Moving from the hazard ratio to the difference in restricted mean survival time in IPD meta-analyses

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Context

- Difference in restricted mean survival time (rmstD)
 is a commonly used survival measure in cost effectiveness analyses
- Cost-effectiveness analyses based on individual patient data meta-analyses (IPD MA) are scarce
- IPD MA of randomized trials has become the gold standard = best evidence for treatment effects
- For this type of hierarchical data, statistical analyses are stratified by trial and treatment effect
 heterogeneity between trials is studied

Objectives

- Investigate if the choice of the method used to estimate the *rmstD*(*t**) impacts the results of a costeffectiveness analysis in the context of an IPD metaanalysis
 - → Motivating case study
- 2. Study and compare methods to estimate the *rmstD(t*)*from an IPD meta-analysis
 → Simulation study
- Illustrate the use of the *rmstD*(*t**) as a measure for the treatment effect in an IPD meta-analysis
 - → Application





HR = 0.63: experimental arm always more efficient than control arm



Meta-analyses methodology

- ✓ Stratification by trial: comparison of patients in the experimental arm from a trial to patients in control arm within the same trial (comparison of like with like)
 → respect the randomization
- Estimation of the overall treatment effect in 2 stages:
 - 1. Treatment effect estimation $\hat{\theta}_j$ in every trial *j*
 - 2. Weighted average : $\hat{\theta}_{overall} = \frac{\sum_{j=1}^{J} \hat{\theta}_{j}}{\sum_{j=1}^{J} \hat{\theta}_{j}}$

$$=\frac{\sum_{j=1}^{J}\theta_{j}w_{j}}{\sum_{j=1}^{J}w_{j}}$$

 $\hat{\theta}_j = \log(\widehat{HR}_j)$ for survival data

 $w_{j} = \frac{1}{\widehat{Var}(\widehat{\theta}_{j})} \text{ fixed effects}$ $w_{j} = \frac{1}{\widehat{Var}(\widehat{\theta}_{j}) + \tau^{2}} \text{ random effects} : \tau^{2} \Leftrightarrow \underline{\text{heterogeneity}}$

Forest-plot example (MAR-LC)

	NO. Deaths	/ No. Enter	ed			
Trial	Mod RT	Conv RT	0-E	Variance	Hazard Ratio	HR [95% CI]
RTOG 8808	155/163	156/163	-6.4	76.9		0.92 [0.74;1.15]
PMCI 88C091	48/48	52/53	-0.8	24.3		0.97 [0.65;1.44]
PMCI 88C091 (CT 51/51	56/56	6.0	25.6		1.26 [0.86;1.86]
CHART	316/338	217/225	-29.4	120.7		0.78 [0.66;0.94]
NCCTG 90245	1 34/39	35/35	-7.0	15.7		0.64 [0.39;1.05]
NCCTG 94245	2 111/125	108/121	-2.6	54.6		0.95 [0.73;1.24]
CHARTWEL	132/150	132/150	0.2	65.8	-	1.00 [0.79;1.28]
CHARTWELCT	40/53	47/53	-6.4	21.2		0.74 [0.48;1.13]
ECOG 2597	51/60	55/59	-7.4	25.8		0.75 [0.51;1.10]
Gliwice 2001	26/29	27/29	-1.4	13.2		0.90 [0.52;1.54]
	964/1056	885/944	-55.2	443.7	•	0.88 [0.80:0.97]. p=

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Two approaches to estimating the overall *rmstD*(*t**) from an IPD meta-analysis

- <u>Approach 1</u>: *rmstD*(*t**) is estimated as the area between the two "pooled" survival curves summarizing the information from the *J* trials
- Approach 2:
 - 1. $rmstD_{i}(t^{*})$ is estimated in each of the J trials
 - 2. Weighted average of the $rmstD_j(t^*)$ using fixed or random effects:

$$\widehat{rmstD}(t^*) = \frac{\sum_{j=1}^{J} \widehat{rmstD_j}(t^*)w_j}{\sum_{j=1}^{J} w_j}$$

1st approach: Naïve Kaplan-Meier

effect

Trials of the meta-analysis are considered as one and only trial; the overall $rmstD(t^*)$ is estimated as the area between the two KM survival curves, thus ignoring trial



1st approach: Peto-quintile

Actuarial method developped by Richard Peto (EBCTCG, 1992) to take into account trial effect for representing suvival curves in IPD meta-analysis.



