

Calibrated predictions of survival based on tumor size dynamics and new lesions in lung cancer via Joint Modeling approach

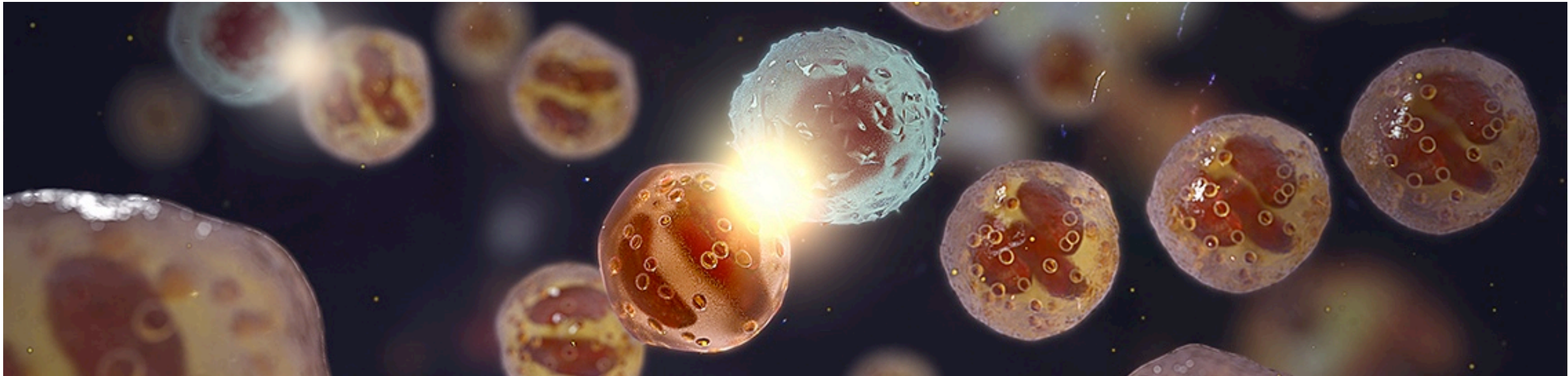
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Executive Summary

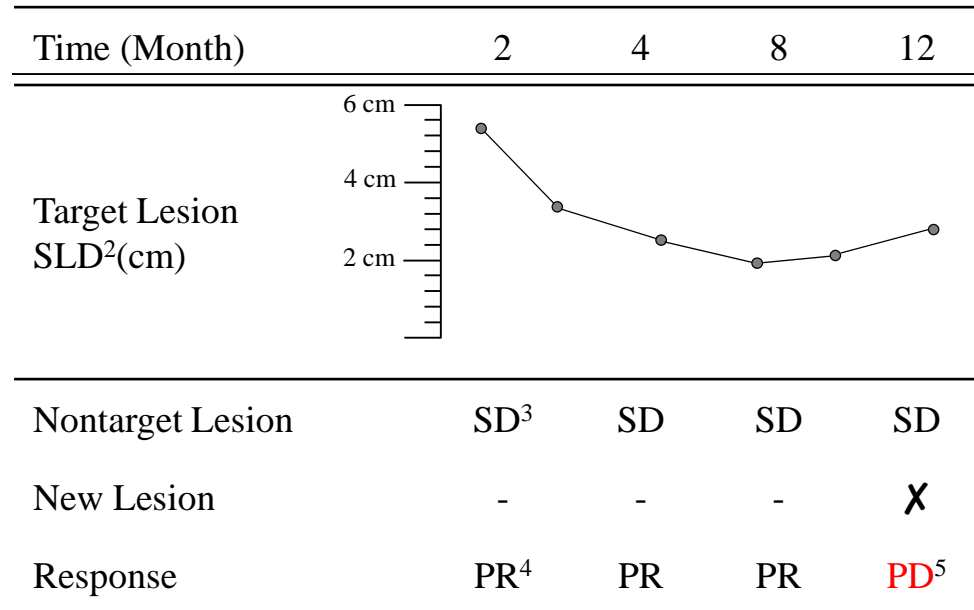
- In oncology, integration of multiple data sources can contribute to:
 - ✓ better prediction for important clinical outcomes
 - ✓ earlier decision making both on trial and individual level
- A statistical basis has been developed and validated to model:
 - ✓ longitudinal response dynamics (Tumor size)
 - ✓ time-to-event (Survival)

(That is so called "joint model")



A problem with RECIST criteria

RECIST¹ data



Reduction to Single Values

- Time to Progression : 12 months
- Best Overall Response : Partial Response
- Best Percent Change in SLD : 33.9%

1. Response Evaluation Criteria In Solid Tumors
2. Sum of Longest Diameters of target lesions
3. Stable Disease
4. Partial Response
5. Progressive Disease

Rich longitudinal tumor dynamic data are reduced to categorical endpoints **with a subsequent loss of information**





