

Dealing with Heterogeneity in Network Meta-analysis

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https://www.nihrcrsu.org/workshops/cochranesymposium2019/

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The Complex Reviews Support Unit is funded by the National Institute for Health Research (project number 14/178/29)





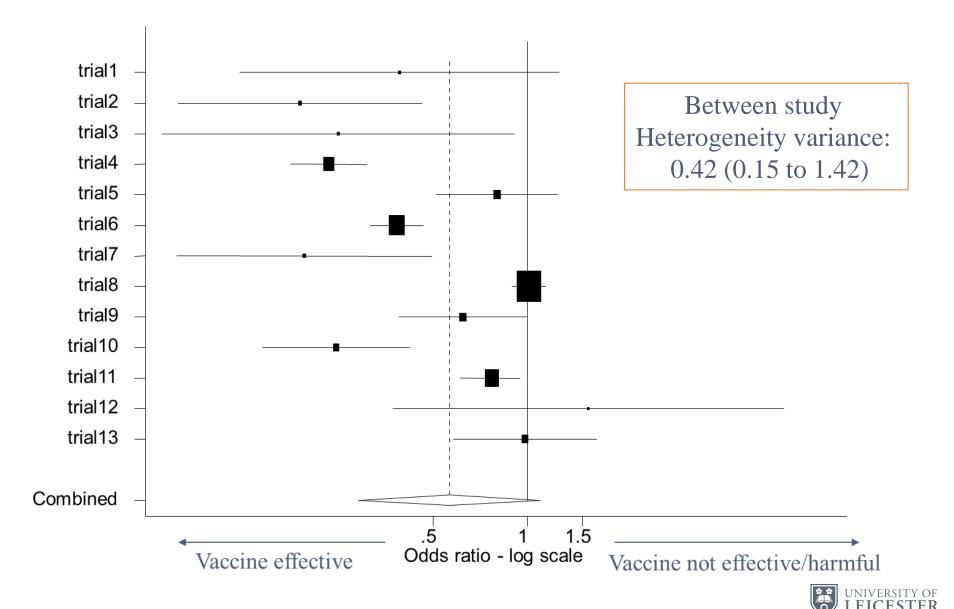


Heterogeneity

- What causes between study heterogeneity?
 - Differences in patients
 - Differences in study design/conduct
 - Chance
- Can fit Random Effects models but these only account for the heterogeneity – they do not explain it!



Example: Vaccine for the prevention of TB



Exploring Heterogeneity

 Subgroup analyses or Meta-regression methods can help to explain heterogeneity by examining associations between study characteristics and treatment effects

Subgroup analysis

• Fits separate analyses to each subgroup; therefore, estimating the between-study heterogeneity (τ^2) separately for each subgroup

Meta-regression

- Fits covariates within the meta-analysis framework; therefore assuming between-study heterogeneity (τ^2) to be the same for all subgroups
- Estimates the difference in intervention effect between subgroups



SUBGROUP ANALYSIS Pairwise and Network Meta-analysis



Subgroup analyses

Two types of subgroup analyses are possible:

- i) Stratification by study characteristics
 - Subsets of "whole" studies defined by study (e.g. length of follow-up) or patient characteristics (e.g. trial eligibility criteria) can be combined separately
- ii) Stratification by patient characteristics
 - "Split" data from individual studies in an attempt to identify effect modifiers (e.g. young/old, etc)
 - Has more power than such analyses of individual trial which may be under-powered
 - Data may not be available in trial reports to do this



Example: Cholesterol data

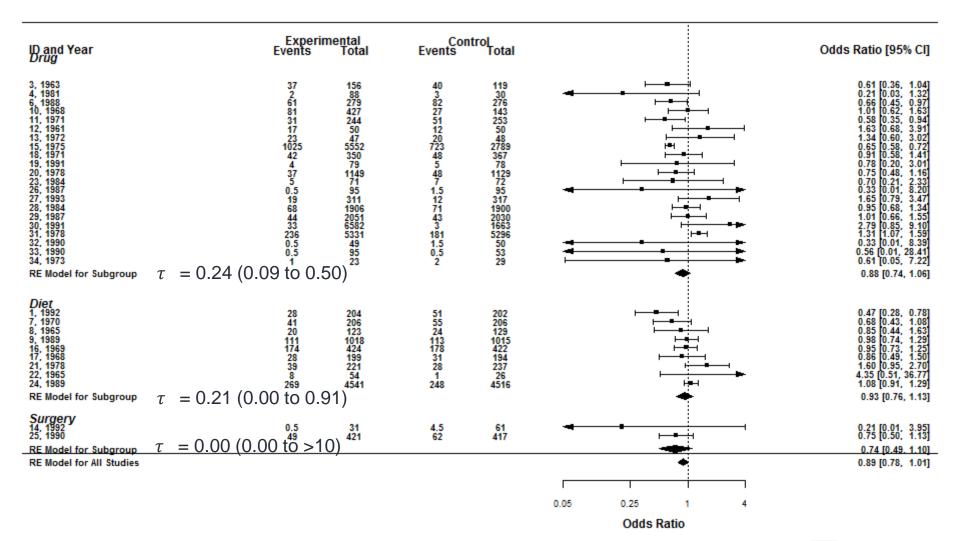
 Meta-analysis of 34 RCTs to assess the effect of cholesterol lowering interventions on overall mortality

