Comparative efficacy and effectiveness via meta-analysis – Health economics approach

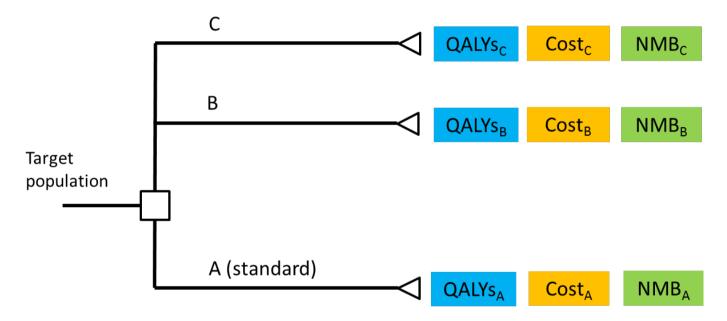
Jeroen Jansen PhD

Chief Scientist – Evidence Synthesis & Decision Modeling

jeroen.jansen@precisionxtract.com



Cost-effectiveness analysis





Decision modeling for cost-effectiveness analysis

- An individual study hardly ever provides information regarding all aspects informing the cost-effectiveness decision of the competing interventions
- Decision models are mathematical frameworks that integrate relevant evidence and provide estimates of resource use and outcomes associated with competing interventions



Decision modeling: Evidence synthesis & extrapolation

- Evidence synthesis
 - Relative treatment effects over time
 - Outcomes over time with standard of care / natural history
 - Relationship between surrogate and clinical endpoints
 - Relationship between clinical and economic endpoints

- Extrapolation
 - beyond the time horizon, interventions, outcomes, and settings observed in the available individual studies



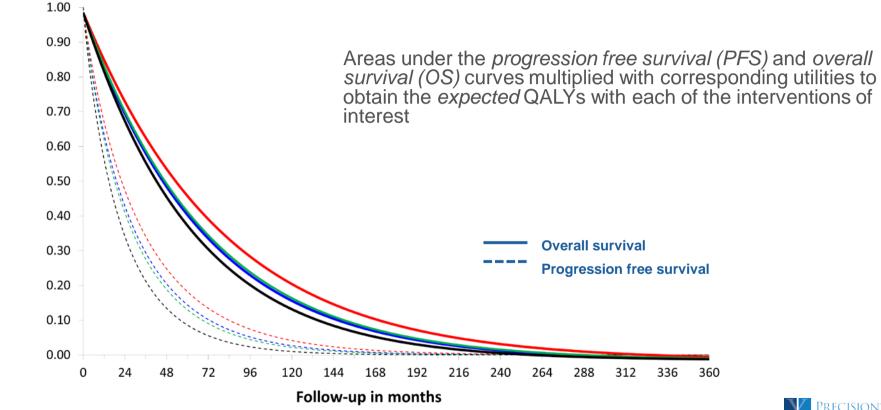
Example research question

What is the cost-effectiveness of available interventions for the xth line treatment of tumor type y?



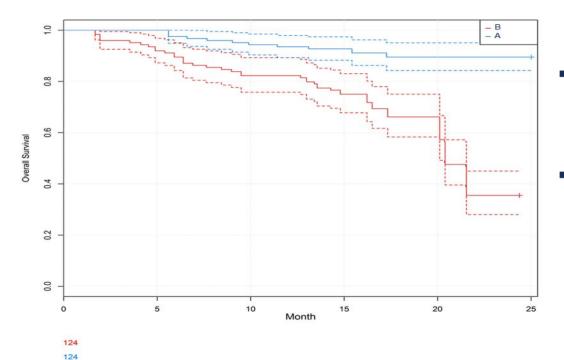
This is what we want: comparative effectiveness estimates

PFS & OS





This is what we have



 A set of randomized controlled trials each comparing a subset of the interventions of interest

