

Predicting power of future studies in the presence of uncertainty about the variance

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Outline

- Introduction & motivating example
- Analysis of historical data
 - Estimate important parameters
- Simulations and comparison with classical power/sample size results

Overview

- Need to design safety studies with adequate power/precision.
- Classical methods assume a known variance.
 - Allow only for sampling variation
 - In reality, the variance may vary between studies.
- Historical data can be used to explore the distribution of the study variances
- This uncertainty can be incorporated into power/sample size calculations

Motivating example

- Telemetered Dog CV Study
- Typically 4×4 crossover
 - Vehicle + 3 doses of compound
- 24-hour telemetry of cardiovascular parameters
 - QT_c, heart rate, blood pressure....
 - 3 or 4 summary time bins
 - E.g. 1-3hr; 4-6hr; 7-14hr; 14-24hr
- Analysed using linear model (ANOVA) for each time bin
 - (fit Animal, Period, Treatment)
 - Precision determined by the residual variance, s^2 .

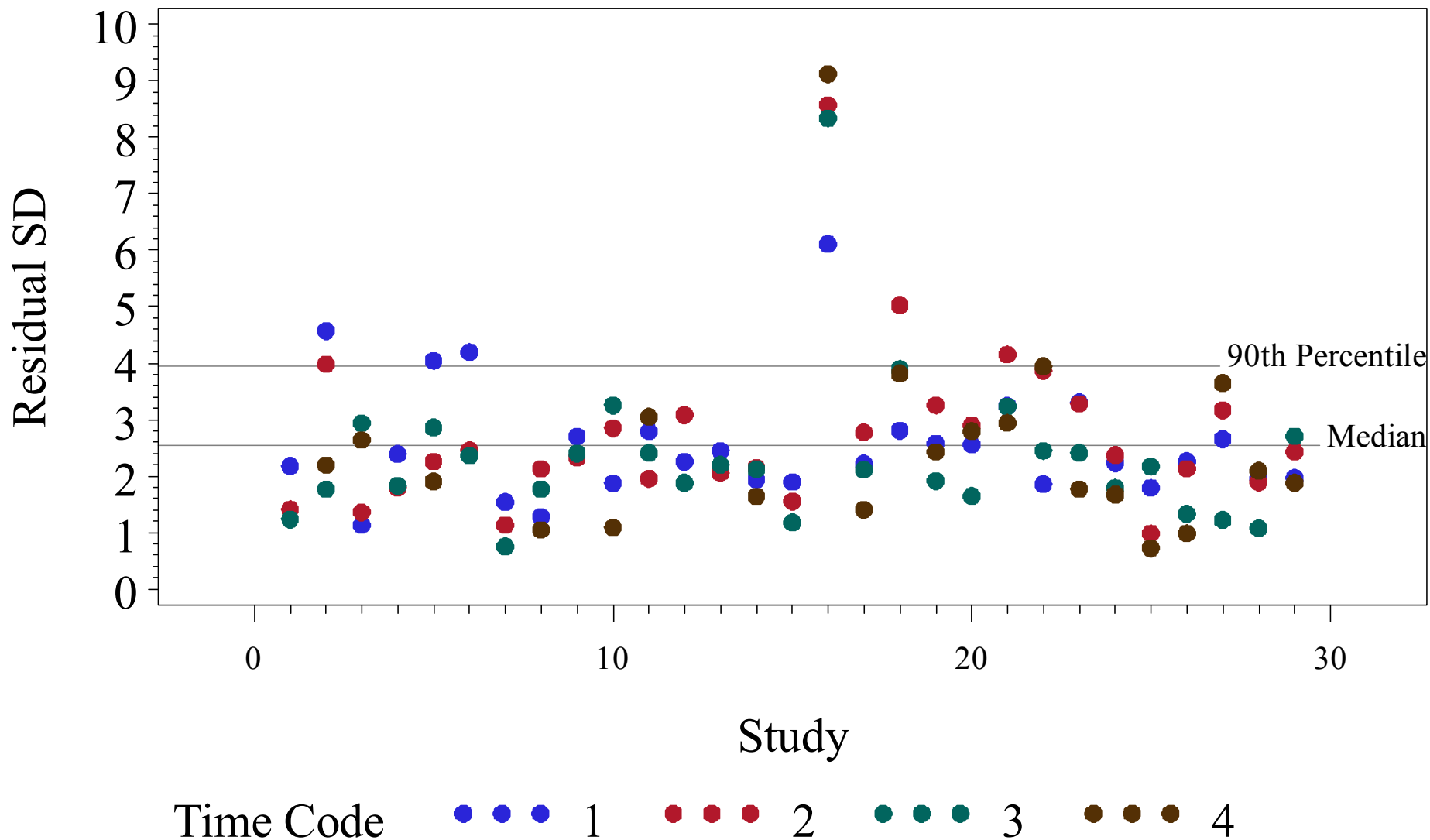
Historical Data

- 29 studies
- Each study has 3 or 4 time bins
- This presentation just considers QTc

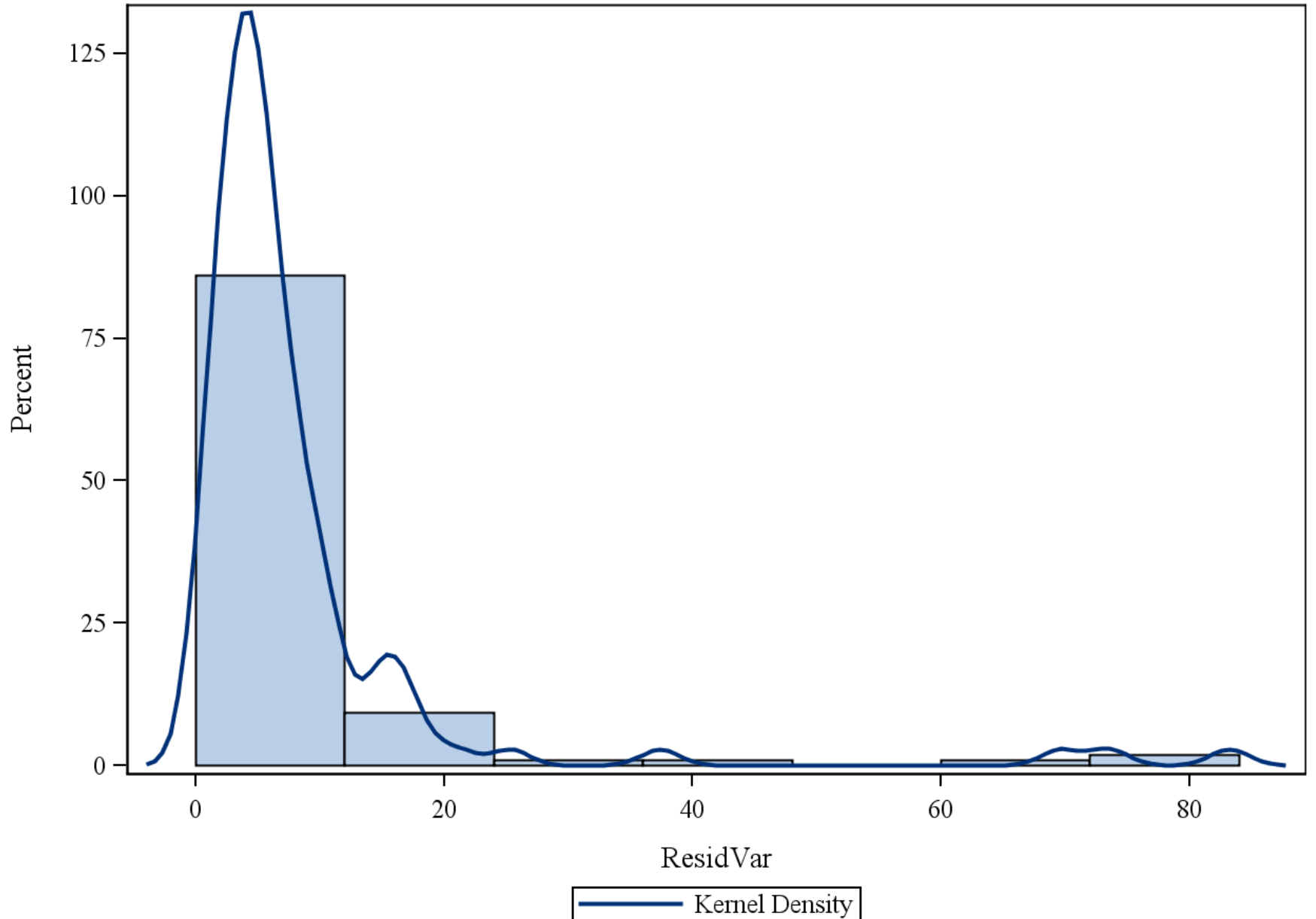
QTc: Residual Variance (s^2 - 6 d.f.)						
n	Mean	Median	Min	Max	90%	IQR
108	8.40	5.04	0.53	83.2	15.6	3.23 – 8.31