Time interval estimation is
based on the quintiles of
number of deaths until *t**
→ each interval contains an
equal number of events

2nd approach: Pooled Kaplan-Meier - Pooled Exponential

- For each trial *j*, *rmstD_j(t*)* is estimated as the area between survival curves <u>Kaplan-Meier</u> or <u>exponential</u>
- 2. Then the $rmstD_j(t^*)$ are pooled using a fixed or random effects model

Motivating case study

Julia Bonastre, Audrey Mauguen, Jean-Pierre Pignon (Gustave Roussy, Inserm) Oliver Rivero-Arias (Oxford University)

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Meta-Analysis of Radiotherapy in Lung Cancer (MAR-LC)

- ✓ IPD MA in non-small cell lung cancer (Mauguen 2012)
- \checkmark N = 2,000 patients and 10 phase III trials comparing :
 - Conventional radiotherapy (RT)
 - Modified RT (hyperfractionated and/or accelerated)
- ✓ Modified RT improved overall survival: HR_{overall} = 0.88 [IC 95%: 0.80-0.97; p = 0.009]

➔ Is modified radiotherapy cost-effective ?

rmstD(t*) and Incremental Cost-Effectiveness Ratio

$$ICER = \frac{\bar{C}_{Mod RT} - \bar{C}_{Conv RT}}{rmstD(t^* = 5)}$$
 expressed as a cost per life year gained

Modified RT more expensive: 4 328 € [1 830€; 6 804€]

Method	<i>rmstD</i> (<i>t*</i>) (months) [95% CI]	ICER (k€) [95% CI]
Peto-quintile	1.7 [0.4 – 3.1]	35 [13 – 98]
Naïve Kaplan-Meier	2.2 [0.6 – 3.7]	27 [11 – 68]
Pooled Kaplan-Meier	2.3 [0.7 – 3.8]	26 [10 – 66]
Pooled Exponential	2.5 [0.7 – 4.2]	24 [10 – 59]

The choice of a survival method to estimate overall *rmstD*(*t**) impacts the cost-effectiveness results

These results were obtained based on a case study using an IPD meta-analysis with proportional hazards, no heterogeneity and a small treatment effect size

need to investigate on other scenarios with simulation study

Ref: Lueza B, Mauguen A, Pignon JP, Rivero-Arias O, Bonastre J. Difference in Restricted Mean Survival Time for Cost-Effectiveness Analysis Using Individual Patient Data Meta-Analysis: Evidence from a Case Study. PLoS One 2016 11(3)

Simulation study

Julia Bonastre, Stefan Michiels, Jean-Pierre Pignon, Federico Rotolo (Gustave Roussy, Inserm)



Simulation of meta-analysis time-to-event data

- For a trial $j \in \{1, ..., J\}$, the hazard function is: $\lambda_j(t) = \lambda_0(t) exp\{a_j + (\beta + b_j)x\}$
- $\lambda_0(t)$ = baseline hazard function (exponential distribut.)
- β = overall treatment effect
- $x = \text{treatment variable} (\pm 1/2 \rightarrow \text{heterogeneity} = 2 \text{ arms})$
- $Var(a_j) = \sigma^2 = baseline hazard heterogeneity$
- $Var(b_j) = \tau^2 =$ treatment effect heterogeneity

Ref: Lueza B, Rotolo F, Bonastre J, Pignon JP, Michiels S. Bias and precision of methods for estimating the difference in restricted mean survival time from an individual patient data meta-analysis. BMC Med Res Meth 2016 16(1):37.