Research goal

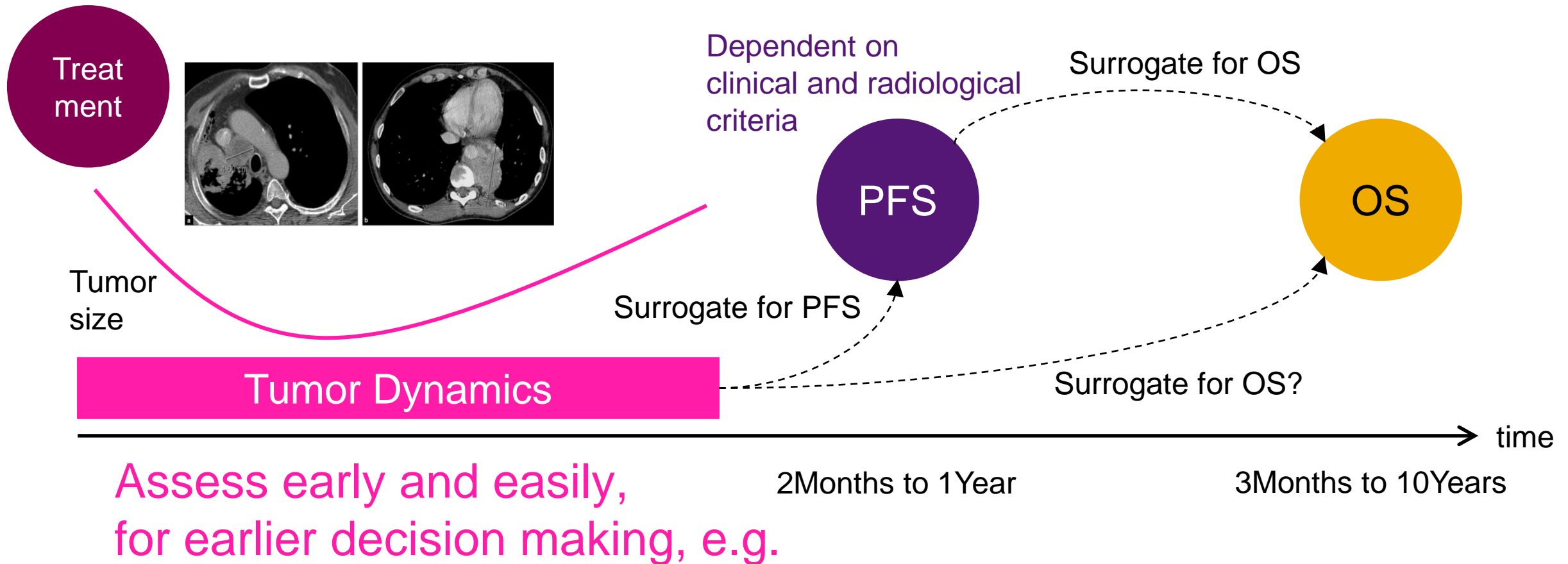
This work develops a joint model of disease progression and survival (PFS/OS) that incorporates

- longitudinal tumor burden
- appearance of new lesions

in NSCLC patients, to interrogate the components of RECIST and to predict survival.



Why monitor tumor growth dynamics ?



Assess early and easily,
for earlier decision making, e.g.

- Early clinical development stage: Decide which compound is better to go with?
- After market stage: Choose what treatment would be better for each patient?

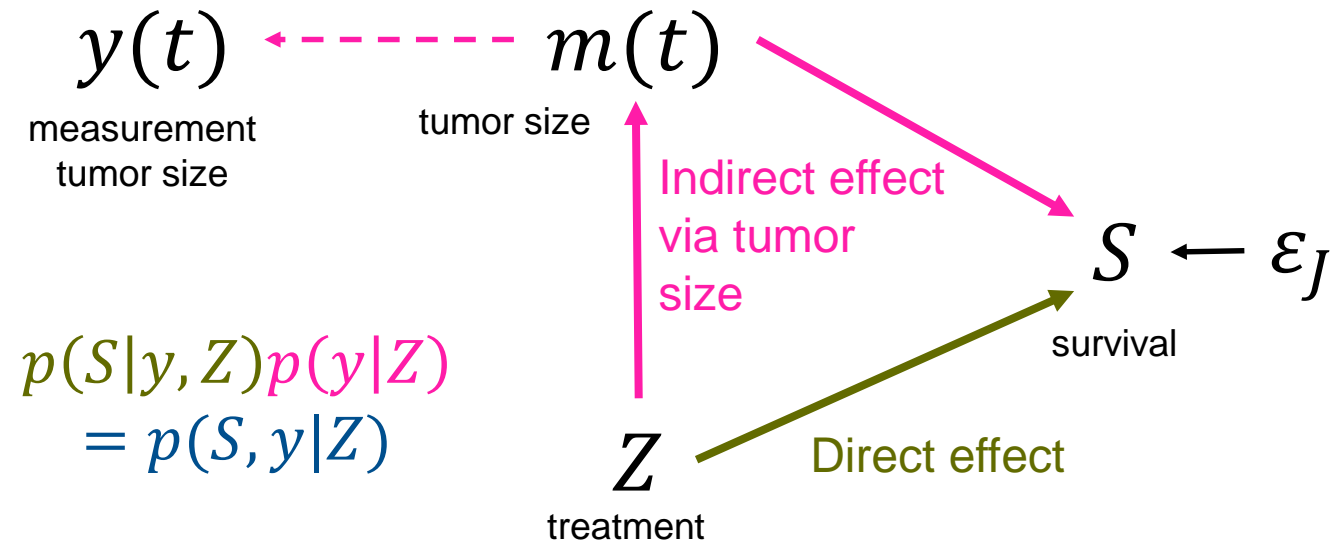


What does Joint model look like?

