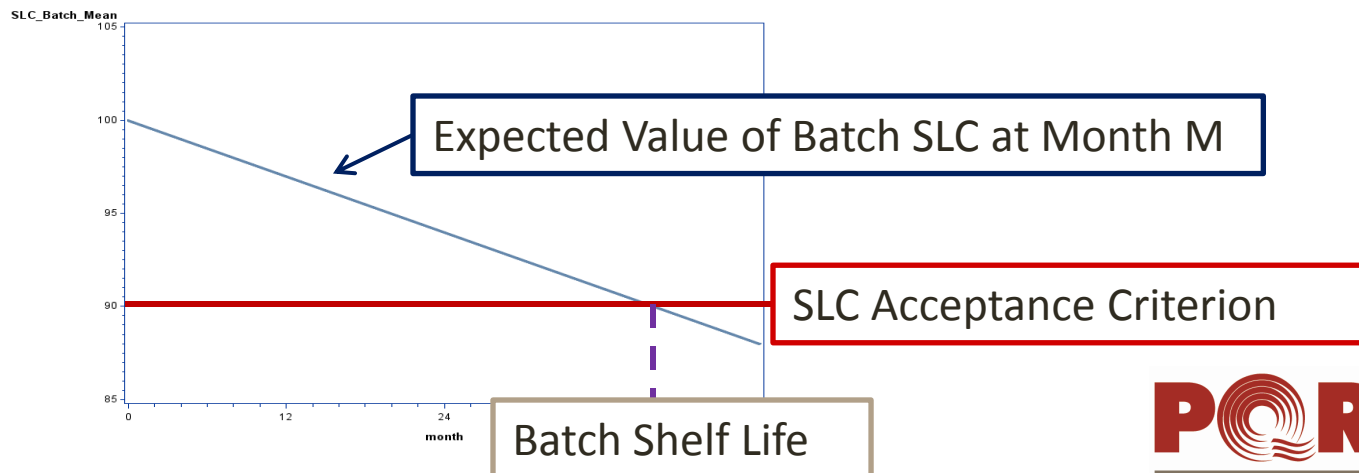
- ❑ Conceptual Framework
- ❑ Current Practice
 - Description
 - Small Sample Behavior
- ❑ Alternatives
 - Alignment with Q1A/Q1E mandate and conceptual framework
 - Description
- ❑ Criteria for Evaluating Proposed Alternatives
- ❑ Results & Next Steps To-Do List

Conceptual framework

- ❑ Big idea: stability limiting characteristic (SLC)
 - gets worse over time
 - change is monotonic
 - shelf life $\equiv$ time after which SLC no longer acceptable