- The assumption of constant σ^2 may not be reasonable

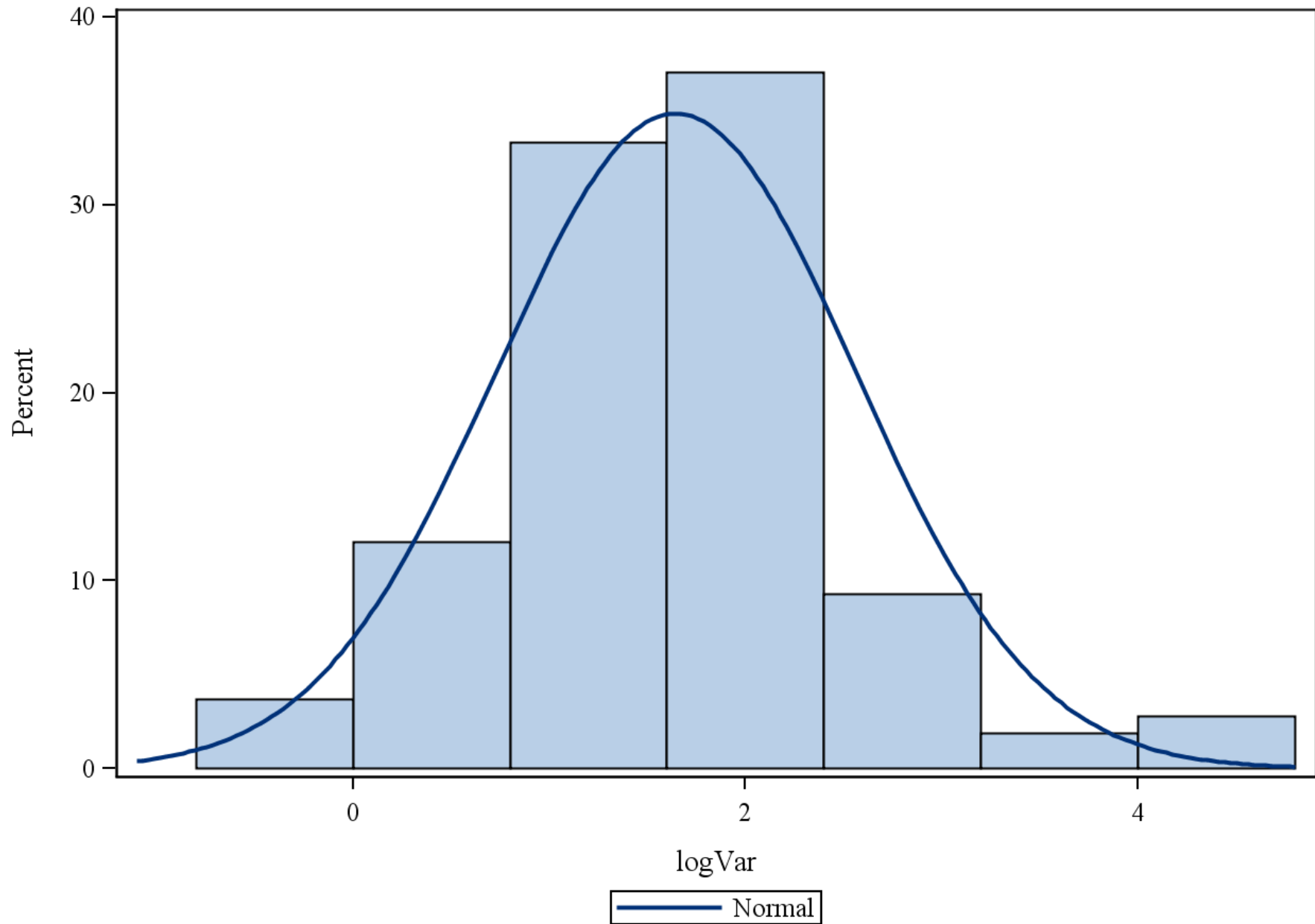
Plot of residual standard deviations



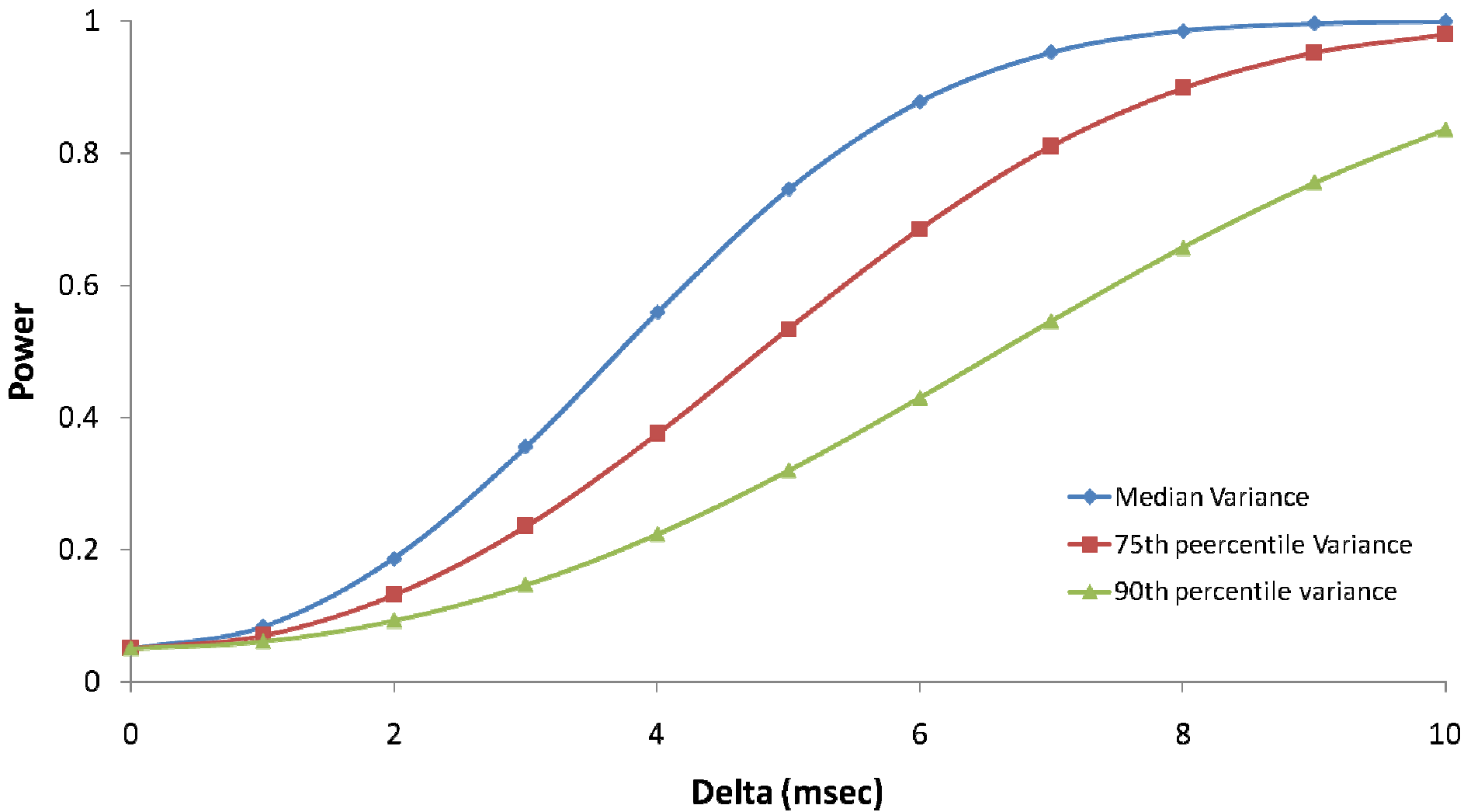
Histograms of Residual Variance for QTc



Histograms of $\log(\text{Residual Variance})$ for QTc



Conventional Power Curves (4x4 crossover - pairwise comparison)



Study to Study variation

- If underlying variance is constant ($= \sigma^2$) then the observed variance, s^2 , has a scaled chi-squared distribution

$$v \cdot s^2 / \sigma^2 \sim \chi^2_{(v)}$$

- If some studies have higher variability than others (σ^2 is not constant), then conventional power/sample size calculations may be misleading.

Fitting distributions

Sample variance has scaled chi-squared distribution, based on true variance for that study

$$s_i^2 \sim \frac{\sigma_i^2}{\nu} \chi_{\nu}^2 \equiv \text{Gamma}\left(\frac{\nu}{2}, \frac{\nu}{\sigma_i^2}\right)$$

