

Improving Strategic Decision-Making with Early Prediction of Survival Outcomes in Oncology Clinical Trials

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Collaborators

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With thanks to the patients and investigators who participated in these clinical trials.

Early decision-making is a goal of all stakeholders

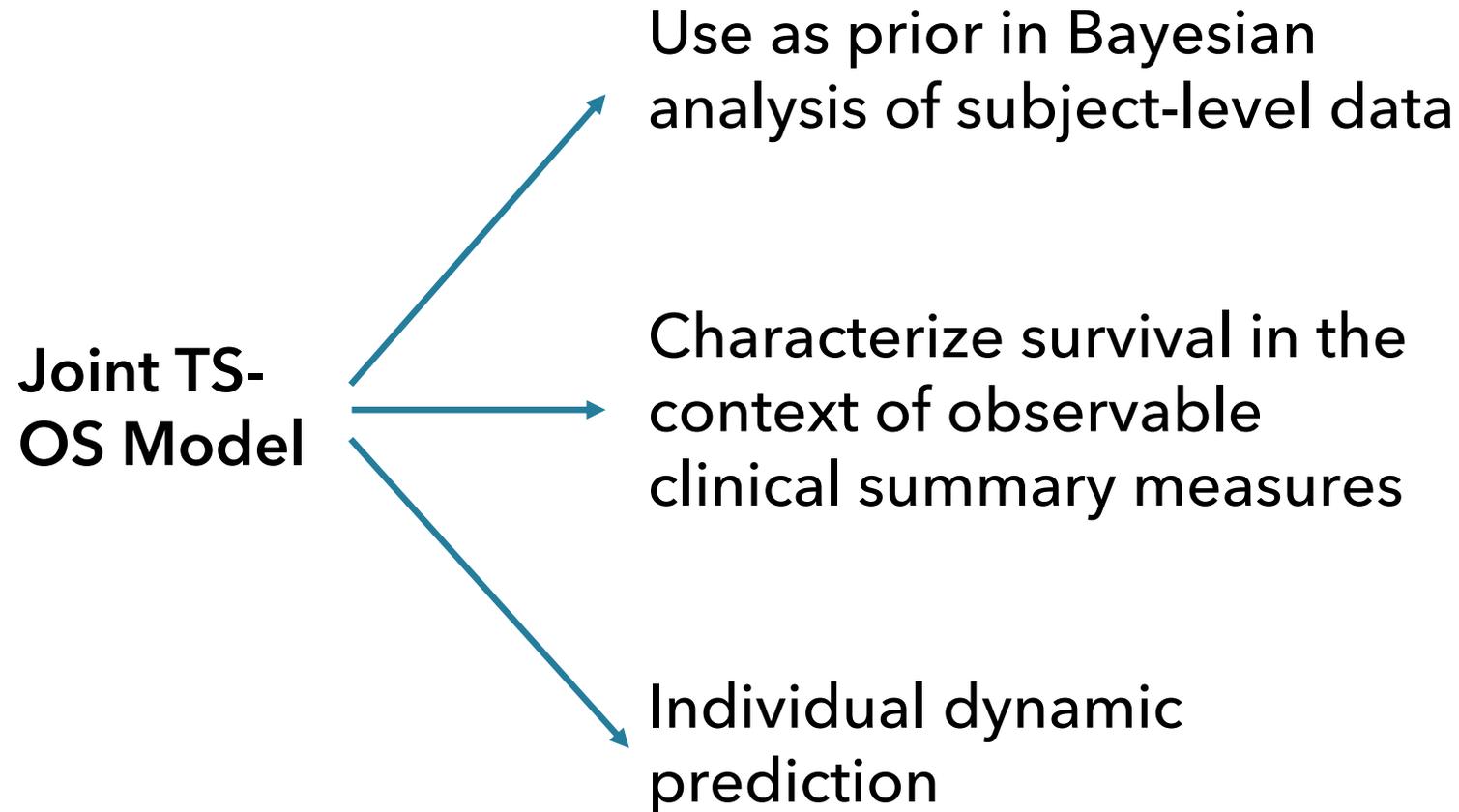
All stakeholders: get safe & effective treatments to patients quickly