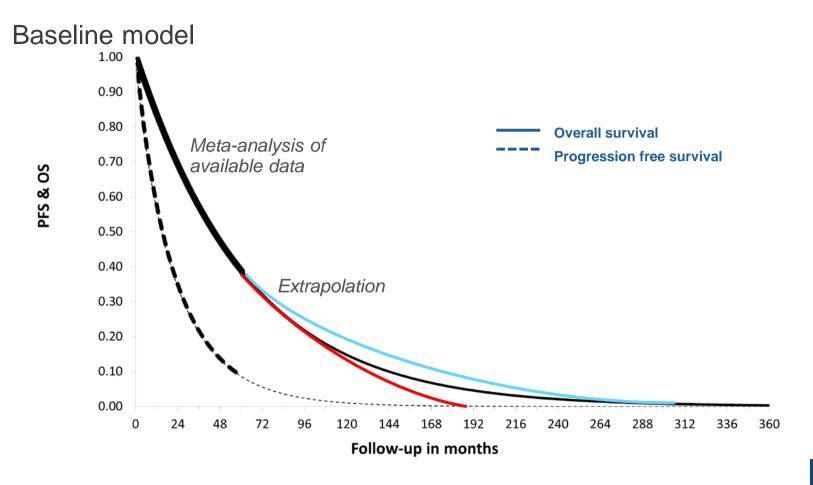
Limited follow-up (15-50 months)



Steps

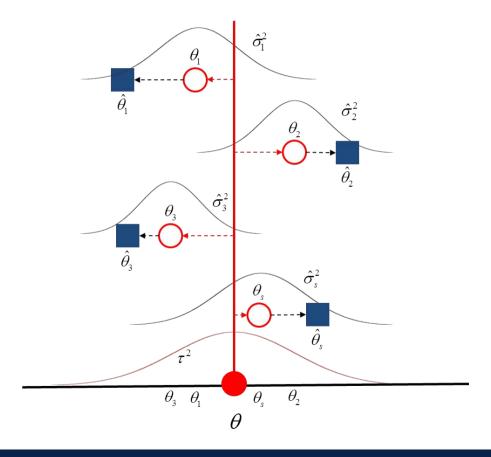
- 1. Meta-analysis of *absolute effect* with reference treatment A; "real-world" data
- 2. Network meta-analysis to obtain relative treatment effects for each intervention relative to A; randomized controlled trials
- 3. Extrapolation of 1 and 2 over time
- 4. Apply extrapolated relative treatment effects to extrapolated absolute effect of A to obtain absolute effects for all interventions







Meta-analysis - random effects model



 $\hat{\theta}_{s} \sim Normal(\theta_{s}, \hat{\sigma}_{s}^{2})$

 $\theta_{s} \sim Normal(\theta, \tau^{2})$



Baseline model – meta-analysis of parametric survival functions

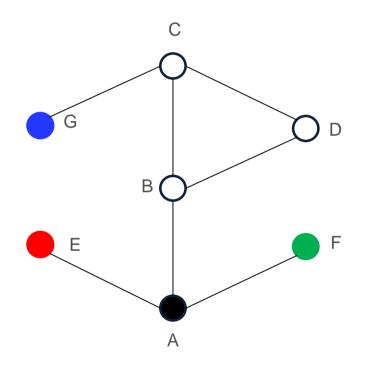
Weibull

$$\ln(h_{s}(t)) = \theta_{0,s} + \theta_{1}\ln(t)$$
$$\theta_{0,s} \sim Normal(\theta_{0}, \tau^{2})$$

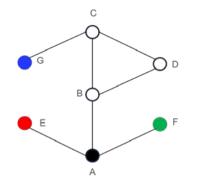
Fractional polynomial

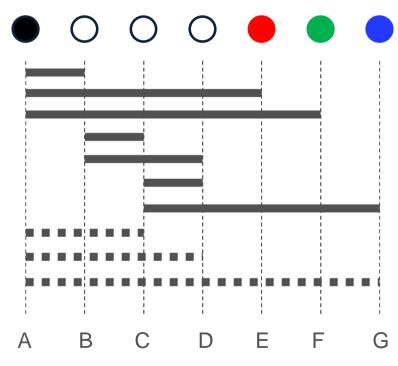
$$\ln\left(h_{s}\left(t\right)\right) = \begin{cases} \theta_{0,s} + \theta_{1}t^{p_{1}} + \theta_{2}t^{p_{2}} & p_{1} \neq p_{2} \\ \theta_{0,s} + \theta_{1}t^{p} + \theta_{2}t^{p}\ln\left(t\right) & p = p_{1} = p_{2} \end{cases} \quad \text{with } t^{0} = \ln\left(t\right) \\ \theta_{0,s} \sim Normal\left(\theta_{0}, \tau^{2}\right) \end{cases}$$