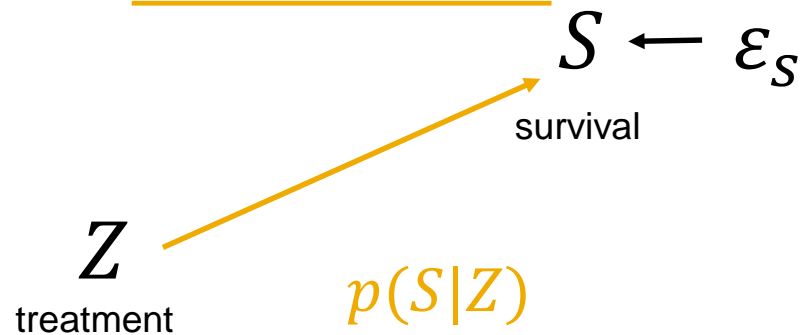
Tumor dynamics model



Joint modeling



Survival Model



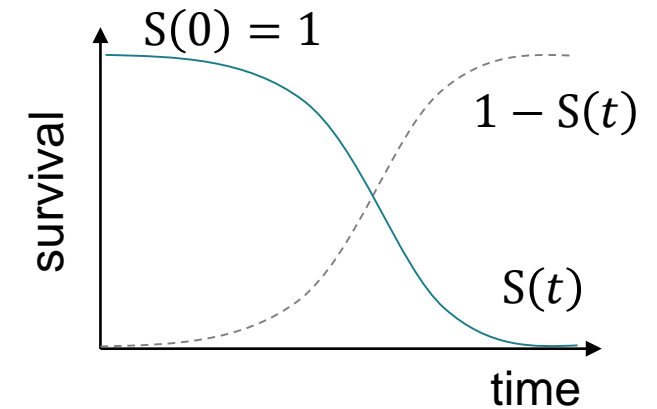
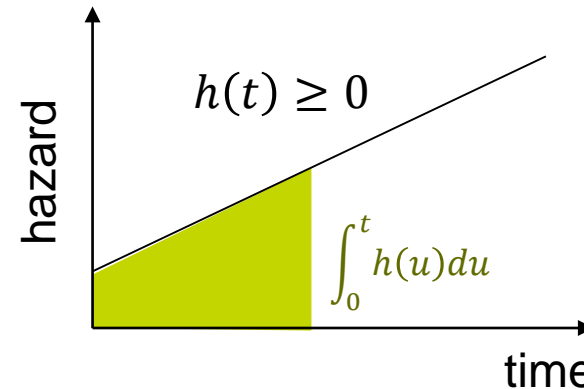
- Directly relate a quantity tumor dynamics to the outcomes OS or PFS (which determine product success).
- Reduce the uncertainty of survival rate.
 - $E[\epsilon_S] > E[\epsilon_J]$



How to get tumor size being involved?

Relation between survival and hazard:

$$S(t) = \exp\left(-\int_0^t h(u)du\right)$$



Proportional hazard model:

$$h(t) = \underbrace{h_0(t)}_{\text{Baseline hazard}} \cdot \exp\left[\underbrace{f(m(t), Z)}_{\substack{\text{Tumor size} \\ \text{Treatment}}}\right]$$

- Hazard is proportional to the baseline hazard
- The function f is a regressor function
- The tumor dynamics $m(t)$ and the treatment Z are included in the proportional part inside the function f

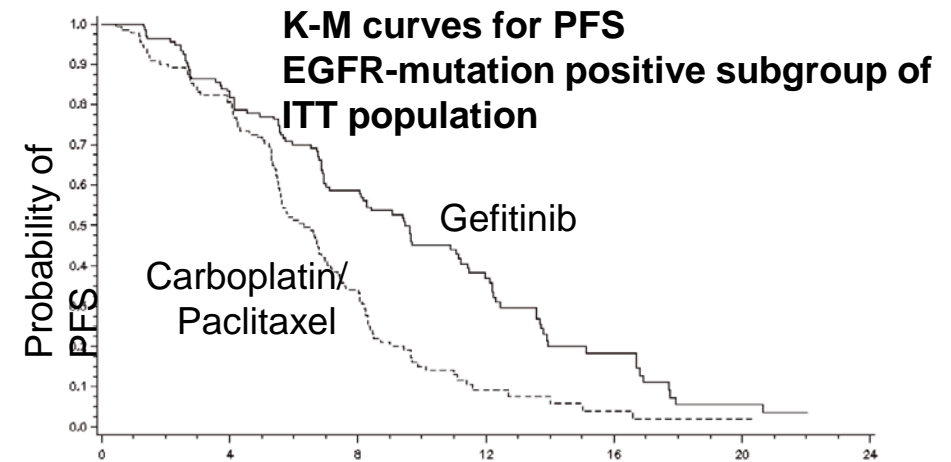
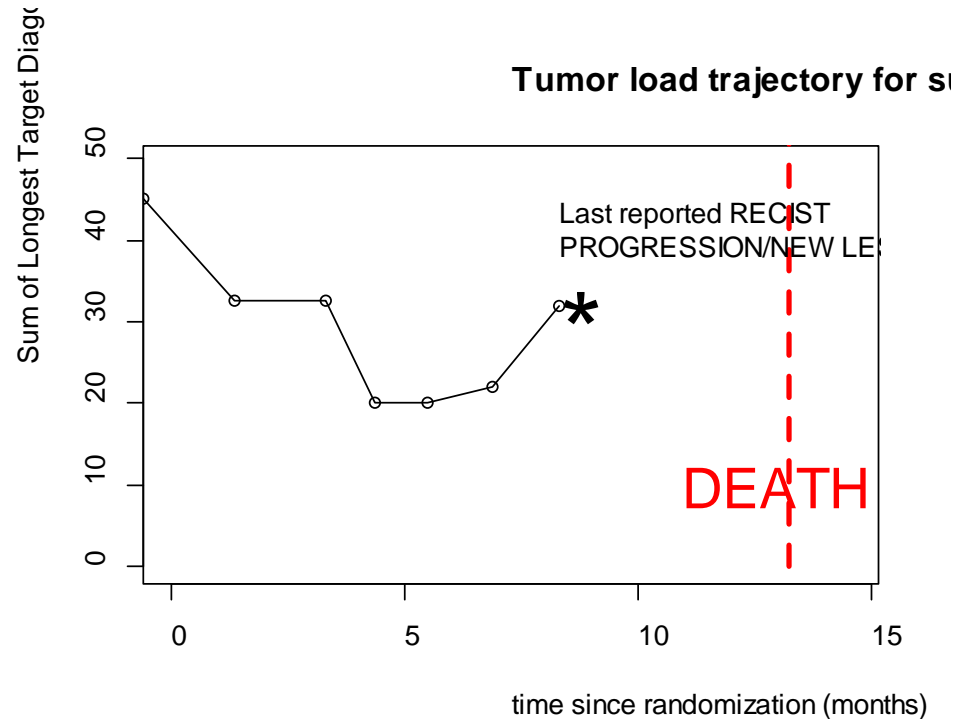


Data from Iressa IPASS Study

Gefitinib (N=609) or Carboplatin + Paclitaxel (N=608)

Hazard ratio for progression or death

- Overall: 0.74; 95% confidence interval [CI], 0.65 to 0.85; P<0.001
- In EGFR-mutant (N=261): 0.48; 95% CI, 0.36 to 0.64
- In EGFR-wild type (N=176): 2.85; 95% CI, 2.05 to 3.98
- 174 subjects progressed due to the appearance of new lesions



Model

- Tumor measurement model

$$y_{ij} = m_i(t_{ij}) + \varepsilon_{ij}, \quad \varepsilon_{ij} \sim \mathcal{N}(0, \sigma^2)$$

- Tumor dynamic model

$$m_i(t) = \beta_i t + s l d_{0,i} e^{-\alpha_i t}, \quad \frac{dm_i(t)}{dt} = \beta_i - \alpha_i s l d_{0,i} e^{-\alpha_i t}$$