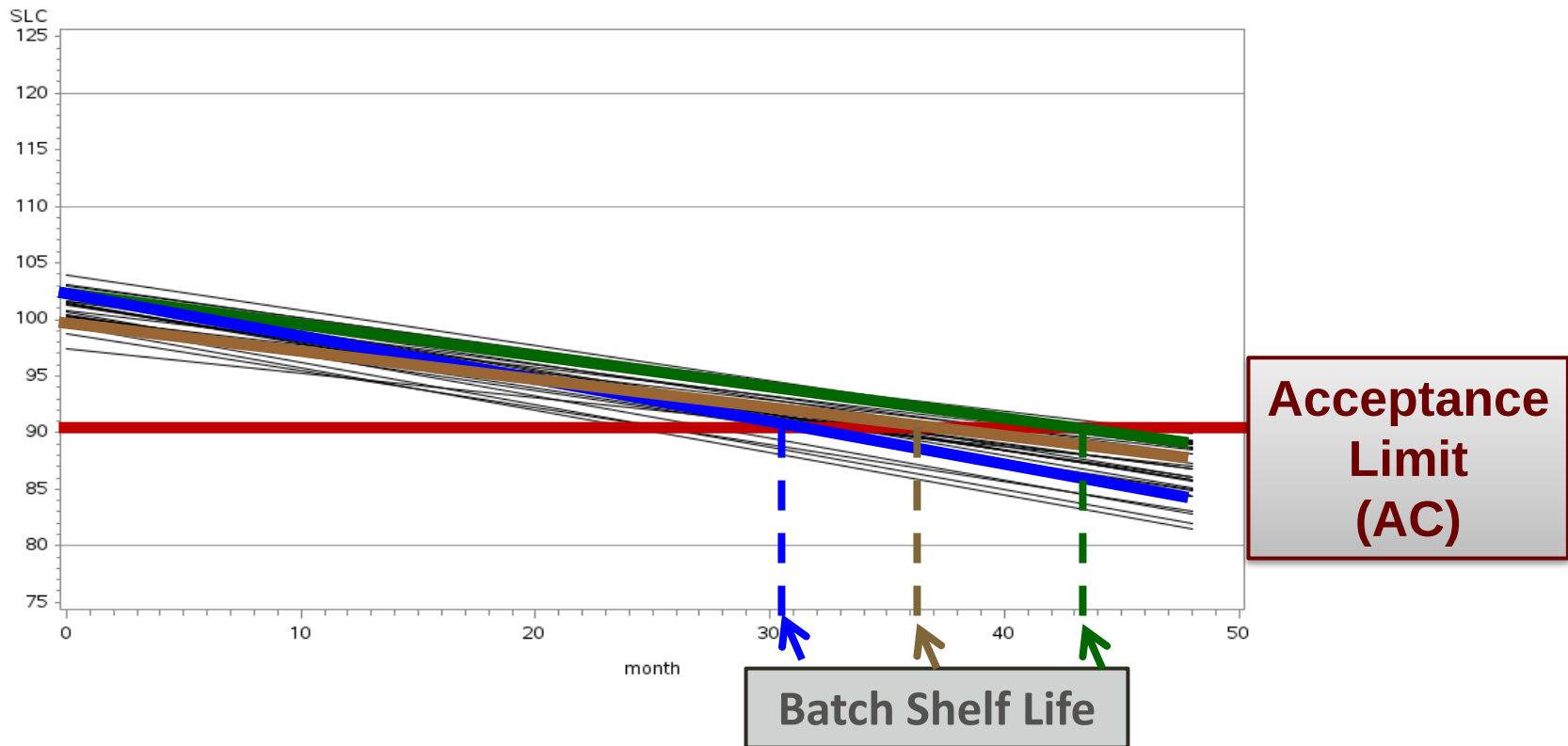
- ❑ Linear Change

- commonly used (but more complex models are often needed)
- Q1E uses linear to illustrate relevant issues
- we follow Q1E's lead...



Conceptual Framework

Distribution of Batch Means



Conceptual Framework – Formal

- ❑ Batches are not identical
- ❑ Mathematical model of variability

“There are no wrong notes,
some are just more right than others.”
- Thelonious Monk

There are no right models.
Some are just less wrong than others.

Conceptual Framework – Formal

- ❑ Batches are not identical
- ❑ Mathematical model of variability
- ❑ Description of how data arise

Source		Distribution
batch (i^{th} batch)	intercept	$\begin{bmatrix} b_{0i} \\ b_{1i} \end{bmatrix} \sim N \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_0^2 & \sigma_{01} \\ \sigma_{01} & \sigma_1^2 \end{bmatrix} \right)$
	slope	
time (j^{th} month)		$\mu_{ij} = \beta_0 + b_{0i} + (\beta_1 + b_{1i})M_j$
unit of observation		$y_{ijk} \mid b_{0i}, b_{1i} \sim N(\mu_{ij}, \sigma^2)$

Current ICH Recommendation

- Start with unequal slopes ANCOVA model

$$\beta_0 + b_{0i} + (\beta_1 + b_{1i})M$$

- Test for equality of slopes (“poolability”) $H_0: \text{all } b_{1i} = 0$

- Possible models

- (1) $\beta_0 + b_{0i} + (\beta_1 + b_{1i})M$
- (2) $\beta_0 + b_{0i} + \beta_1 M$
- (3) $\beta_0 + \beta_1 M$

- If model (1) or (2) focus on shortest-lived batch

- If model (3) use pooled regression

- $\sup_M \{M: \text{lower conf bound of } \hat{Y} > AC\}$

- if batches $\uparrow$ model (1) increasingly likely

Current ICH Recommendation

- ❑ Current ICH: batch effects **fixed**

- ❑ However...

- nothing special about batches observed per se
- repeat stability trial need not (unlikely to be able to) use same batches
- requirement: observed batches **represent** the target population
- **Mandated inference space:** “**future batches**”

- ❑ The above are characteristics of **random** effect:

- ❑ **Current practice inconsistent with above**

- ❑ Practical Reality

- small-sample behavior of current practice is problematic
- see Capen, et al. 2017; Stroup & Quinlan, 2015; Quinlan, et al. 2013, Schwenke, 2010)

Block Effect Random $\Rightarrow$ Mixed Model

- $\rightarrow$ Align analysis model with process giving rise...

$$\beta_0 + b_{0i} + (\beta_1 + b_{1i})M,$$

$$\begin{bmatrix} b_{0i} \\ b_{1i} \end{bmatrix} \sim N \left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} \sigma_0^2 & \sigma_{01} \\ \sigma_{01} & \sigma_1^2 \end{bmatrix} \right)$$

- No need / reason to test equality of slopes; variation among slopes is assumed
- Focus on batch-specific regression