Drug developers: stage investment of unpromising candidates

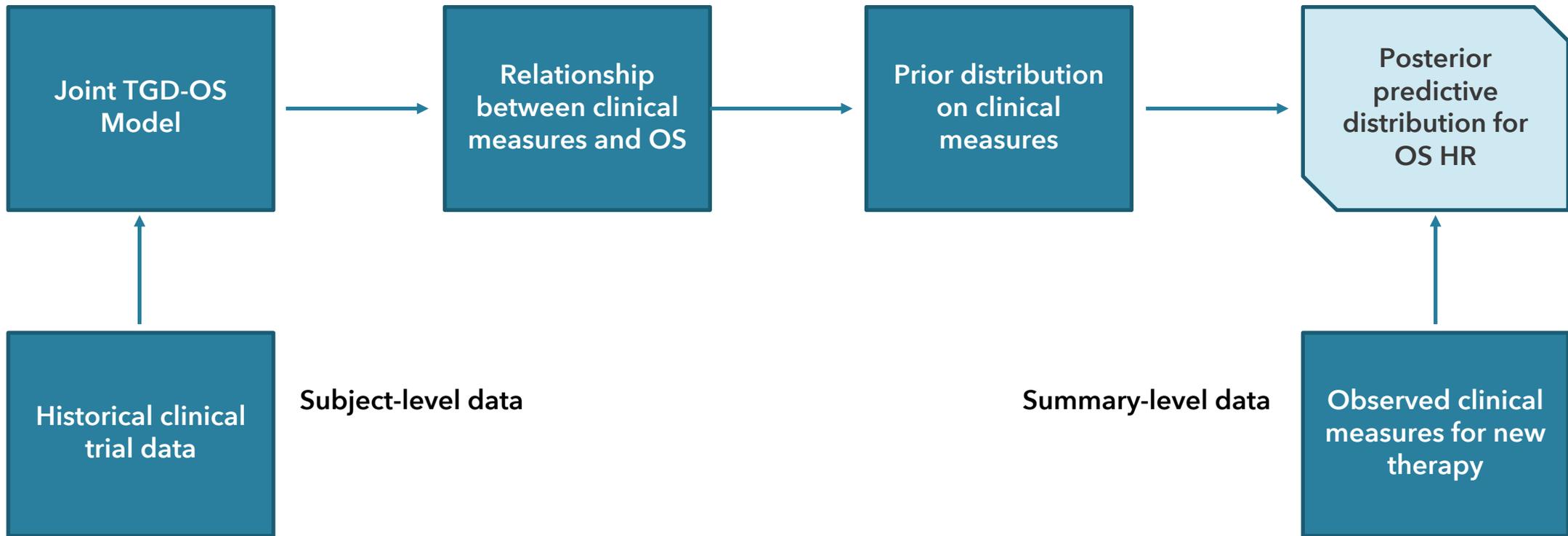
Use of modeling & simulation has grown substantially over the past 15 years

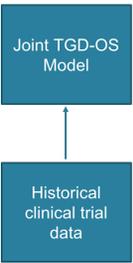
- Broad recognition of its utility (e.g., PDUFA VI)
- Impacting a variety of decisions (patient treatment, drug development, regulatory)

How do we leverage existing data to make decisions about new therapies?



Flow of proposed approach





Joint model for tumor size and overall survival

- Data from 4 clinical trials of Pembrolizumab in NSCLC (N > 2500)
 - Chemotherapy (N=720; 28%)
 - Pembrolizumab (N=1324; 52%)
 - Pembrolizumab + Chemotherapy (N=497; 20%)

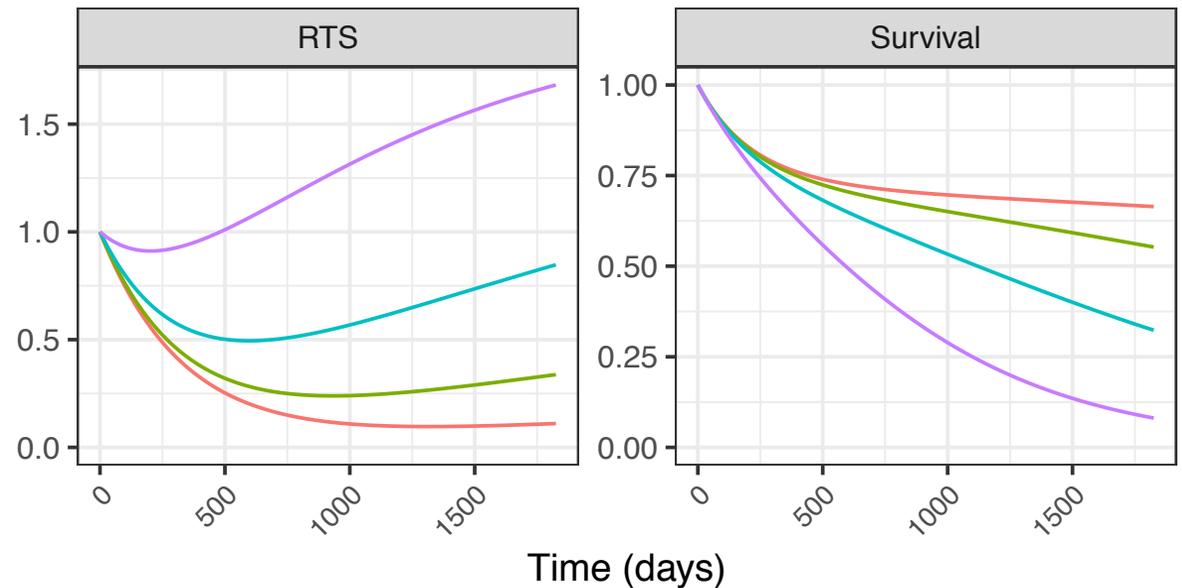
Moore model¹ for asymptotic tumor growth:

$$TS_i(t) = TS_{0,i}(5TS_{max,i})(1 - e^{-k_g,i t}) + TS_{i,0}e^{-k_d,i t}$$

Hazard function with cure fraction:

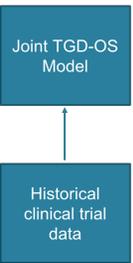
$$h_i(t|X_i) = a(X_i)e^{\beta \cdot \log(RTS_i(t))}e^{-\lambda t}$$

where $RTS(t) = \frac{TS(t)}{TS_0}$, α and λ are distributional parameters, and X_i is a vector of baseline predictive factors and effects.