- Hazard for survival

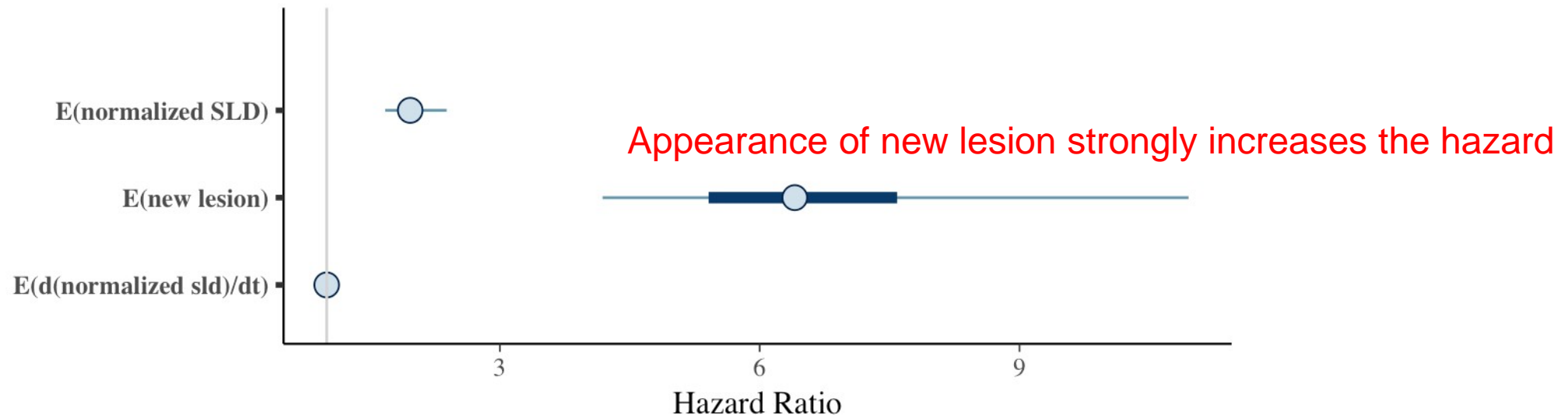
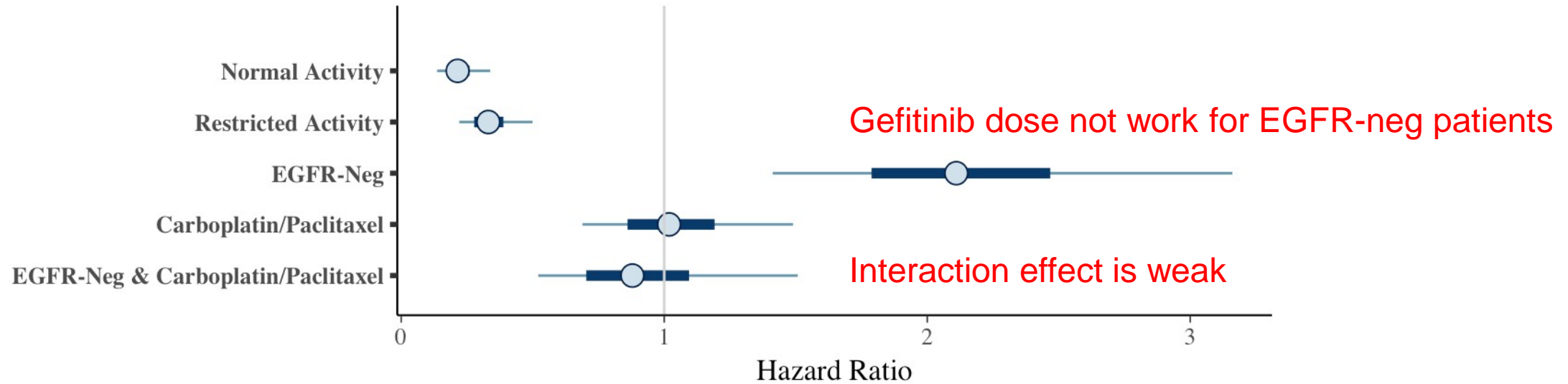
$$h_i(t|m_i) = h_0(t) \exp \left[\underbrace{\boldsymbol{\gamma}^T \boldsymbol{\omega}_i}_{\text{Base line covariates}} + \underbrace{\alpha_l l(t)}_{\text{New lesion Appearance (0/1 value)}} + \underbrace{\alpha_m m_i(t)}_{\text{Tumor size}} + \underbrace{\alpha_{m'} \frac{dm_i(t)}{dt}}_{\text{Change in tumor size}} \right]$$

$$\boldsymbol{\omega}_i = [\omega_{i0} \quad \omega_{i1} \quad \omega_{i2} \quad \omega_{i3} \quad \omega_{i4} \quad \omega_{i5}]$$

Intercept Normal Activity (0/1 value) Restricted Activity (0/1 value) EGFR Negative (0/1 value) Chemothe rapy (0/1 value) Interaction, ω_{i3} and ω_{i4} (0/1 value)