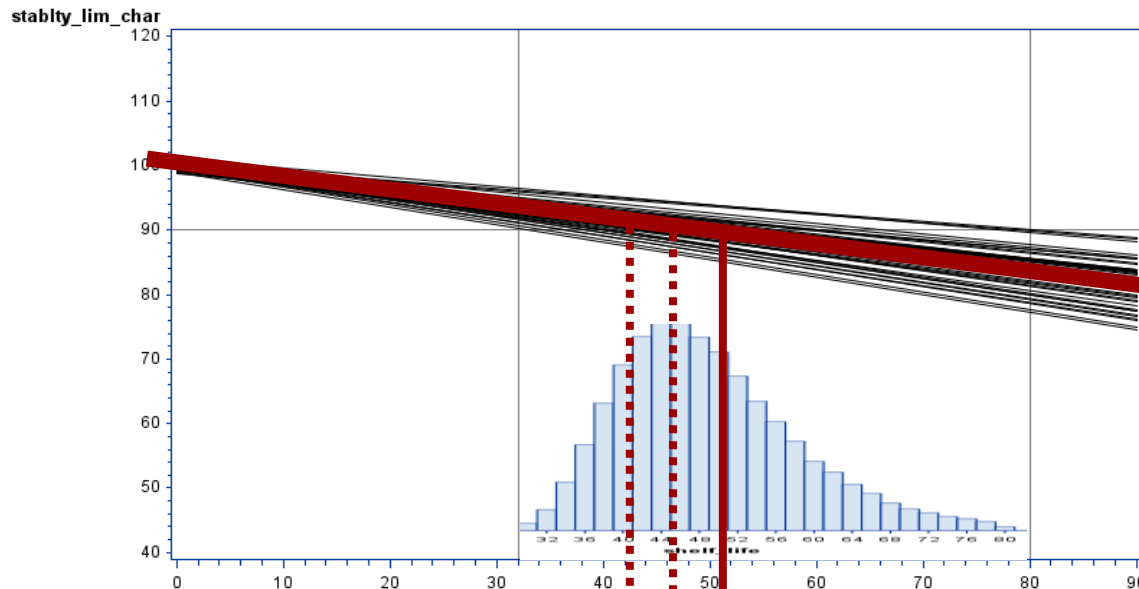
“Naive” Application of Mixed Model

- ❑ Use random coefficient regression
- ❑ Obtain 95% lower confidence bound $\hat{Y}|M$
- ❑ Use $\sup_M \{M: \text{lower conf bound of } \hat{Y}|M > AC\}$

```
proc glimmix data=stability_demo;  
class batch;  
model y=month / ddfm=kr2 s cl;  
random intercept month / subject=batch;  
estimate 'yhat at 31' intercept 1 month 31/ cl;  
estimate 'yhat at 32' intercept 1 month 32/ cl;
```

- ❑ Why “naive”? **wrong inference space** - fails to address “all future batches” objective of shelf-life estimation

Why Do We Say “Naive”?



mean of
batch mean
distribution

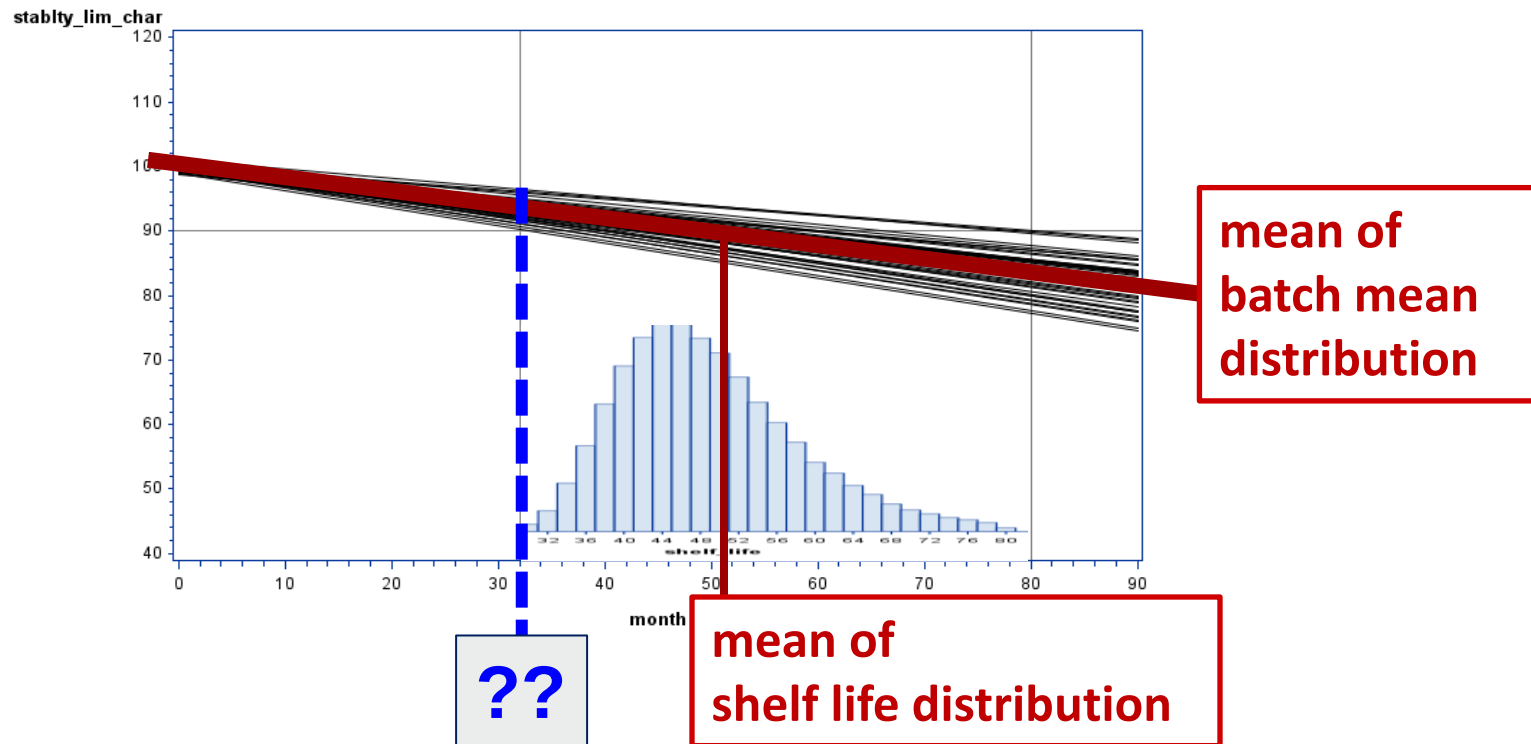
“Naive”
Mixed Model
Expected Estimate, 3 batches