Assume true study variance has either logNormal or Gamma distribution

$$\log(\sigma_i^2) \sim \text{Normal}(\mu, \theta^2)$$

$$\sigma_i^2 \sim \text{Gamma}(r, \mu)$$

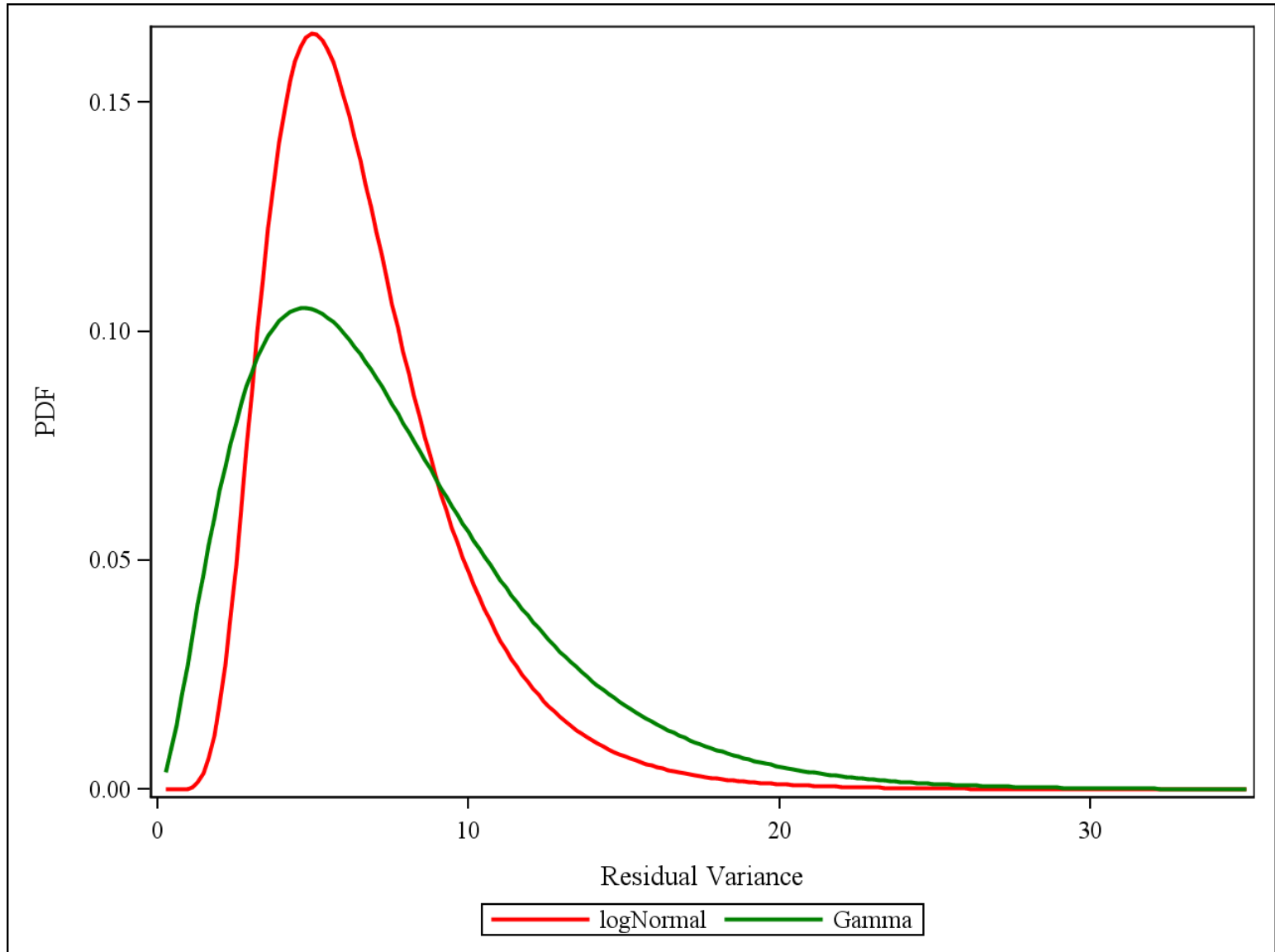
Estimate parameters (using WinBUGS) with vague priors

Model comparisons

- LogNormal and Gamma models fitted for σ_i^2
 1. Variance constant within a study ($i=1\dots 29$)
 2. Variance unconstrained ($i=1\dots 108$)
- Deviance information criterion (DIC) used to compare models

Constant				σ^2	DIC
				8.40	757
LogNormal	Study-based	μ	θ	6.05	576
	Unconstrained	1.81	0.50		596
Gamma	Study-based	r	μ	7.44	580
	Unconstrained	2.51	0.33		599