1,000 simulated meta-analyses per scenario

✓ Baseline hazard and treatment effect heterogeneity:

		Var(b _j) = τ ² heterog _{trt}			
		Low (0.01)	High (0.10)		
$Var(a_i) = \sigma^2$	Low (0.01)	1	2		
heterog _{hazard}	High (0.10)	3	4		

- ✓ Treatment effect size: β =0 (HR=1)/-0.2 (0.8) /-0.7 (0.5)
- ✓ Time horizon :
 - t* = 5 years : follow-up long enough for all trials
 - t* = 10 ans : too short follow-up for some trials
- Proportional or non-proportional hazards (piecewise exponential)

Compared methods and evaluation criteria

- 4 methods (fixed/random effects):
 - 1st approach (area between 2 « pooled » curves):
 Naïve Kaplan-Meier, <u>Peto-quintile</u>
 - 2nd approach (weighted average of areas):
 <u>Pooled Kaplan-Meier</u>, <u>Pooled Exponential</u>
- Evaluation criteria:
 - Bias = Average of the 1,000 estimated rmstD(t*)
 True rmstD(t*)
 - Empirical standard error = Standard deviation of the rmstD(t*) over the 1,000 replicates
 - Average standard error = Average of the 1,000 analytically estimated standard errors

Standard error well estimated with Pooled KM/Exp





Peto-quintile biased when B increases

Bias





Similar results but smaller in magnitude (t*=5)



Pooled Exponential strongly biased



Pooled KM/Expo and Peto-quintile biased (t* = 10)



No major impact for other investigated scenarios

- ✓ Negative correlation between random effects a_i and b_i
- ✓ Deleterious treatment effect
- ✓ Number of trials and nb patients per trial fixed/random:
 - 5 trials and 200 patients per trial (N=1,000)
 - 5 trials and <u>nb patients random</u> (N=1,000)
 - 20 trials and 100 patients (N=2,000)

Conclusion

- Pooled Kaplan-Meier with random effects formed the best compromise in terms of bias and variance
- Treatment effect size:
 - Bias for Peto-quintile which increases with effect size
- High treatment effect heterogeneity:
 - Empirical Std Err increases no matter the method
 - Std Err well estimated (empirical = average) only for Pooled Kaplan-Meier and Pooled Exponential
- Non-proportional hazards:
 - Strong bias for Pooled Exponential

Application to an IPD meta-analysis



Radio-Therapy Timing in Small Cell Lung Cancer RTT-SCLC

- IPD meta-analysis in small cell lung cancer, using both hazard ratio (primary measure) and *rmstD*(*t**) (secondary measure)
- ✓ Control RT versus experimental RT : HR = 1.01; p=0.87
- ✓ Strong treatment effect heterogeneity: p=0.003; $I^2 = 67\%$

Ref: De Ruysscher D*, Lueza B*, Le Péchoux C, et al. Impact of thoracic radiotherapy timing in limited-stage small-cell lung cancer: usefulness of the individual patient data meta-analysis. Annals of Oncology 2016 27(10), 1818–1828.

Interaction remains significant using rmstD

Same conclusions with either HR or *rmstD*($t^* = 5$ years)