“Naive”
Mixed Model
E(Estimate), >3 batches

as batches $\uparrow$
E(estimate) $\rightarrow$ **mean**

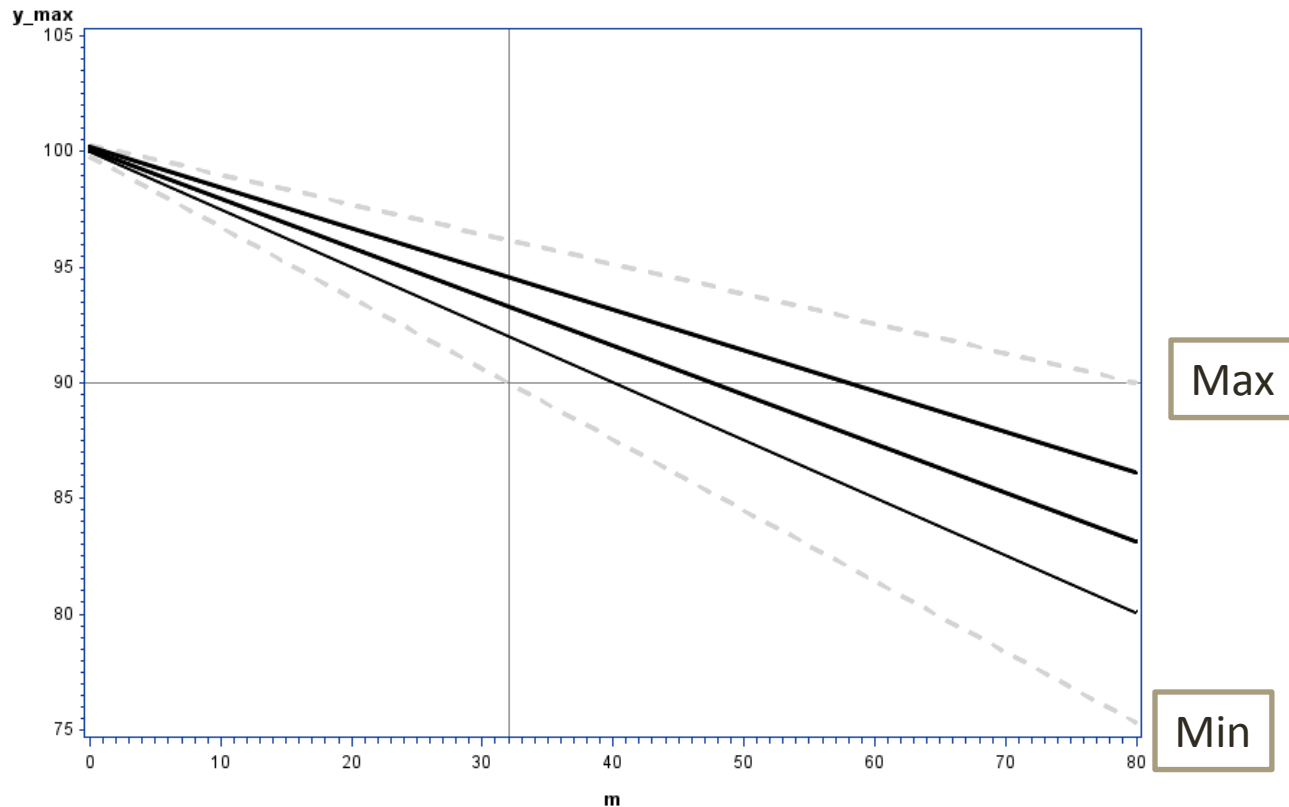
area to **left** of estimate
= $\Pr\{\text{future batch SLC} < \text{AC before labelled shelf life}\}$
if mean is target, this probability is 0.5

What does “all future batches” mean?