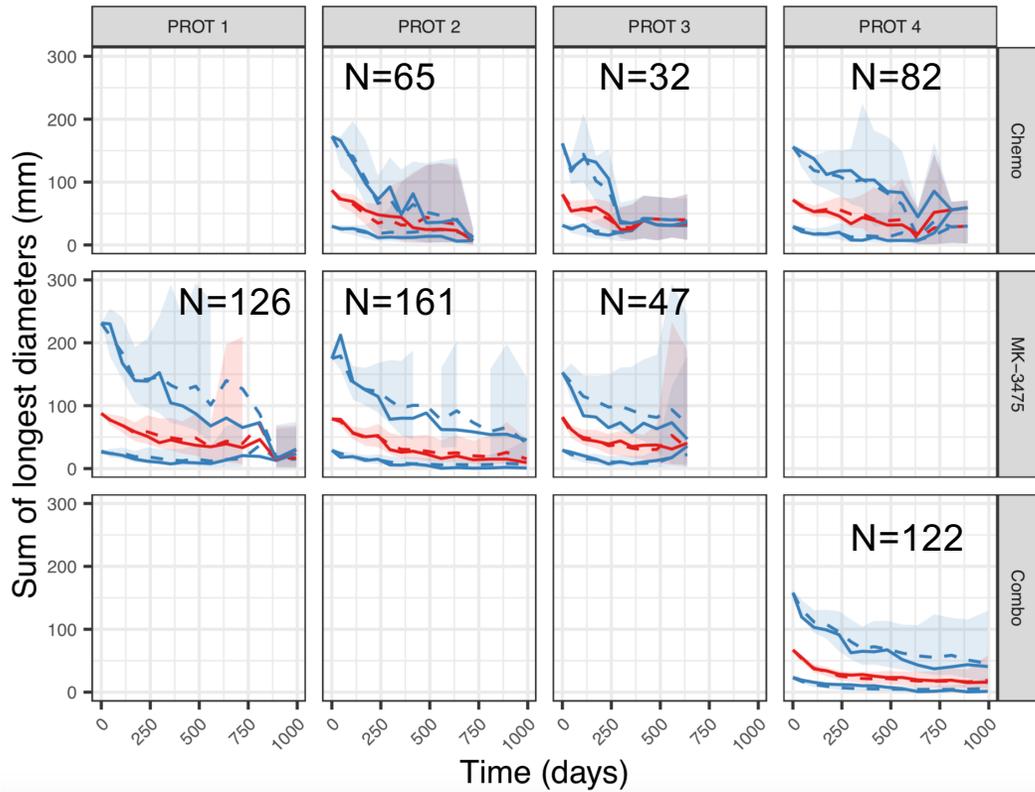


1. Moore, H. A New Tumor Dynamics Mathematical Model. *American Conference on Pharmacometrics* (2016):Poster W-29.

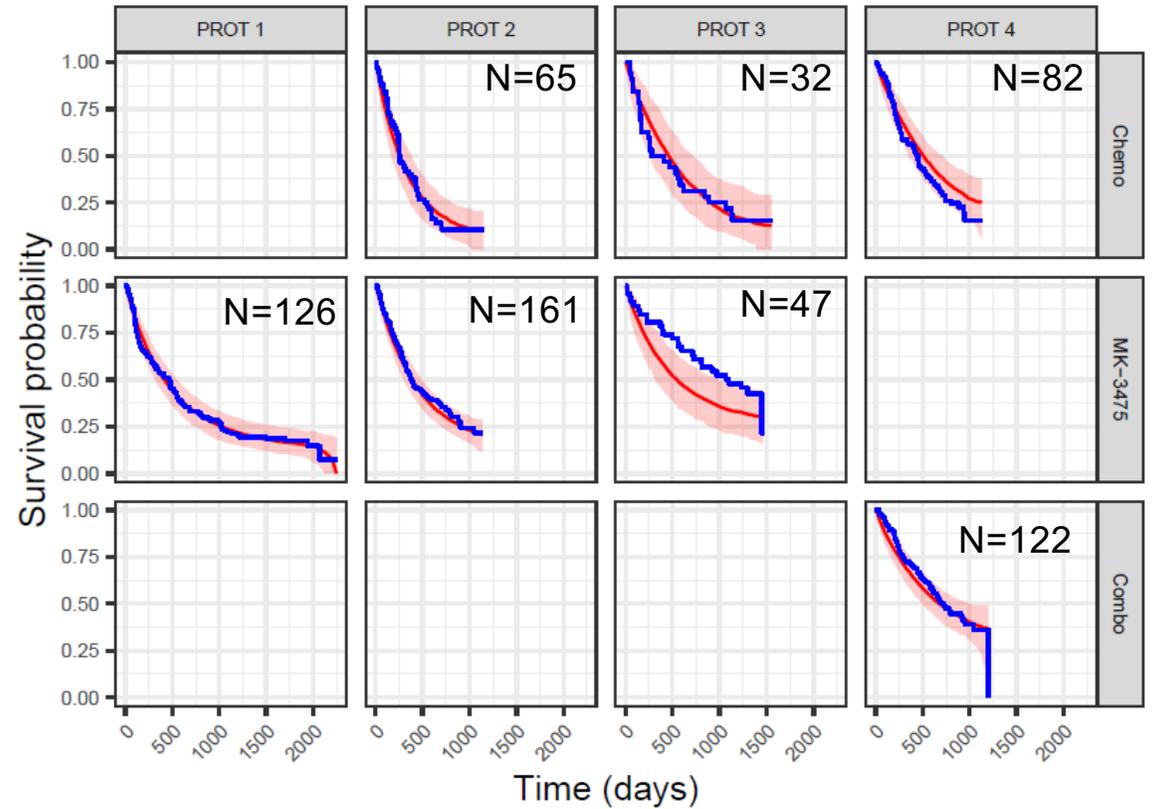
Joint model provides good out-of-sample prediction of tumor dynamics and OS



Percentiles — 10 — 50 — 90 Data — Observed — Simulated



95% Prediction Interval Observed Survival Simulated Survival



Validation Data (n= 635)

Modulation of individual TS parameters highlights dynamic impact on OS outcomes.