Essai	Nb Décès / RT Cont	Effectif tota RT Exp	I 0-А	Varianc	e Hazard F	Ratio	HR [IC 95 %]	Bénéfice de su	rvie restreint rm	stD [IC 95 %]
(a) Similar C	T complia	ance betw	veen a	rms						
BR.6	149/164	146/168	20,6	72,1	-		1,33 [1,06;1,68]		l ⊢−−−−−−−−−−−−−−−−−−−−−−−−−−−−−−−−−−−−	4[1,3,9,4]
ECOG3588	194/206	190/211	17,5	94,8			1,20 [0,98;1,47]	F	3,0	0 [-0,8 , 6,9]
JCOG9104	96/117	88/114	11,5	45,3			1,29 [0,96;1,73]	F	 _ 4,6	3[−0,4, 9,6]
Sous-total (a) 439/487	424/493	49,6	212,2		\diamondsuit	1,26 [1,10;1,45]			4,2 [1,8 , 6,7]
(b) Different	CT comp	liance be	tween	arms				,		
CALGB8083	146/154	127/138	-12,1	66,0			0,83 [0,65;1,06]	⊢o	-4,0	[-7,8 , -0,2]
03PCL88	71/76	83/88	-10,1	37,9			0,77 [0,56;1,05]	L	-3,9	9[−7,8, 0,0]
EORTC0887	7 161/174	166/175	-15,3	80,3			0,83 [0,66;1,03]	⊢— <u> </u>	⊢ ⊢ −2,9	9[−6,1, 0,3]
LLCG93	136/166	135/159	-9,8	67,0			0,86 [0,68;1,10]	L	-3,0) [-7,2 , 1,2]
HeCOG93	35/39	37/42	1,3	17,6			1,08 [0,68;1,72]		□ 2,7	[-5,2 , 10,5]
Sous-total (b) 549/609	548/602	-46,0	268,9	\bigcirc		0,84 [0,75;0,95]		-3,1	[-4,9 , -1,3]
Total (a)+(b)	988/1096	972/1095	3,6	481,0	•		1,01 [0,92;1,10]		0,	0 [-2,9 , 2,8]
Test d'hétérogé	néité: $\chi_7^2 = 2$	1,4 p=0,003 9,5 p<0,00	3 l² = 6 1	0,5 7% E	1,0 n faveur de	2,0 En faveur de BT Exp		En faveur de RT Cont	Test d'hétérogénéité: p<0,001, l ² Test d'interaction: p<0,001 <i>En faveur de RT Exp</i>	= 72%
	· · ·							8 -6 -4 -2	0 2 4 6 8 10	29

Varying time horizon t*

- *rmstD*(*t**) estimated using Pooled Kaplan-Meier (random effects) varying *t**
- ✓ $rmstD(t^*)$ significantly ≠ 0 and increases for $t^* \in [0;10 \text{ yrs}]$



Discussion



Conclusion

- Case study showed that the choice of a method to estimate *rmstD*(*t**) exerts an impact on cost-effectiveness results in the context of an IPD meta-analysis
- Simulation study, through various scenarios, allowed us to recommend the Pooled Kaplan-Meier method with random effects which formed the best compromise bias / variance
- We have highlighted the pros of using rmstD(t*) versus
 HR (non-proportional hazards, more intuitive) and have
 noted that clinical conclusions were similar with these two
 measures using 3 different IPD meta-analyses

Discussion

- ✓ PRISMA-IPD guidelines suggest to report both absolute and relatives measures (Stewart 2015)
- Royston and Parmar proposed to use the $rmstD(t^*)$ to analyze and design a clinical trial (2011, 2013, 2016) + 1st simulation study for $rmstD(t^*)$ in the context of metaanalysis using also flexible parametric model (Wei 2015)
- ✓ In a publication of a phase III RCT, for which Parmar was co-author, *rmstD(t*)* was the primary outcome **measure** with non-proportional hazards (Oza 2015)
- \checkmark To report the *rmstD*(*t*^{*}) in an article can also be usefull for future economic evaluation 33

Should RCT or IPD MA publications include ?

- *rmstD*(*t**) should be a secondary measure **systematically** reported in addition of a hazard ratio
- ✓ Proportional hazards test

→Only one HR ? Average HR? Time varying HR?

- Restricted mean survival times in the 2 arms and *rmstD(t*)* considering different time horizons t*
- ✓ Graphic with *rmstD(t*)* varying time horizon t*
- → We now include rmstD(t*) in the protocols of the IPD meta-analyses performed at Gustave Roussy

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Survival curves MAR-LC



Acceptability curves: 1,000 replicates bootstrap



Estimation des Coûts : perspective Assurance Maladie

Poste de coût	Ressource MAR-LC	Coût unitaire	Source	Pourcentage coût total
Traitement par radiothérapie	Nombre total de fractions reçues	1 004€ dosimétrie + 138€/fraction d'irradiation	PMSI 2012	21%
Transports pour la radiothérapie	Nombre total de fractions reçues	40€/fraction d'irradiation	Martin, 2003	5%
Traitement de la rechute	Temps de survie après rechute	3 073€/mois	Braud, 2003	73%
Traitement de l'œsophagite	Toxicité oesophagienne aigüe sévère	1 745€ si présence de toxicité	PMSI 2012	1%