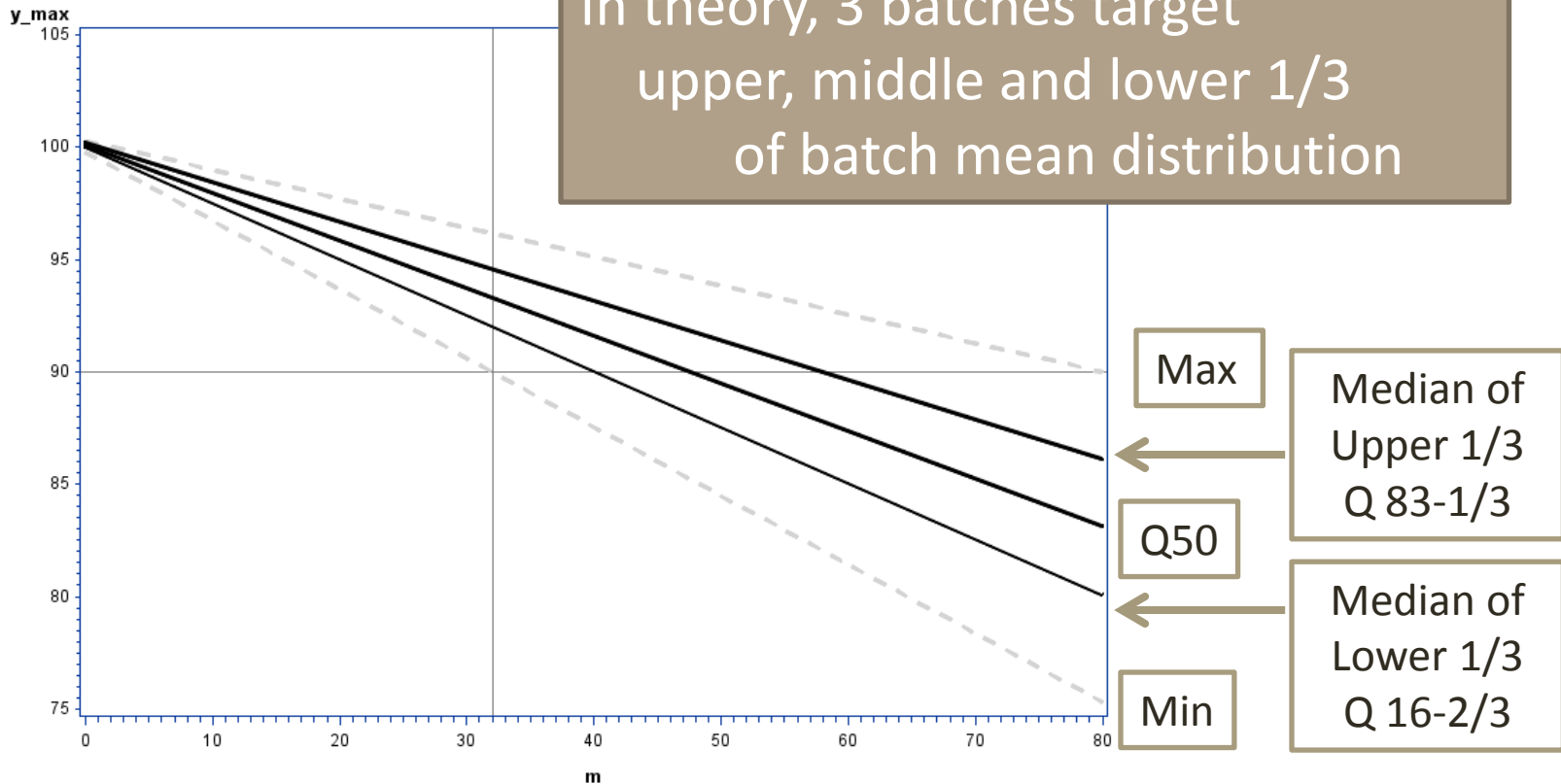


assuming estimate $\Rightarrow$ labelled shelf life, area to **right**
= $\Pr\{\text{future batch SLC remains} > \text{AC for } \geq \text{labelled shelf life}\}$
don't we want this to be $\gg 0.5$??