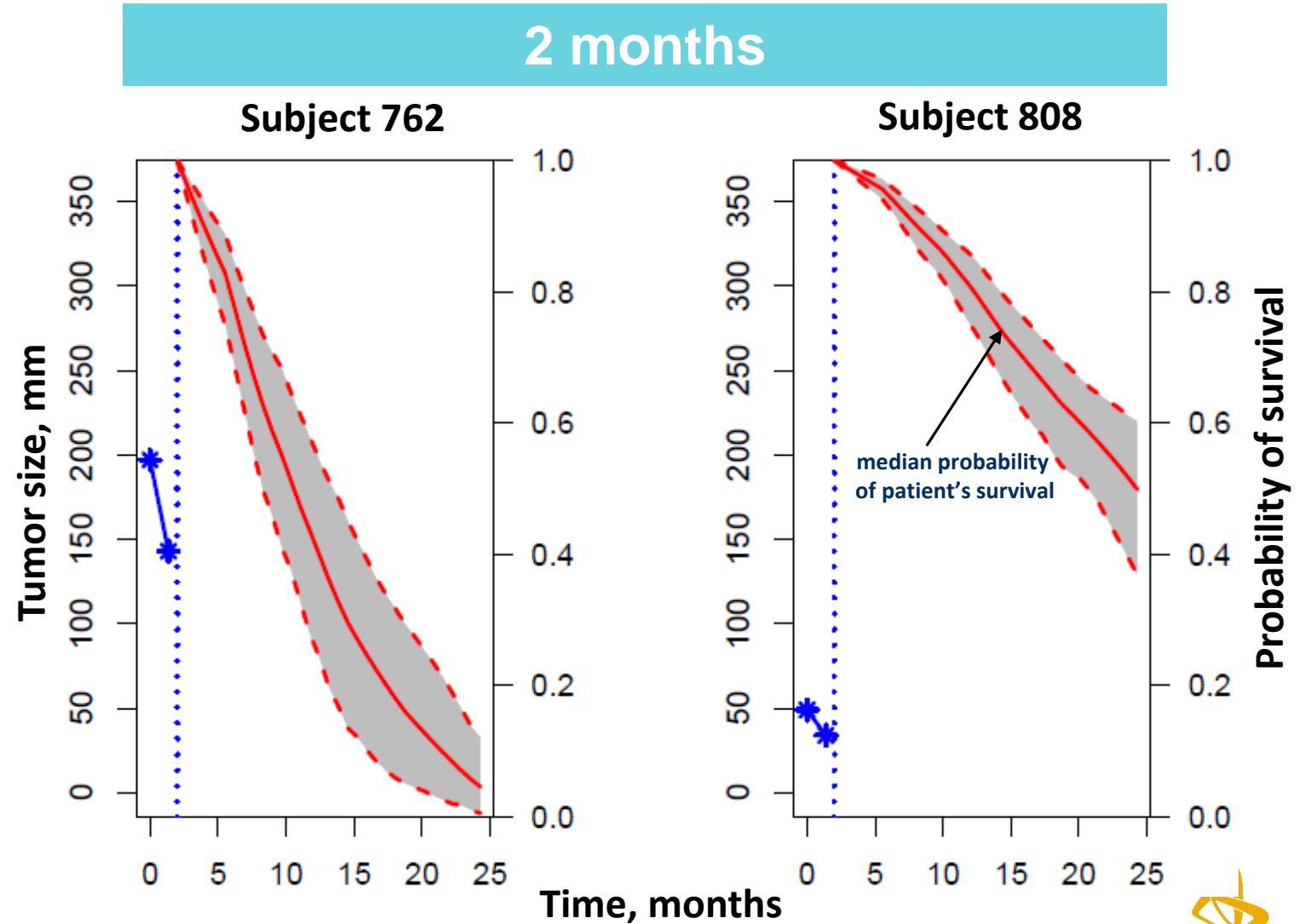


Selected result: Survival Model Coefficients



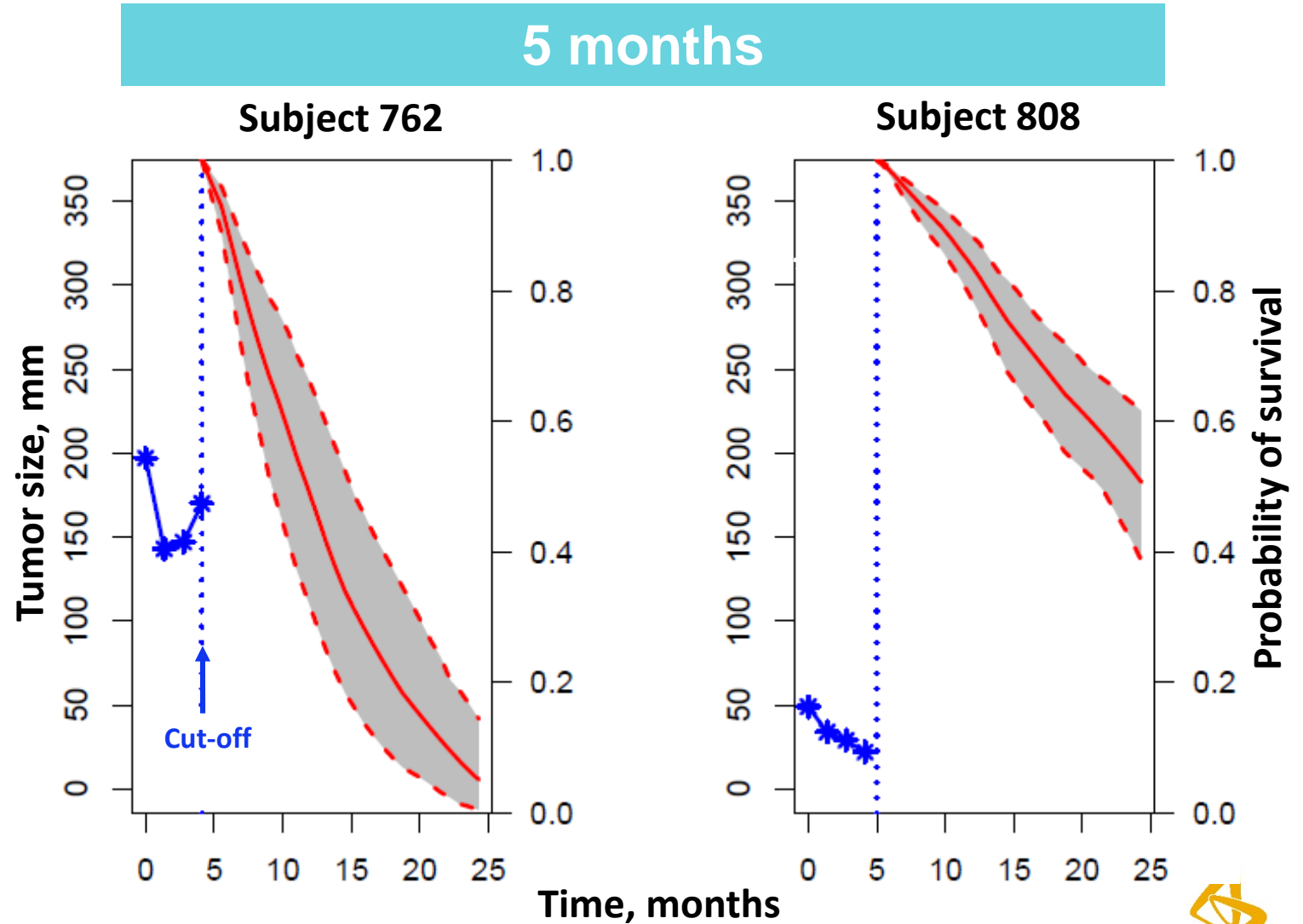
Simulation example, Gefitinib

- Consider 2 patients with same baseline covariates (same dosing, EGFR status, WHO performance status)