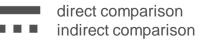






$$d_{bk} = d_{Ak} - d_{Ab}$$

Assumption: No differences in effect-modifiers between studies indirectly compared





$$\hat{\delta}_{sa} \sim Normal(\delta_{sa}, \hat{\sigma}_{sa}^{2})$$
$$\delta_{sa} \sim Normal(d_{1k_{sa}} - d_{1k_{s1}}, \tau^{2})$$



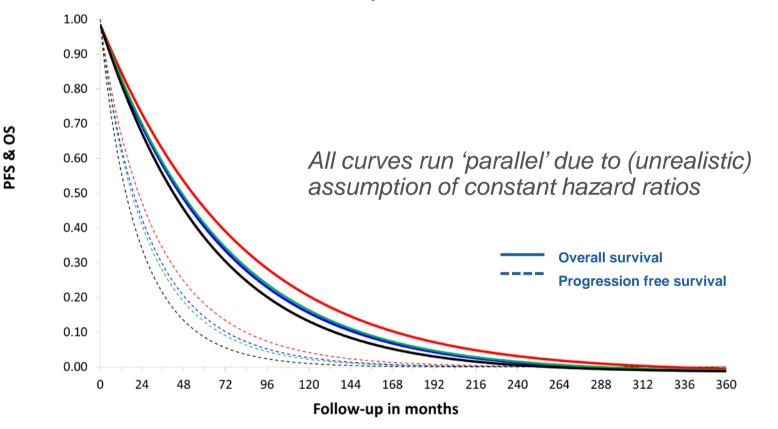
А	0.22	0.32	0.44	1.26	1.11	1.09
	(0.11 - 0.45)	(0.13 - 0.8)	(0.2 - 0.96)	(1.01 - 1.58)	(0.93 - 1.33)	(0.78 - 1.52)
4.47	В	1.44	1.95	5.66	4.98	4.85
(2.25 - 8.89)		(0.78 - 2.66)	(1.31 - 2.89)	(2.75 - 11.58)	(2.45 - 10.1)	(2.28 - 10.43)
3.09	0.69	С	1.35	3.91	3.45	3.35
(1.25 - 7.66)	(0.38 - 1.28)		(0.69 - 2.63)	(1.55 - 9.96)	(1.37 - 8.67)	(1.28 - 8.83)
2.30	0.51	0.74	D	2.90	2.56	2.49
(1.05 - 5.06)	(0.35 - 0.76)	(0.38 - 1.45)		(1.28 - 6.55)	(1.14 - 5.76)	(1.06 - 5.89)
0.79	0.18	0.26	0.34	E	0.88	0.86
(0.63 - 0.99)	(0.09 - 0.36)	(0.1 - 0.64)	(0.15 - 0.78)		(0.66 - 1.17)	(0.57 - 1.29)
0.90	0.20	0.29	0.39	1.13	F	0.98
(0.75 - 1.07)	(0.1 - 0.41)	(0.12 - 0.73)	(0.17 - 0.88)	(0.85 - 1.51)		(0.67 - 1.42)
0.92	0.21	0.30	0.40	1.16	1.03	G
(0.66 - 1.29)	(0.1 - 0.44)	(0.11 - 0.78)	(0.17 - 0.95)	(0.78 - 1.75)	(0.7 - 1.5)	