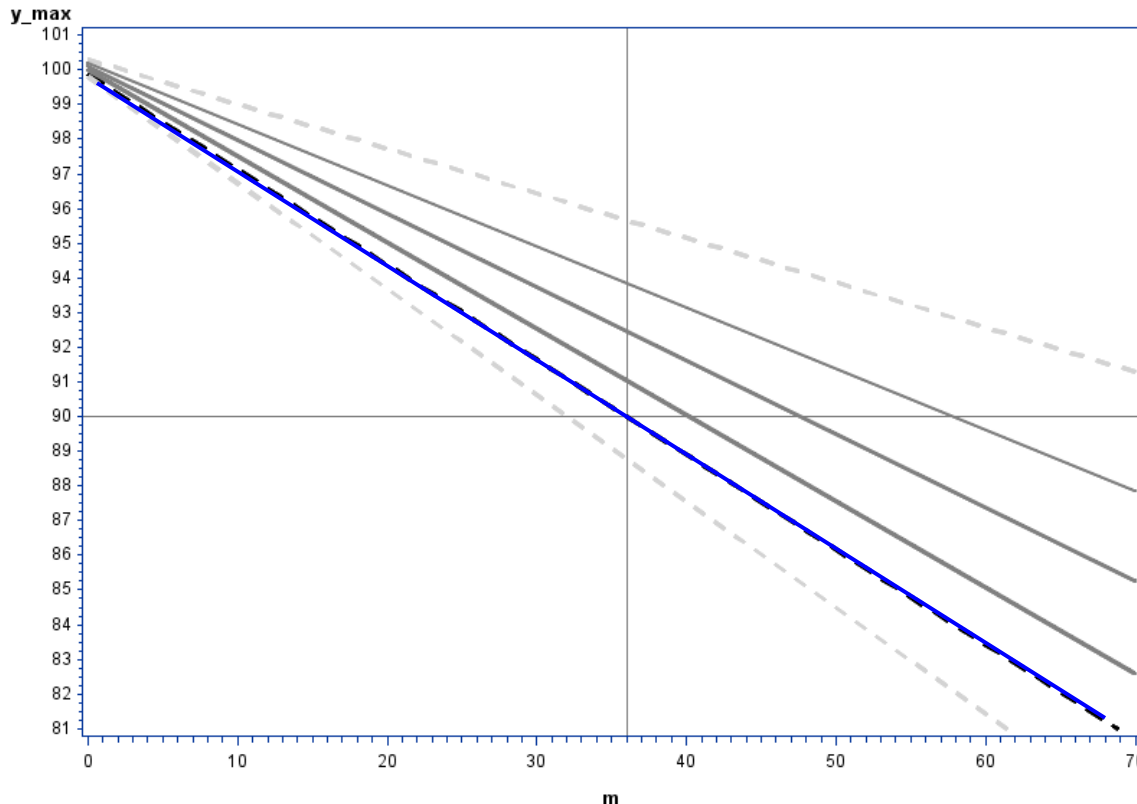
What does each batch target?



What does each batch target?



Mixed Model BLUP – Quantile Regression



Goal: Predict M corresponding to desired Quantile

Mixed Model quantile regression?

One viable approach...

...LCL of BLUP of shortest-lived batch – align with desired Quantile

LMM Quantile via LCL BLUP

- ❑ Let S_i denote shelf life of i^{th} batch
- ❑ $AC = \beta_0 + b_{0i} + (\beta_1 + b_{1i})S_i$
- ❑ therefore $S_i = \frac{AC - (\beta_0 + b_{0i})}{\beta_1 + b_{1i}}$
- ❑ Using BLUP of shortest lived batch targets Q16-2/3
- ❑ Using LCL of confidence interval with $\alpha = 0.30$
targets Q05 (5th percentile of batch mean distribution)
- ❑ $\Rightarrow$ use $\hat{S}_i = \frac{AC - (\hat{\beta}_0 + \hat{b}_{0i})_{LCL}}{(\hat{\beta}_1 + \hat{b}_{1i})_{LCL}}$

Another Approach – Direct LMM-based

- ❑ Assuming $\sigma_{01} = 0$, $y_{ij}|M \sim N(\mu_{ij}, \sigma_0^2 + M^2\sigma_1^2 + \sigma^2)$
- ❑ $\mu_{ij} = \beta_0 + \beta_1 M$
- ❑ Given M , proportion of distribution between $\beta_0 + \beta_1 M \pm Z_{\alpha/2} \sqrt{\sigma_0^2 + M^2\sigma_1^2 + \sigma^2}$ is $(1 - \alpha)$
- ❑ Shelf life is M such that $AC = \beta_0 + \beta_1 M - Z_{\alpha/2} \sqrt{\sigma_0^2 + M^2\sigma_1^2 + \sigma^2}$
- ❑ With estimated regression coefficients and variance components, use t rather than Z

Bayesian

- Fit Random Coefficient LMM

- Shelf Life Definition 1: $\hat{S} = \frac{AC - \hat{\beta}_0}{\hat{\beta}_1}$

- Shelf Life Definition 2:

- $y_{ij} | b_{0i}, b_{1i} \sim N(\beta_0 + b_{0i} + (\beta_1 + b_{1i})M, \sigma^2) \Rightarrow$

- $\alpha = Pr\{AC < Y\} = Pr\left\{\frac{AC - \mu}{\sigma} < Z_\alpha\right\}$, where $\mu = \beta_{0i} + \beta_{1i}S$

- Solving for S $\Rightarrow \hat{S}_i = \frac{AC - \hat{\beta}_{0i} - \hat{\sigma}Z_\alpha}{\hat{\beta}_{1i}}$