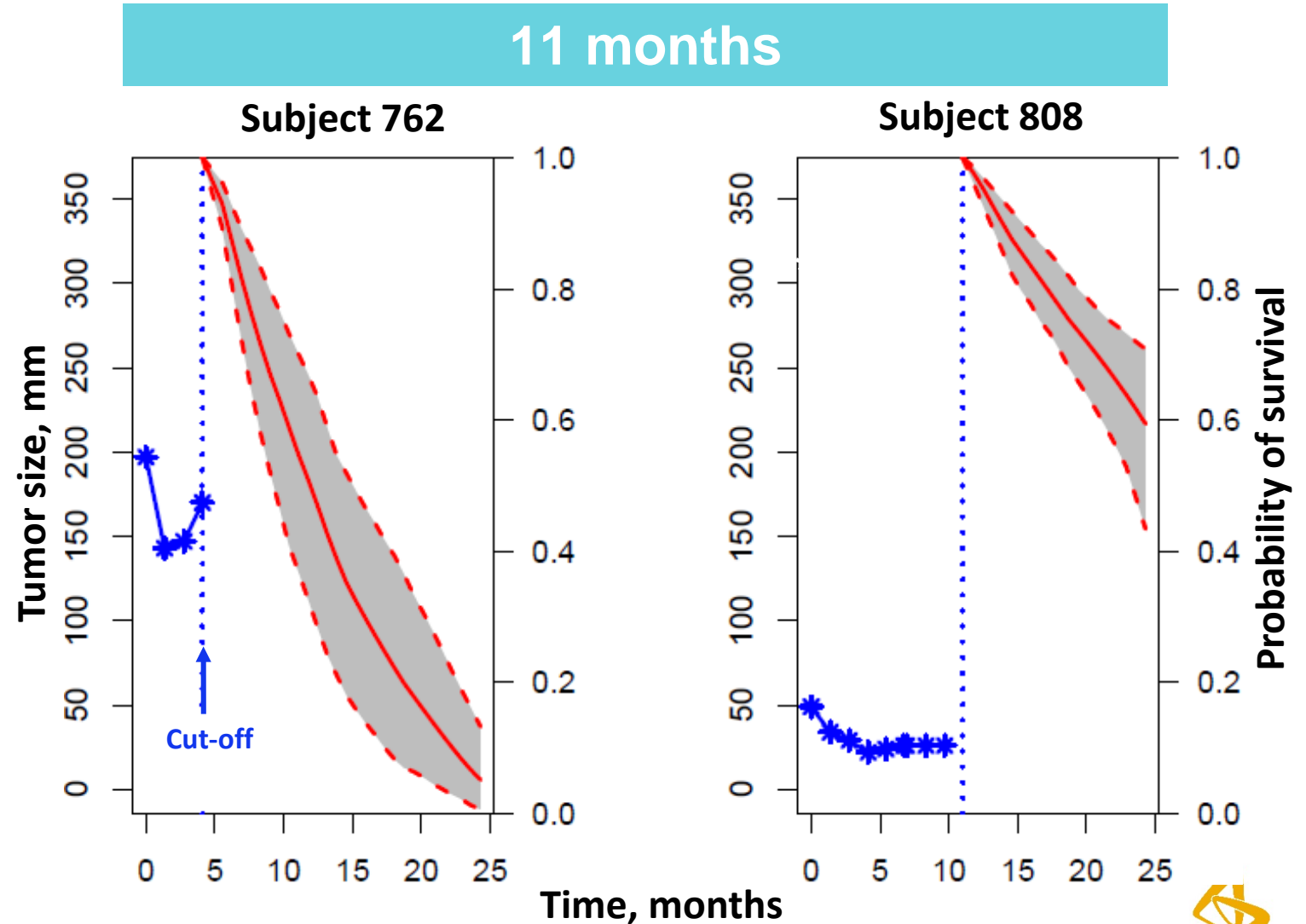
Simulation example, Gefitinib

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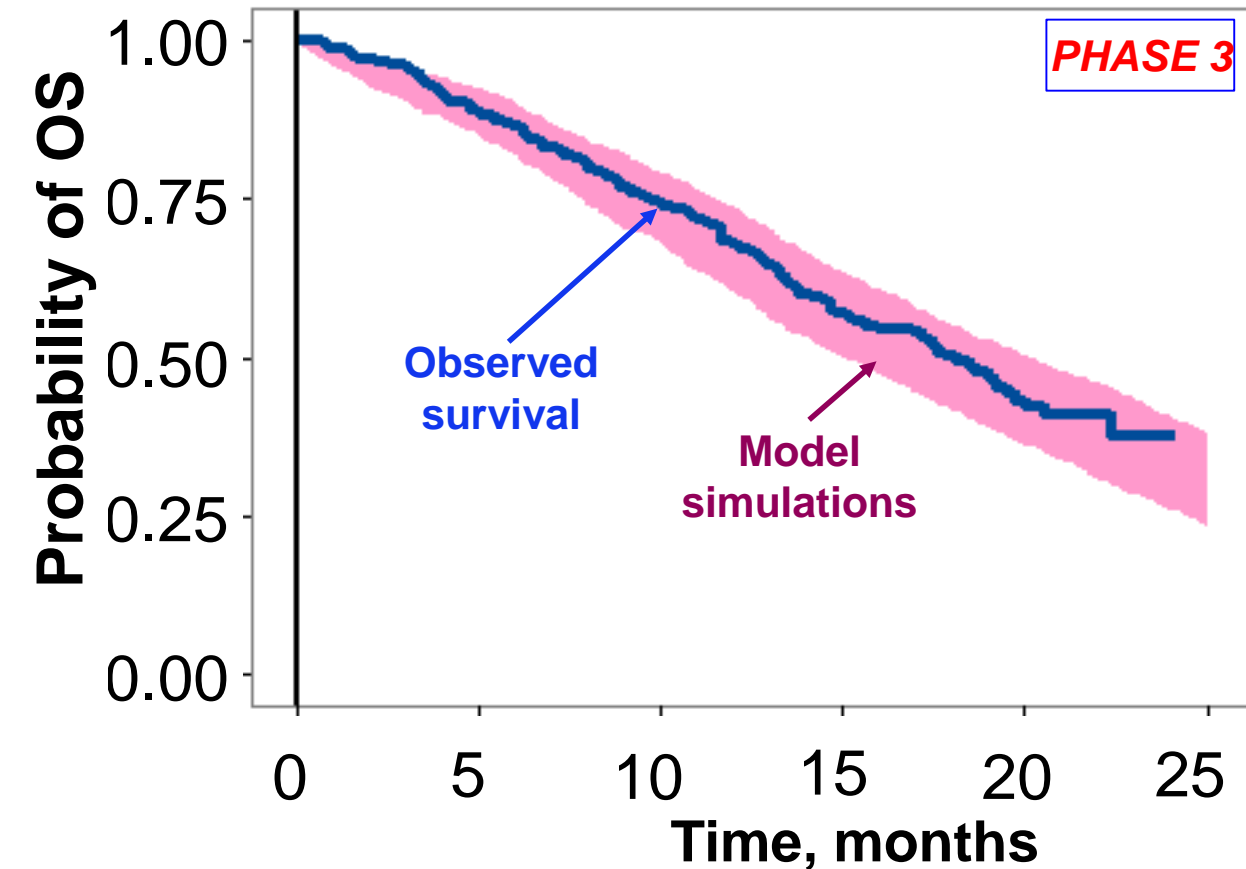
Simulation example, Gefitinib

- Consider 2 patients with same baseline covariates (same dosing, EGFR status, WHO performance status)
- Their therapeutic prognoses differ only because of differences in tumor dynamics (baseline & trajectory)

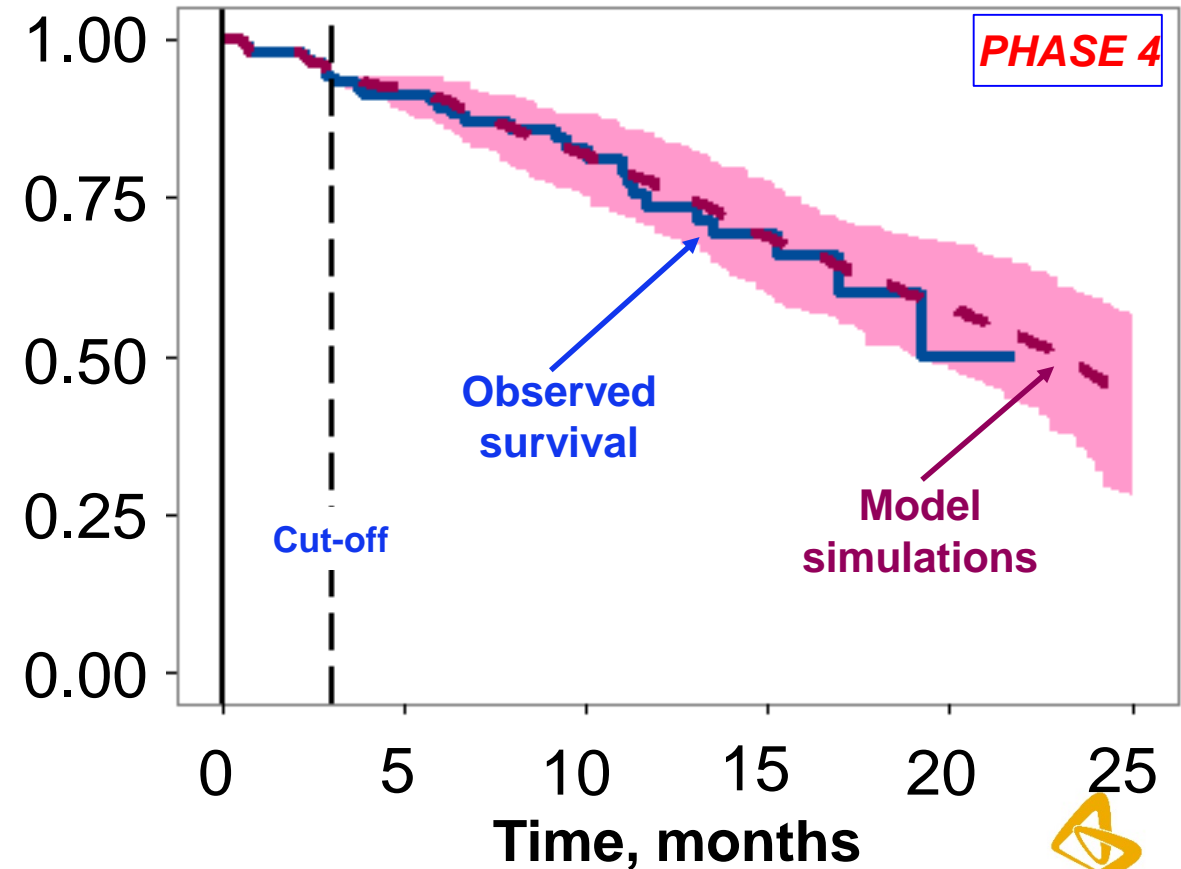


Simulation example, Gefitinib (2 studies)