Conventionnelle = 25 331 € ; IC95% [23 630€ ; 27 115€]

Modifiée = 29 659 € ; IC95% [27 845€ ; 31 507€]

7 methods to estimate the rmstD(t*)

	Take into account					
Method	Stratification	Heterog	jeneity	Non-		
	by trial	Treatment effect	Baseline hazard	proportional hazards		
Naïve Kaplan-Meier	No	Νο	Νο	Yes		
Stewart-Parmar	Yes	Yes	Νο	No£		
Peto-month Peto-year Peto-quintile	Yes	Yes	Νο	Yes ^µ		
Pooled Kaplan-Meier	Yes	Yes	Yes	Yes		
Pooled Exponential	Yes	Yes	Yes	Νο		

[£] Non-proportionality of hazards can however be taken into acocunt by using a time varying HR $^{\mu}$ HR_{i,overall} can vary between time intervals

Varying the heterogeneity $\lambda_{i}(t) = \lambda_{0}(t)exp\{\boldsymbol{a}_{i} + (\beta + \boldsymbol{b}_{i})x\}$ (ici: $\beta = -0,7 \rightarrow HR = 0,5$) Trial 2 : $a_i = 0$ Trial 1 : *a_i* = -1 Trial 3 : **a**_i = 1 1.0 1.0 Contrôle Expérimental 5 months 0.8 0.8 0.8 0.6 0.0 0.6 9 months $b_{i} = 0$ 0.4 0.4 0.4 12 months 0.2 0.2 0.2 0.0 0.0 0.0 \rightarrow Var $(a_i) = \sigma^2$: variation of baseline hazard heterogeneity Trial 1 : **b**_i = -1 Trial 2 : $b_i = 0$ Trial 3 : **b**_i = 1 Contrôle Expérimenta 0^{.8} 0.8 0.8 0.6 0.6 0.6 9 months 22 months $a_i = 0$ 0.4 0.4 0.4 - 4 months 0.2 0.2 0.2 0.0 0.0 0.0 2 \rightarrow Var(b_i) = τ^2 : variation of treatment effect heterogeneity

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- ✓ Similarly to the work by Trinquart *et al* (2016) : comparison of treatment effect measured by
 - <u>Hazard ratio</u> (Peto estimator)
 - <u>*rmstD(t*)*</u> (Kaplan-Meier + Brown)
- ✓ 42 trials included in 3 meta-analyses
- ✓ $t^* = 5$ years (MAR-LC, RTT-SCLC) or 10 years (MAC-NPC2)
- Test for hazards proportionality: Grambsh and Therneau test (1994) threshold = 5%

3 trials (7%) with non-proportional hazards



Hazard ratio



Hazard ratio

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2 trials with different direction of treatment effect but both HR and rmstD(t*) non significant



Hazard ratio

Formules

Cochran test for heterogeneity:

$$Q = \sum_{j=1}^{J} w_j (\hat{\theta}_j - \hat{\theta}_{overall,fixed})^2 \sim \chi_{J-1}^2$$

Random effecs model

Random effects model:

$$w_{j} = \frac{1}{\widehat{Var}(\widehat{\theta}_{j}) + \widehat{\tau}^{2}}$$

$$\widehat{\theta}_{overall} = \frac{\sum_{j=1}^{J} \widehat{\theta}_{j} w_{j}}{\sum_{j=1}^{J} w_{j}}$$
with:

$$\widehat{\tau}^{2} = \frac{Q - (J - 1)}{\sum_{j=1}^{J} w_{j} - \frac{\sum_{j=1}^{J} w_{j}^{2}}{\sum_{j=1}^{J} w_{j}}}$$

- $\hat{\tau}^2$ is estimated by the method of moments from DerSimonian and Laird
- I² Higgins : $I^2 = \frac{Q (J 1)}{Q} \times 100$ with *J* the number of trials