- Use MCMC to obtain posterior distributions

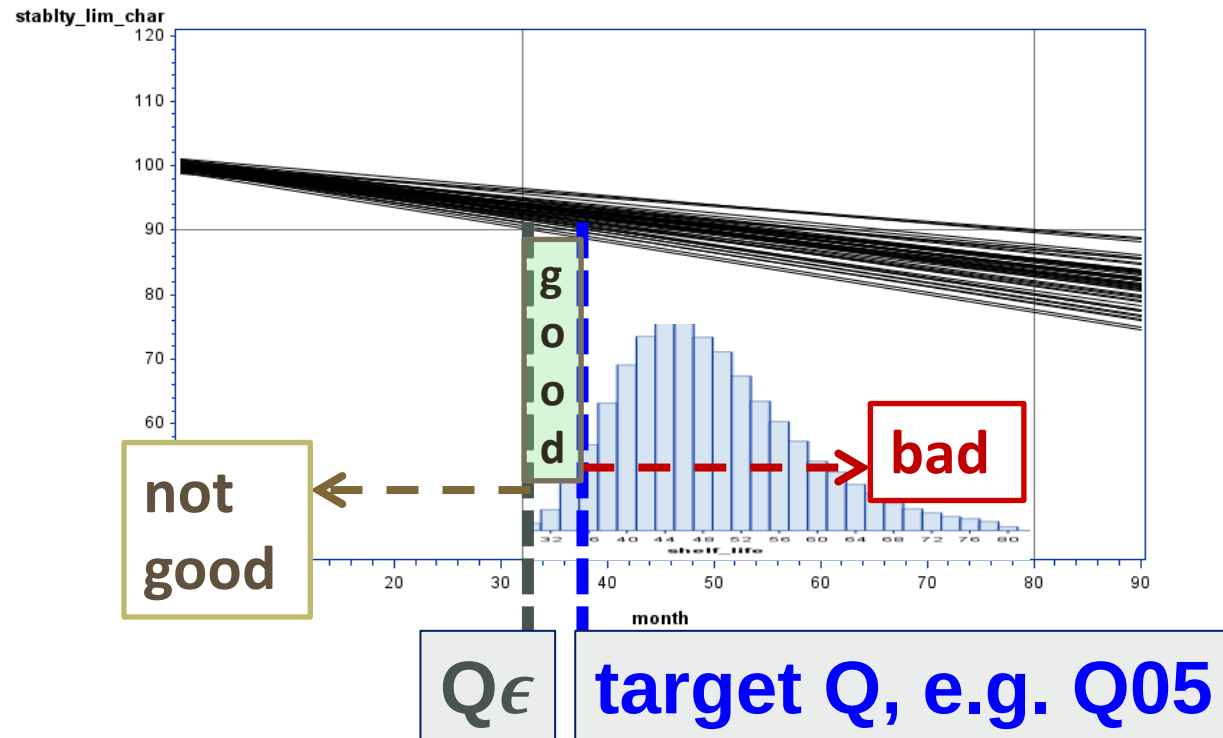
- Use lower credible interval bound corresponding to Q

Criteria for Assessing Performance

- All future batches mandate
 - how to interpret
 - needed: operating definitions
 - of target of shelf life estimator / predictor
 - of “good” estimator / predictor
- Example: suppose target is 5th percentile (Q05)
 - $\hat{S}$ should target Q05 of the shelf-life distribution
 - “Price is Right” criterion (as close to target without going over)
 - with regard to patient and Prob {product “fails” before stated lifetime}
 - $\hat{S} > Q05$ **unacceptable**
 - $\hat{S} = Q05$ **ideal**
 - $\hat{S} < Q05$ (but close) **good**
 - $\hat{S} \ll Q05$ (especially below $Q\epsilon$ where $\epsilon \rightarrow 0$) **not good**

Visualize Criteria

■ Coverage



■ Truncated Mean Square Prediction Error (MSPE)

- Good: $\propto \sum I(\widehat{SL} \leq Q05)(\widehat{SL} - Q05)^2$
- Bad: $\propto \sum I(\widehat{SL} > Q05)(\widehat{SL} - Q05)^2$