Joint model validated on **IPASS** data

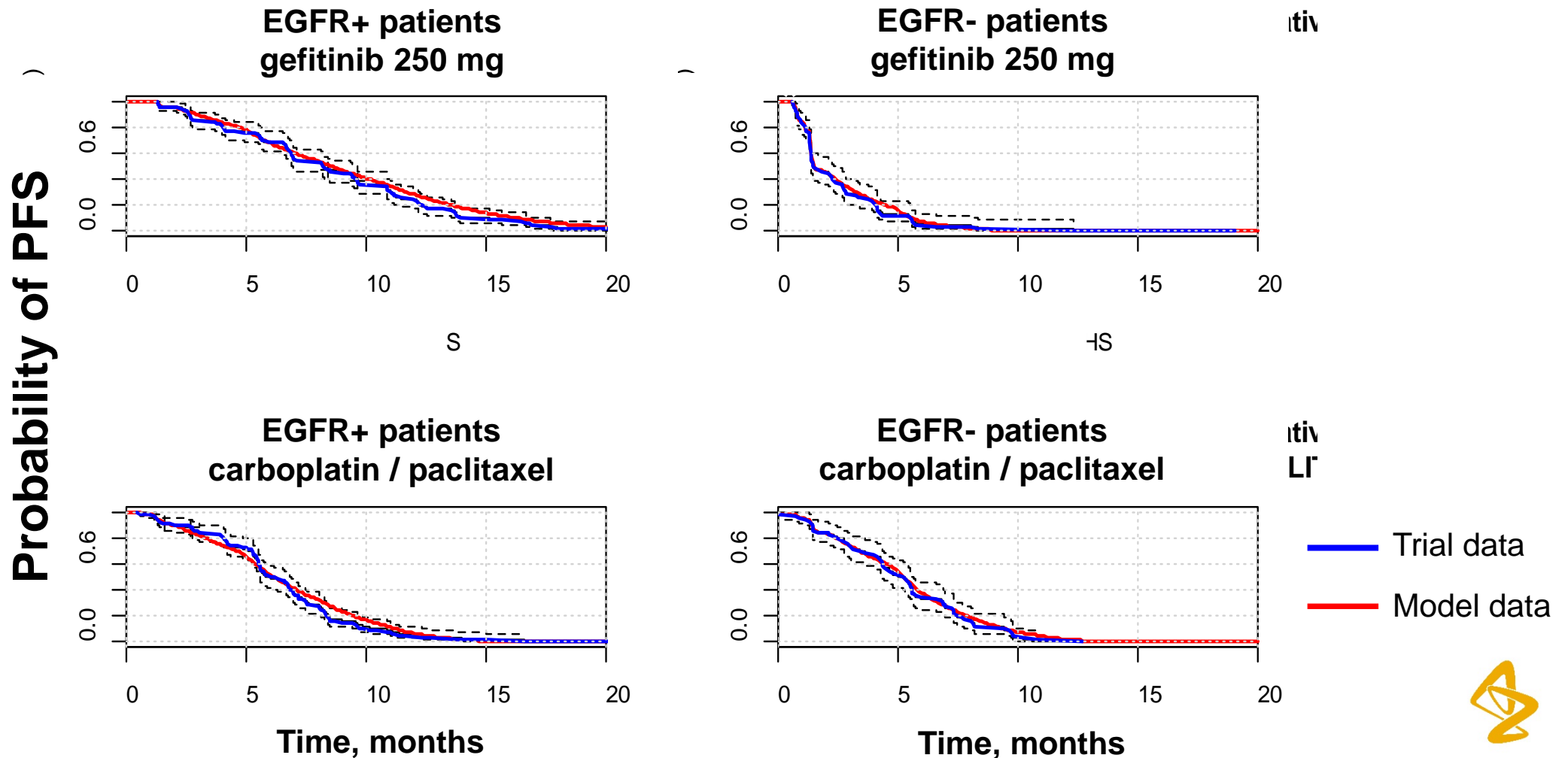


Model predicts **IFUM** OS using 3-month data cut-off



Simulation example, Gefitinib and chemo.

2-month tumor size data predict 2-year PFS outcome for both an EGF-R inhibitor & chemotherapy, in NSCLC patients





Conclusion

- Successfully validated a statistical method
 - ✓ Development of joint models of tumor dynamics and survival can be used to predict survival based upon tumor dynamics in a new trial
 - ✓ Magnitude of contribution of tumour size to survival varied across drugs and EGFR mutation status
- It can contribute to:
 - ✓ making better clinical development strategy (Go/No-go decision)
 - ✓ delivering better treatment tailored for each patient
- Next Step:
 - ✓ Evaluate how to broaden this approach across tumour types and drugs
 - ✓ Develop multivariate joint modeling (ctDNA, new lesions, individual lesion dynamics and other factors related to OS)





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Back-up

Likelihood function for joint model

Maximize the joint distribution of “Survival time(S_i)” and “Tumor size(y_i)”, and it can be divided into 3 parts, given “the tumor size model (m_i)”, for patient i .

$$\prod_{i=1}^n p(S_i, \mathbf{y}_i) = \prod_{i=1}^n \int p(S_i, \mathbf{y}_i, m_i) dm_i = \prod_{i=1}^n \int p(S_i, \mathbf{y}_i | m_i) p(m_i) dm_i = \prod_{i=1}^n \int p(S_i | m_i) p(\mathbf{y}_i | m_i) p(m_i) dm_i$$

1. Survival model:
(Proportional hazard model)

$$p(S_i | m_i) = (h_0(S_i) \cdot \exp[f(m_i(S_i), Z)])^{\Delta_i} \exp\left(-\int_0^{S_i} h_0(u) \cdot \exp[f(m_i(u), Z)] du\right)$$

where Δ_i is indicator variables $\Delta_i = 0$ means censored and $\Delta_i = 1$ means occurrence of an event

2. Tumor size model:

$$p(\mathbf{y}_i | m_i) = \prod_{j=1}^{n_i} p(y_{ij} | m_i)$$

3. Model variability:

$$p(m_i) = p(m_i | m)$$



Numerical methods used

Part	Integrate out the inter individual tumor size model variability	Baseline hazard function	Integrate the hazard from 0 to survival time
	$\int^* dm_i$	$h_0(t)$	$\int_0^{S_i} h(u) du$
Method	<i>MCMC sampling</i>	<i>Cubic spline with 6 nots</i>	<i>Gauss-Konrad quadrature with 13 quadrature points</i>
	<ul style="list-style-type: none"> Using sampling instead of integration 	<ul style="list-style-type: none"> Divide interval into 6 parts Approximate by 3rd order polynomial curve for each interval Connect them smoothly, up to 2nd order derivative to be equal 	<ul style="list-style-type: none"> Standard numerical method for definite integral Weighted sum of function value at a certain argument points The argument points and weights are prespecified to be the most efficient for any functions