Needed for our

CEA



Modeled PFS and OS curves by treatment - constant hazard ratios



16

Network meta-analysis – time-varying hazard ratios

• Weibull
$$\ln(h_{sa}(t)) = \theta_{0,sa} + \theta_{1,sa} \ln(t)$$
$$\begin{pmatrix}\theta_{0,sa}\\\theta_{1,sa}\end{pmatrix} = \begin{pmatrix}\mu_{0,s}\\\mu_{1,s}\end{pmatrix} + \begin{pmatrix}\delta_{0,sa}\\d_{1,1k_{sa}} - d_{1,1k_{s1}}\end{pmatrix}$$
$$\delta_{0,sa} \sim Normal(d_{0,1k_{sa}} - d_{0,1k_{s1}}, \tau^2)$$

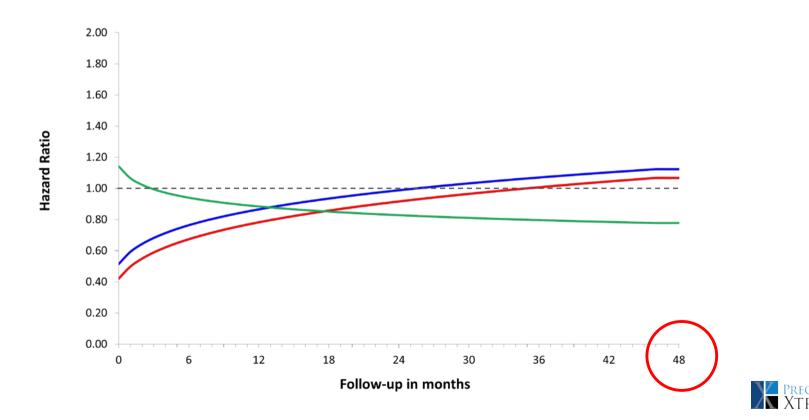
Fractional polynomial

$$\ln(h_{sa}(t)) = \begin{cases} \theta_{0,sa} + \theta_{1,sa}t^{p_{1}} + \theta_{2,sa}t^{p_{2}} & p_{1} \neq p_{2} \\ \theta_{0,sa} + \theta_{1,sa}t^{p} + \theta_{2,sa}t^{p} \ln(t) & p = p_{1} = p_{2} \end{cases} \text{ with } t^{0} = \ln(t)$$

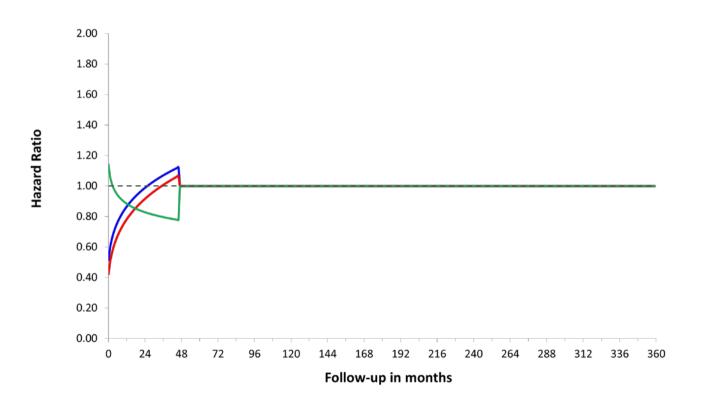
$$\begin{pmatrix} \theta_{0,sa} \\ \theta_{1,sa} \\ \theta_{2,sa} \end{pmatrix} = \begin{pmatrix} \mu_{0,s} \\ \mu_{1,s} \\ \mu_{2,s} \end{pmatrix} + \begin{pmatrix} \delta_{0,sa} \\ d_{1,1k_{sa}} - d_{1,1k_{s1}} \\ d_{2,1k_{sa}} - d_{2,1k_{s1}} \end{pmatrix}$$