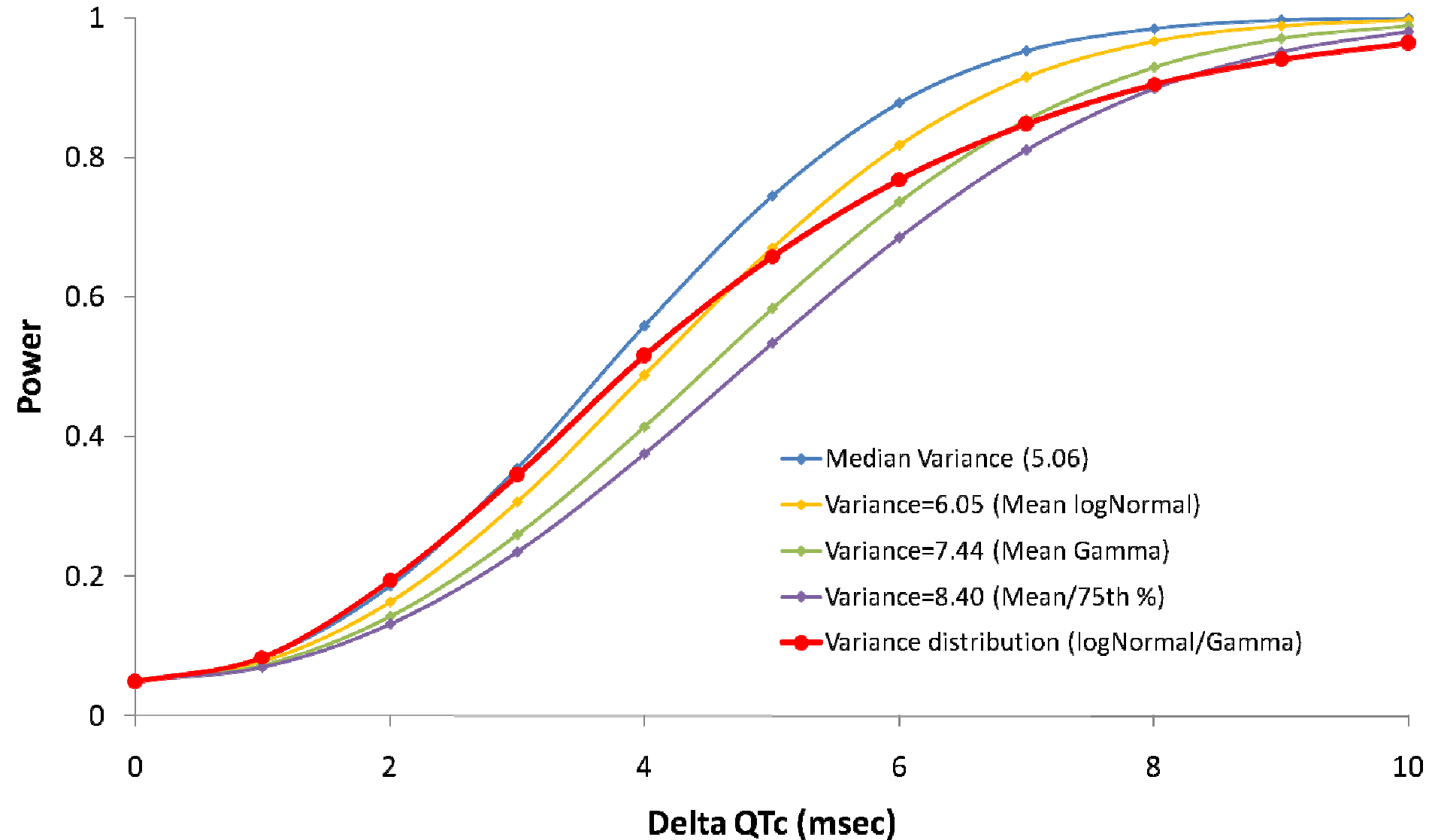
Fitted PDFs



Simulations (pairwise comparison)

- Simulated the true variance, σ^2
 - LogNormal - Mean=1.80; SD=0.44
 - Gamma – $r=2.69$; $\mu=0.36$
- Simulated sample variance, s^2
 - Chi-squared, v d.f. (v=6 for 4×4 crossover)
- Simulated observed difference, d
 - Normal(δ , $2\sigma^2/n$) (n=4 for 4×4 crossover)
 - $\delta = 0, 1, 2 \dots 10$
- Calculated SED, t-statistic, P-value, confidence limits
- 10000 simulated studies per combination

Comparison of Power Curves (4x4 crossover)



Results/Conclusions

- Power predictions from logNormal and Gamma distributions are indistinguishable
- Simulated power is less than conventionally calculated power (using median σ^2)
- At power of $>75\%$, simulated power is similar to conventional power using 75th percentile σ^2
- Sample sizes calculated by conventional methods may have less power than anticipated.