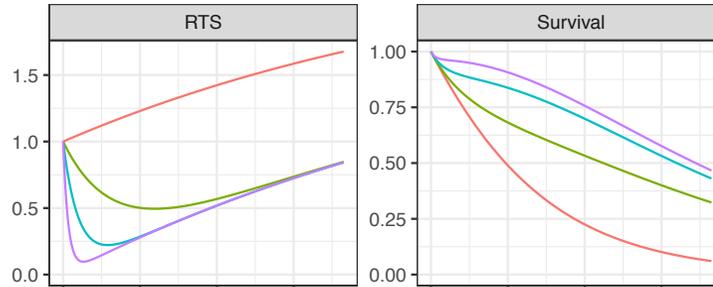
Joint TGD-OS
Model

Relationship
between
clinical metrics

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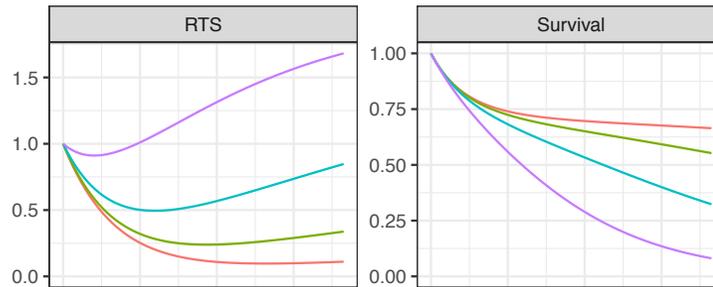
Depth

Modulate
Kdying



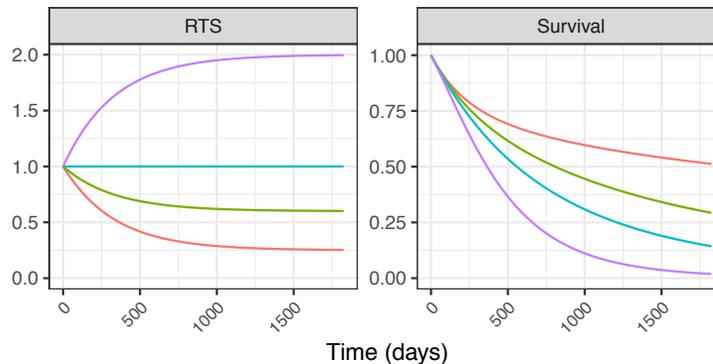
Durability

Modulate
Kgrow



Depth & Durability

Modulate
Plateau



Difficult to predict how modulation of >1 parameter will impact OS.

Moore model¹ for asymptotic tumor growth:

$$TS_i(t) = TS_{i,0} (5TS_{i,max}) (1 - e^{-k_i g t}) + TS_{i,0} e^{-k_i d t}$$

Hazard function with cure fraction:

$$h_i(t|X_i) = a(X_i) e^{\beta \cdot \log(RTS_i(t))} e^{-\lambda t \lambda}$$

Multiple clinical measures could be used to describe tumor response

Joint TGD-OS
Model

Relationship
between
clinical metrics

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Effects on depth of response

- Difference in mean best relative change from baseline at $t \leq T$.
- Difference in mean relative change from baseline at $t=T$.
- Difference in proportion of patients with best change from baseline at $t \leq T$ of $\leq 0, 10, 30, 50\%$.

Effects on durability of response

- Hazard ratio for time-to-rebound (20% growth from nadir; "tPFS").