$$\delta_{0,sa} \sim Normal(d_{0,1k_{sa}} - d_{0,1k_{s1}}, \tau^{2})$$

Network meta-analysis – time-varying hazard ratios

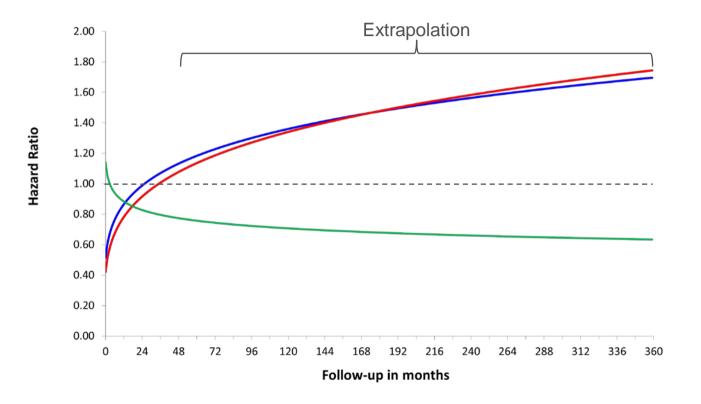


Extrapolation of relative treatment effects





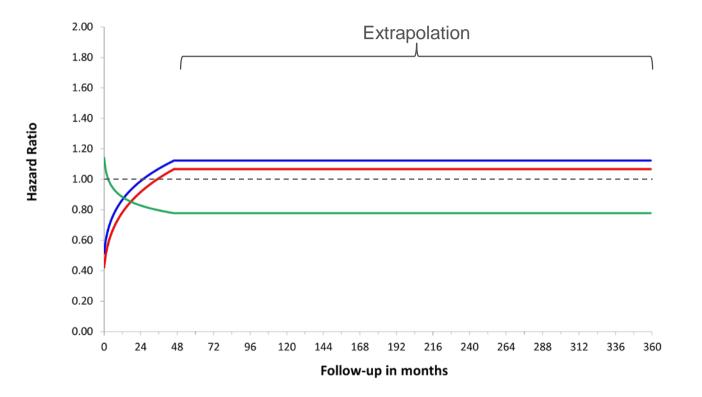
Extrapolation of relative treatment effects





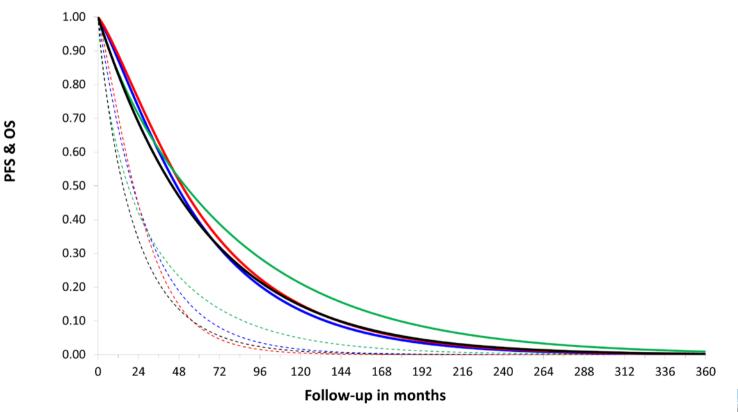
20

Extrapolation of relative treatment effects





Modeled PFS and OS curves by treatment – time-varying hazard ratios





Key issues to consider

- Target population(s) of interest
 - Subgroups
 - Meta-regression
 - Use of IPD
- Model selection for evidence synthesis
 - Fit to the data
 - Extrapolation
 - Use of external evidence



Summary: Evidence synthesis for cost-effectiveness analysis

- It is the absolute difference between treatments that will determine the value of a treatment
- Assumption: absolute efficacy of a treatment may vary with the study population, the relative effect remains relatively stable
- Evidence synthesis
 - Baseline model: Absolute effect with "standard care" in routine practice
 - Relative treatment effects
- Need for extrapolation
 - Time-horizon
 - Population
 - Setting
 -



References

- Dias S, Ades AE, Welton NJ, Jansen JP, Sutton AJ. Network meta-analysis within costeffectiveness analysis. In: Network meta-analysis for decision making. Chichester UK: John Wiley & Sons Ltd, 2018; p.155-178
- Jansen JP Cope S. Meta-regression models to assess heterogeneity and inconsistency in network meta-analysis of survival outcomes. BMC Medical Research Methodology 2012;12:152