What we know to date

- ❑ Simulation study, Stroup and Quinlan, 2015

- ❑ Characteristics drawn from

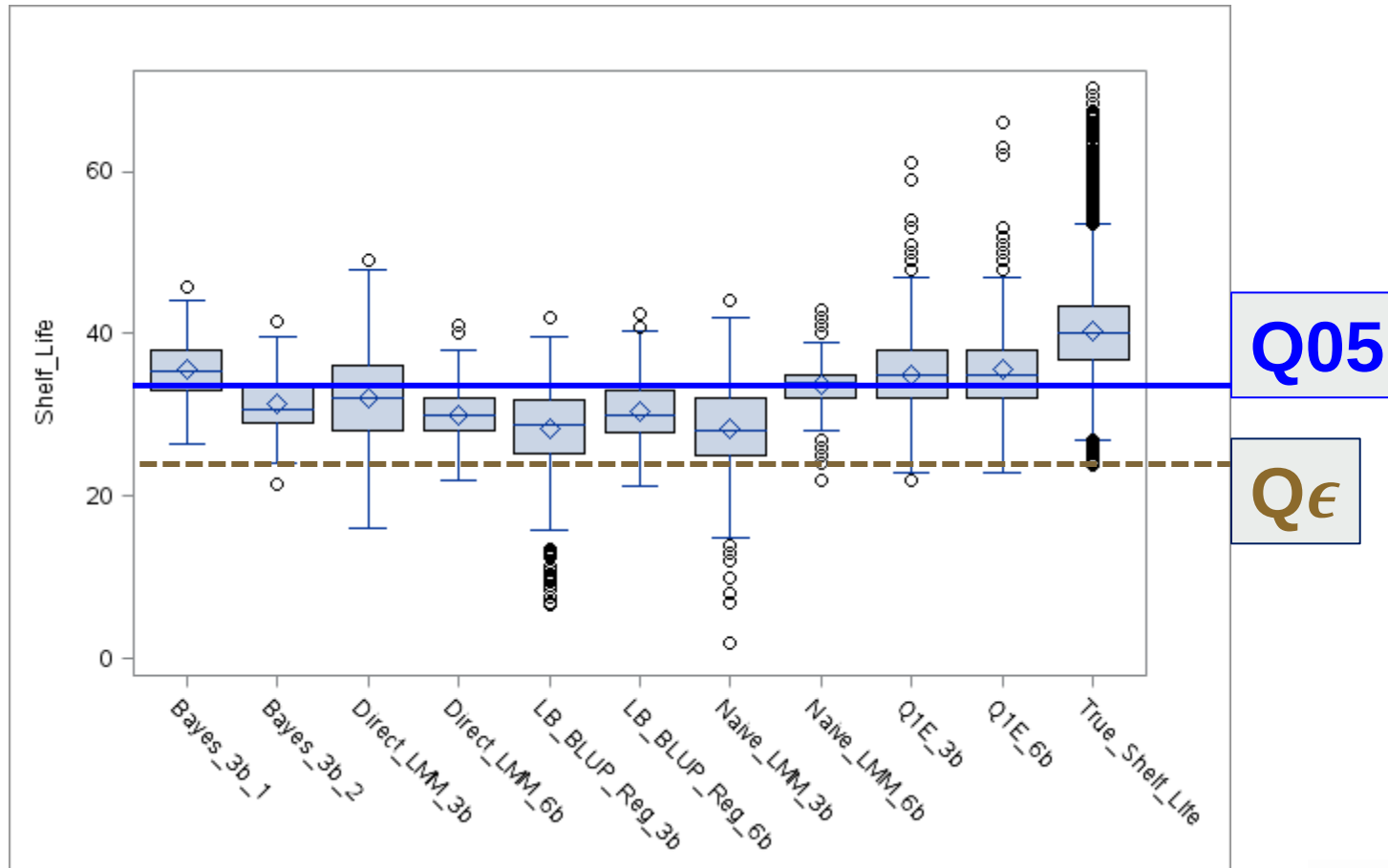
- Alton, et al. 2013, survey of stability trial parameter estimates
- Capen, et al. 2017, industry data provided to PQRI SSL WG

- ❑ Simulation Description

- 1000 simulated trials with 3 batches and 1000 with 6 batches
- $\beta_0 = 100, \beta_1 = -0.25, \sigma_0^2 = 0.5, \sigma_1^2 = 0.000625, \sigma^2 = 0.5, \sigma_{01} = 0$
- Assume one assay per batch at each time of measurement
- $\hat{S}$ computed from Q1E, naive LMM, LB BLUP, Direct and Bayes
- **Plot** distribution of $\hat{S}$ relative to $Q05$ and $Q\epsilon$
- **Table**
 - MS(prediction error)
 - “Coverage” – proportion $Q\epsilon < \hat{S} < Q05$

What we know to date

- distribution of $\hat{S}$ by method and number of batches



What we know to date

□ Performance of $\hat{S}$ by method and number of batches

Method	Number Batches	MSPE			Coverage %
		Good	Bad	Net*	
Q1E	3	3.22	28.35	-25.12	49
	6	2.73	35.78	-33.04	42
Naive LMM	3	39.06	3.72	35.34	67
	6	2.17	8.30	-6.14	64
LB BLUP	3	40.31	1.87	38.44	72
	6	11.61	2.93	9.38	83
Direct	3	14.27	16.64	-2.36	60
	6	11.76	1.43	10.33	89
Bayes – Defn 1	3	1.06	26.24	-25.18	31
Bayes – Defn 2	3	8.57	4.76	3.81	78

* Net MSPE should be positive and small

Summary

❑ All future batches mandate $\Rightarrow$ predictor for $\hat{S}$

❑ Q1E Current Practice

- Inconsistent with how data arise and mandated inference space
- Small sample behavior disquieting

❑ Alternatives

- LMM
- But LMM with attention to mandated inference space

❑ Assessment of Alternatives

- simulation
- criteria – we use Good/Bad MSPE and “coverage” --- other ideas?

❑ With 3 batches

- upper limit on ability to predict future performance
- but LB BLUP and Bayes, Definition 2 show promise

Future Work

- ❑ More simulation scenarios
- ❑ Other Methods Under Consideration
 - Tolerance Interval
 - Refine BLUP and Bayes
 - Other Bayes Methods, e.g. Predicted Probability Distribution
- ❑ Eventual Goal: propose method(s)
 - that show consistently desirable behavior
 - can be implemented with available software
 - e.g all computations in this presentation used SAS® PROC GLIMMIX or PROC MCMC

References

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Acknowledgements

PQRI Stability Shelf-Life Working Group Membership (2017)

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That's all - thanks



Questions?

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