$T = [18, 27, 36, 45, 54, 63, 72]$ weeks

Prior distributions for new theoretical treatments

Relationship
between
clinical
measures and
OS

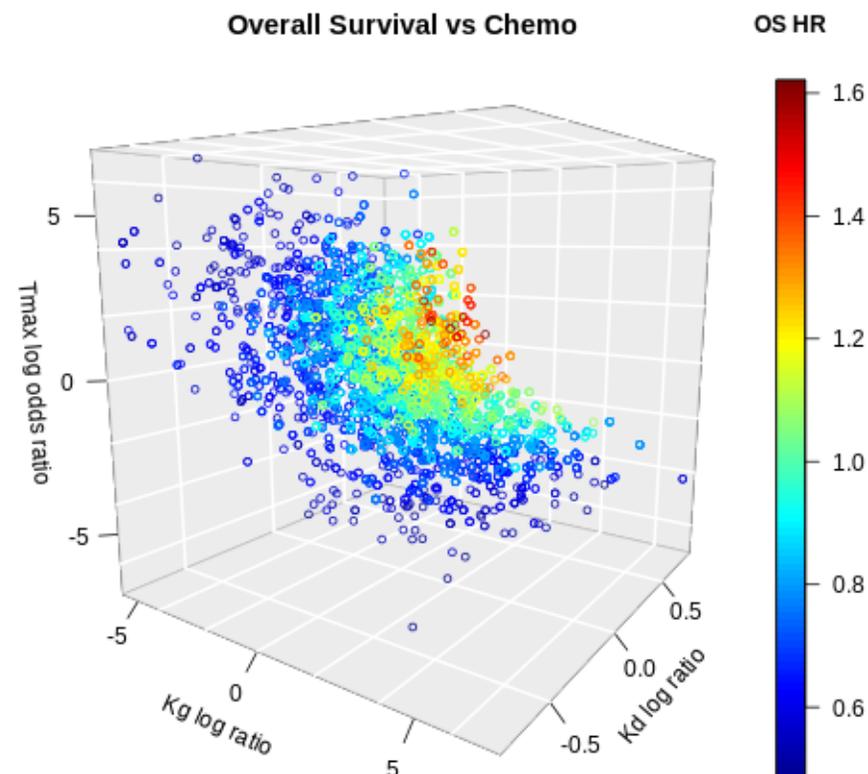
Prior
distribution on
clinical
measures

Using the reference model as a prior distribution for a new therapy, we constrain parameter space by the likely correlations between parameters observed previously

Derivation of Priors in THETA-space for simulation of novel therapies

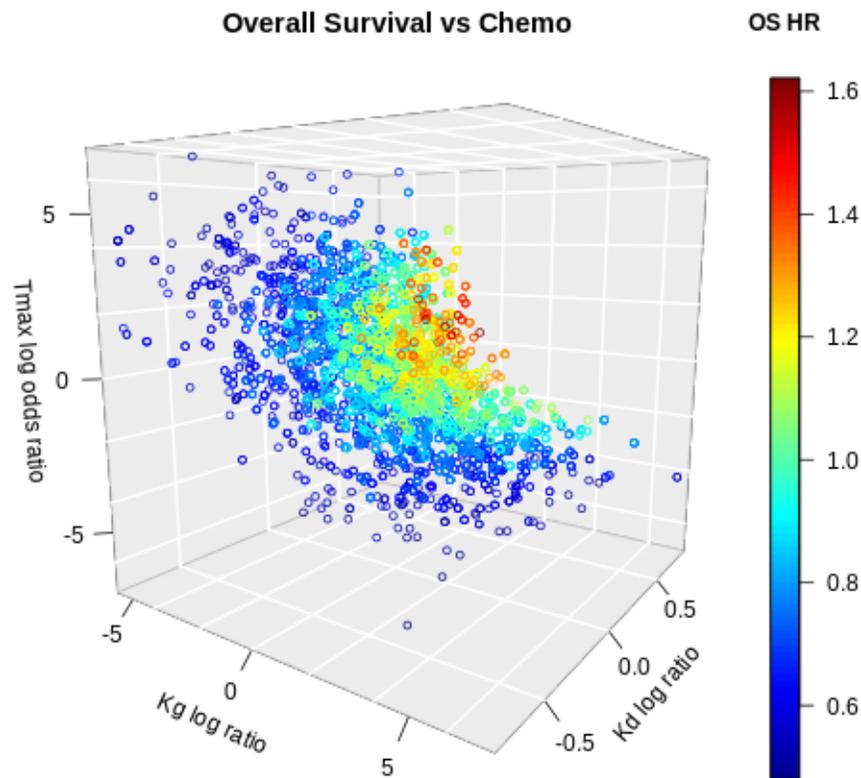
	TS main effects	Other parameters
Chemo arm	Reference model standard error	Reference model standard error
New arm	Standard deviation = 1 "Pembro effect"	Reference model standard error

This gives ~16% probability that the novel therapy has an effect greater than Pembro.

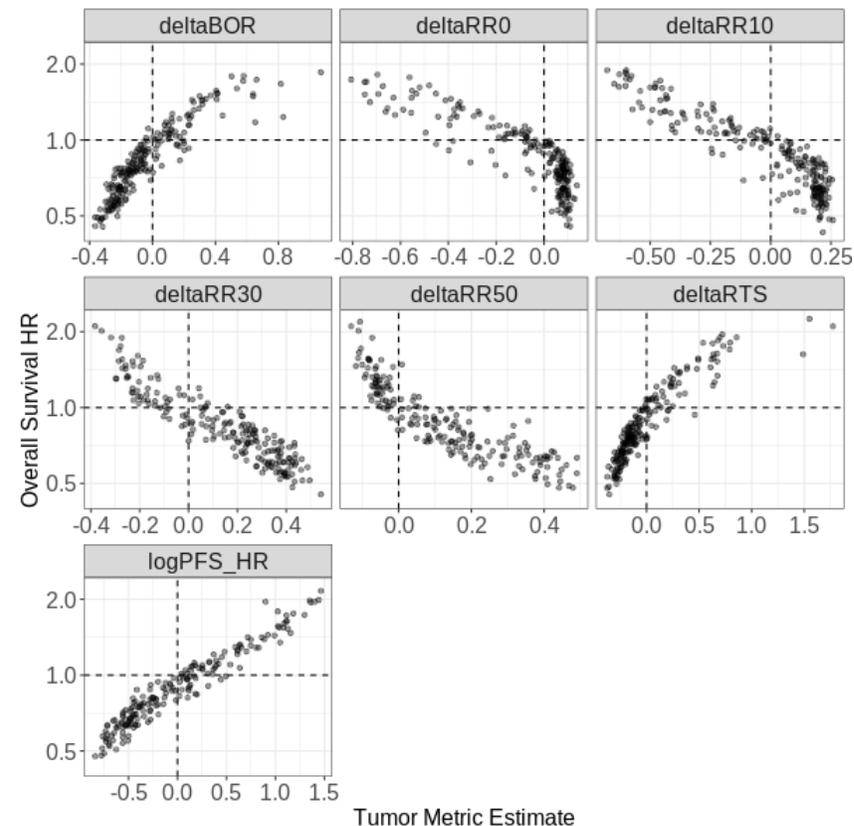


OS is predicted to improve ($HR < 1$ relative to chemo) when Kg and Tmax decrease, or Kd increases.

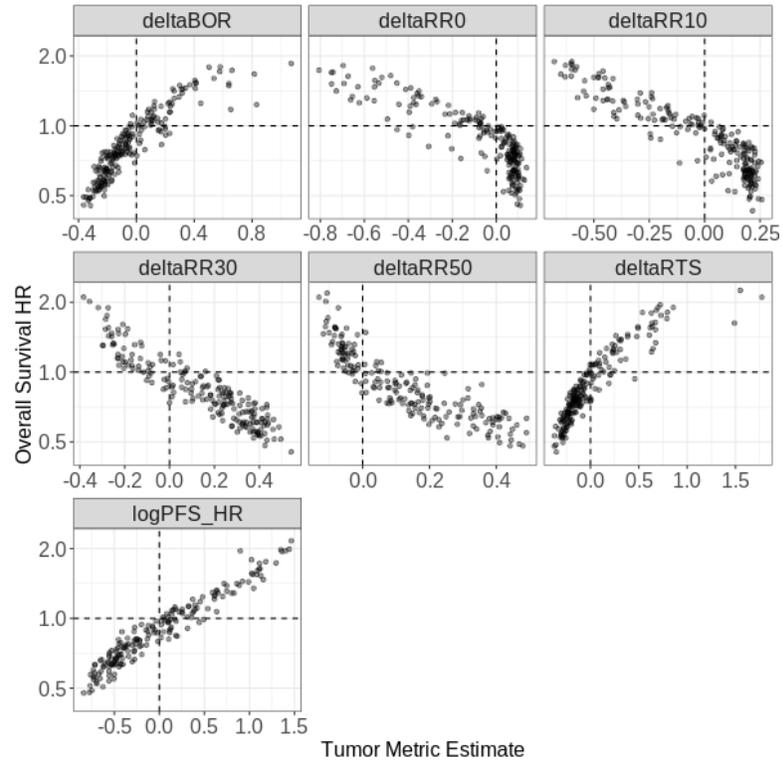
Converting THETA-space priors into clinical-space priors



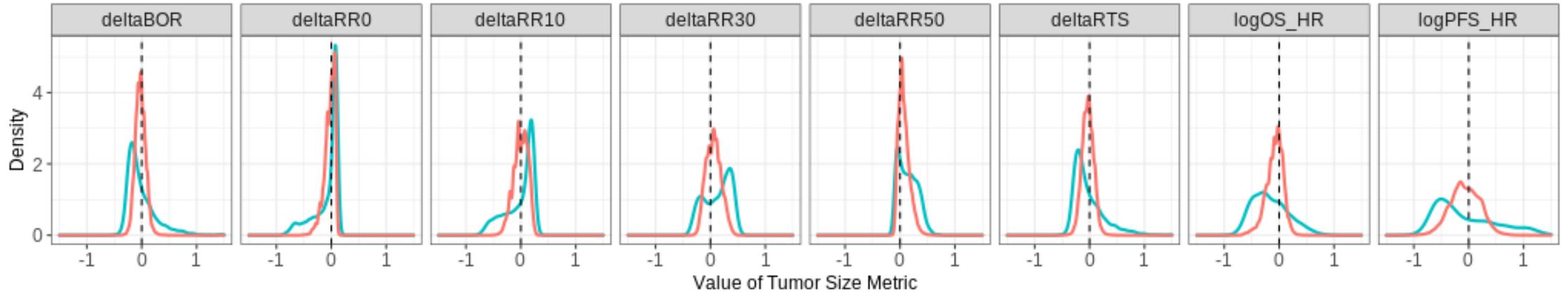
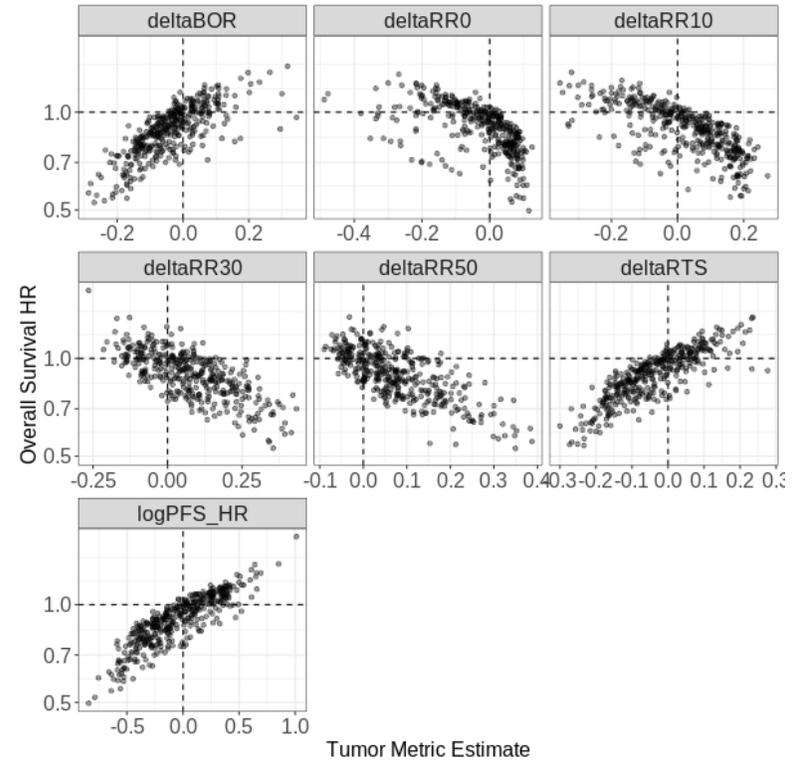
*Mapping
via simulation*



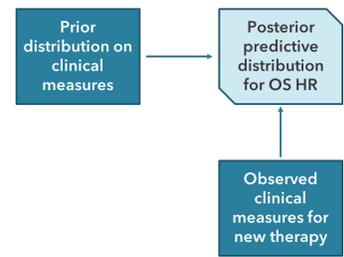
Modifying priors on clinical measures



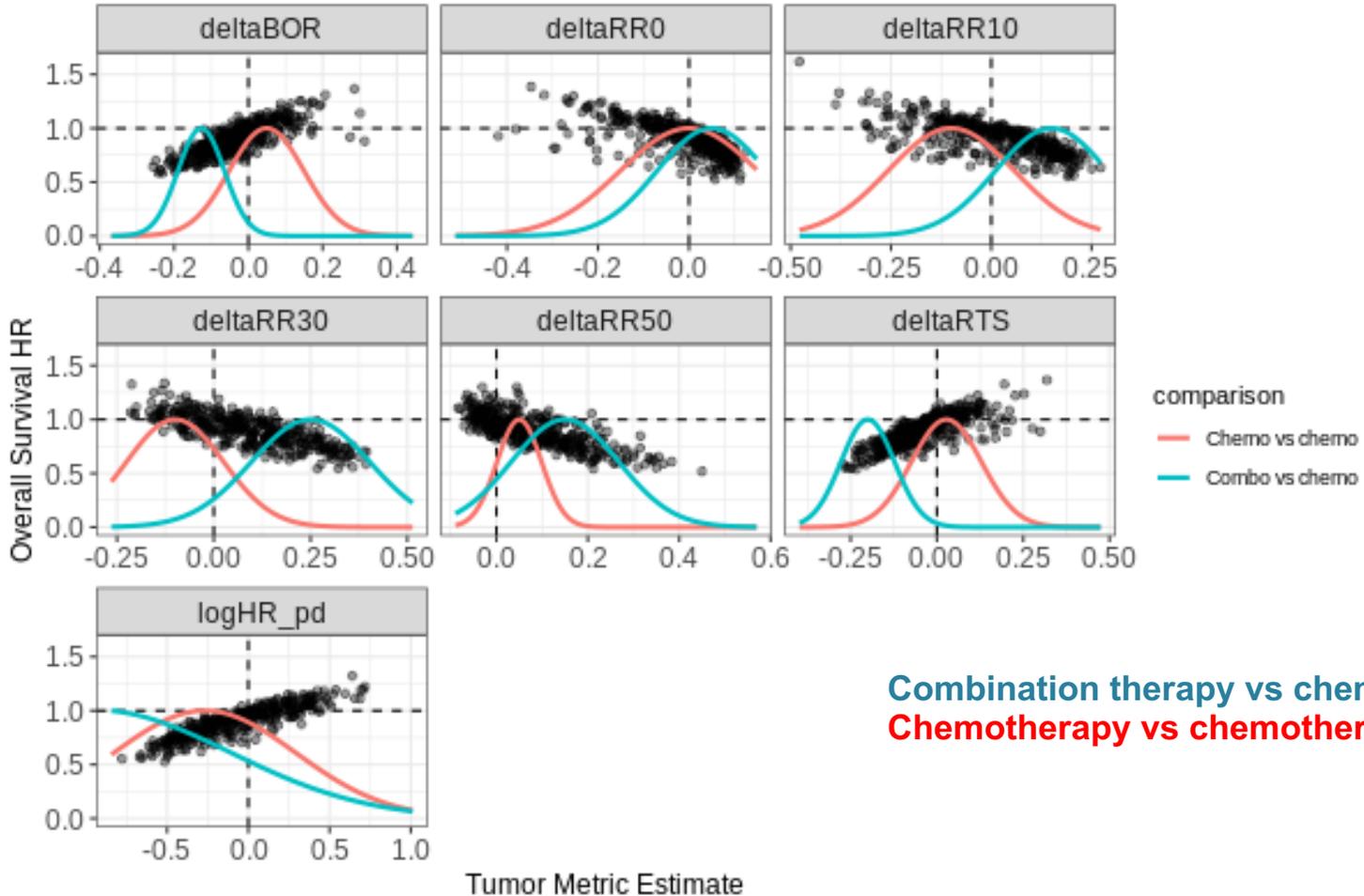
Importance sampling
→



Application of model to two hypothetical therapies

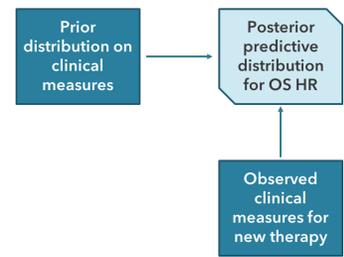


Observed data at 18 weeks from randomly sampled data set of 20 patients/arm.

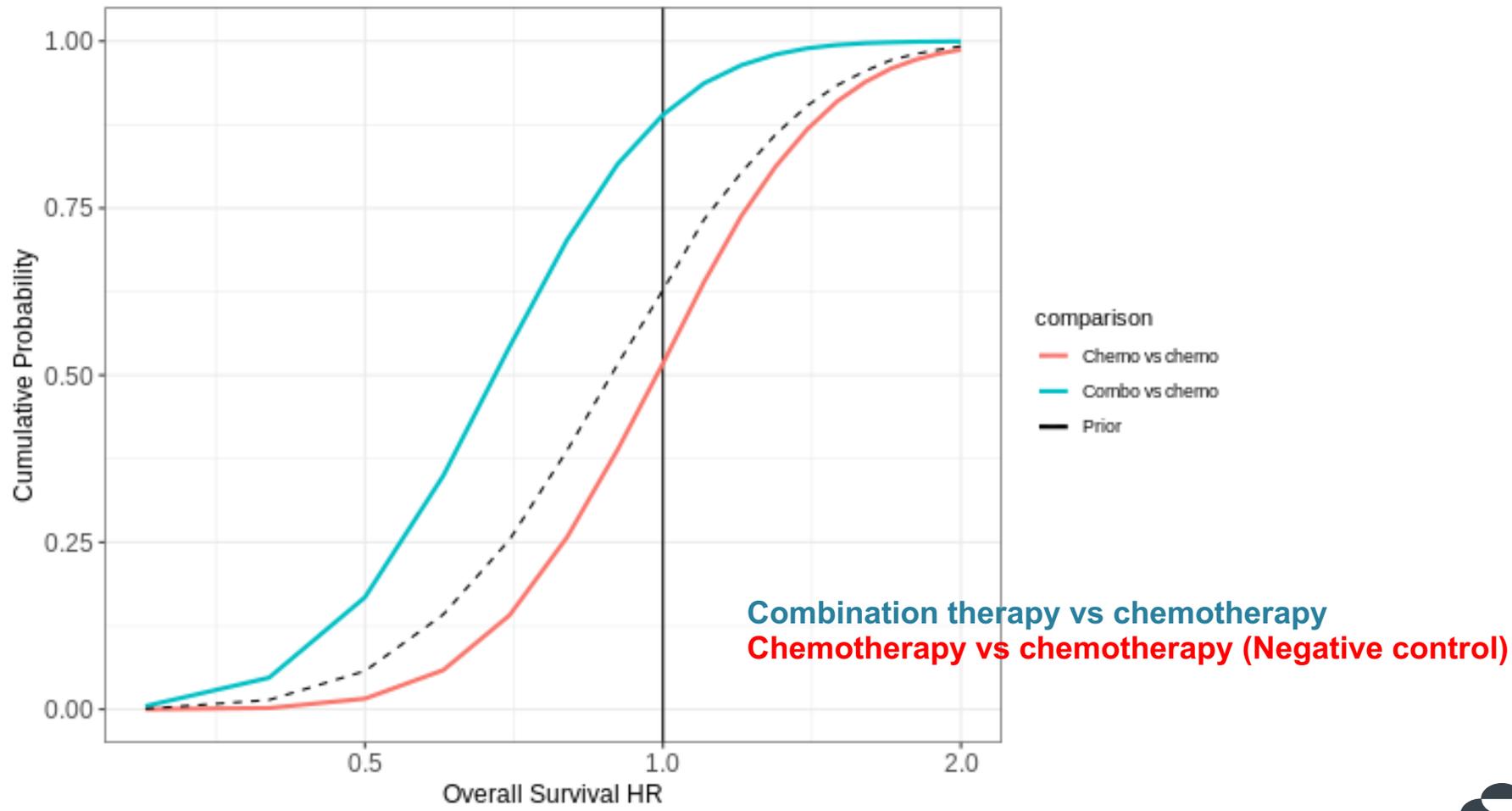


Combination therapy vs chemotherapy
Chemotherapy vs chemotherapy (Negative control)

Application of model to two hypothetical therapies



80% power to predict survival benefit with summary data from 20 patients/arm at 18 weeks, even with very strong prior distribution.



Conclusions

- M&S enables integration of information across a spectrum of clinical observations
- In non-linear models, prior distributions in parameter space don't result in normal priors in clinical space
- Importance sampling can be used to generate multi-dimensional normal priors.
- Summary level data from a small cohort of patients can be leveraged to simulate expected clinical benefit.
- Further work:
 - Use likelihood profiles to dissect the specific contribution of each metric to OS
 - Understand how the likelihoods of each TS metric change over time
 - Apply this approach in comparator analysis setting with summary level data from literature.