> 1 = drug, 2 = diet, 3 = surgery

id	pub	nt	nc	rt	rc	chol_red	treat	fup
1	1992	204	202	28	51	7	2	2
3	1963	156	119	37	40	3	1	5
4	1981	88	30	2	3	8	1	1
6	1988	279	276	61	82	13	1	5
7	1970	206	206	41	55	14	2	5
8	1965	123	129	20	24	7	2	3
9	1989	1018	1015	111	113	4	2	2
10	1968	427	143	81	27	6	1	3
•••								
30	1991	6582	1663	33	3	24	1	1
31	1978	5331	5296	236	181	9	1	5
32	1990	48	49	0	1	25	1	2
33	1990	94	52	1	0	25	1	3
34	1973	23	29	1	2	10	1	1



Cholesterol data: Subgroup analysis stratified by treatment type (32 RCTs)





META-REGRESSION Pairwise and Network Meta-analysis



Meta-regression

- Continuous or categorical study level covariates can be included in Pairwise and Network Meta-analysis models to explore/adjust for systematic differences between studies
 - e.g. average age, % of patients female
- In Network Meta-analysis incorporation of study-level covariates can reduce both heterogeneity and inconsistency by allowing systematic variability betweentrials to be explained.
 - i) **Heterogeneity** variation in treatment effects between trials within pairwise contrasts, and
 - ii) **Inconsistency** variation in treatment effects between pairwise contrasts

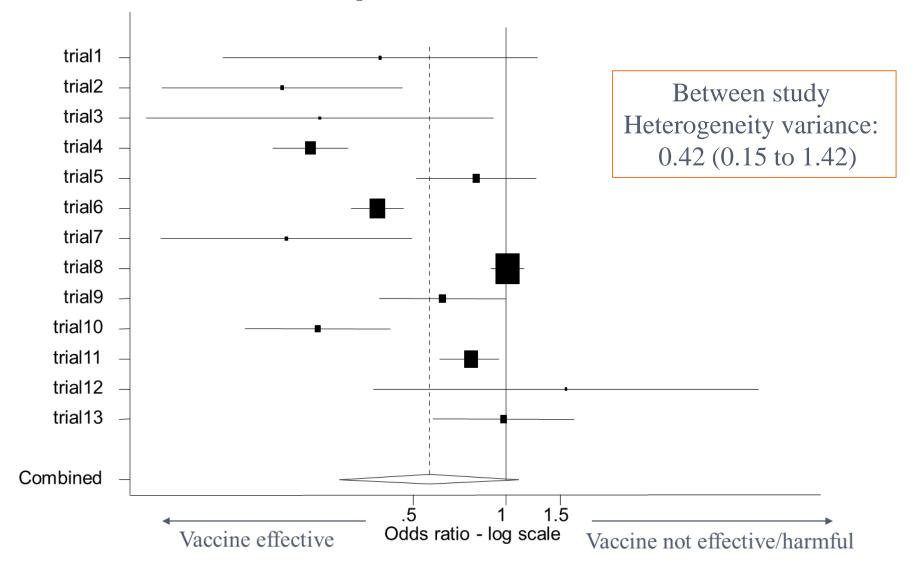


Example: BCG vaccine for the prevention of TB

Trial	Latitude (degrees from the equator)	Vaccinated		Not vaccinated		
	- · -	Disease	No	Disease	No	
			Disease		Disease	
1	44	4	119	11	128	
2	55	6	300	29	274	
3	42	3	228	11	209	
4	52	62	13,536	248	12,619	
5	13	33	5,036	47	5,761	
6	44	180	1,361	372	1,079	
7	19	8	2,537	10	619	
8	13	505	87,886	499	87,892	
9	-27	29	7,470	45	7,232	
10	42	17	1,699	65	1,600	
11	18	186	50,448	141	27,197	
12	33	5	2,493	3	2,338	
13	33	27	16,886	29	17,825	

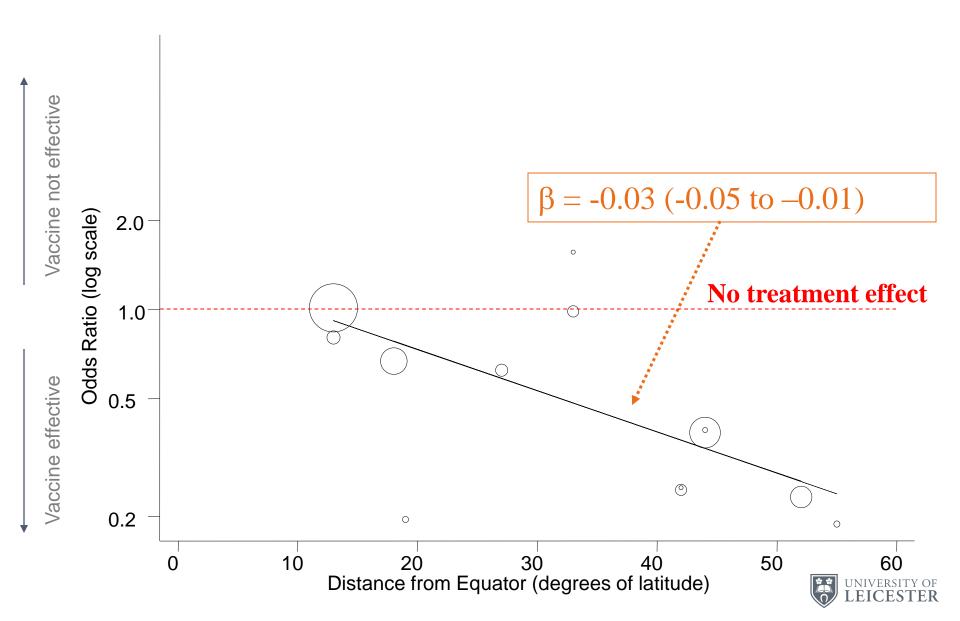
• It is suspected that the *absolute* distance from the equator affects the efficacy of the vaccine (*Berkey 1995*)

Pairwise Meta-analysis: Vaccine for the prevention of TB





Meta-regression Results

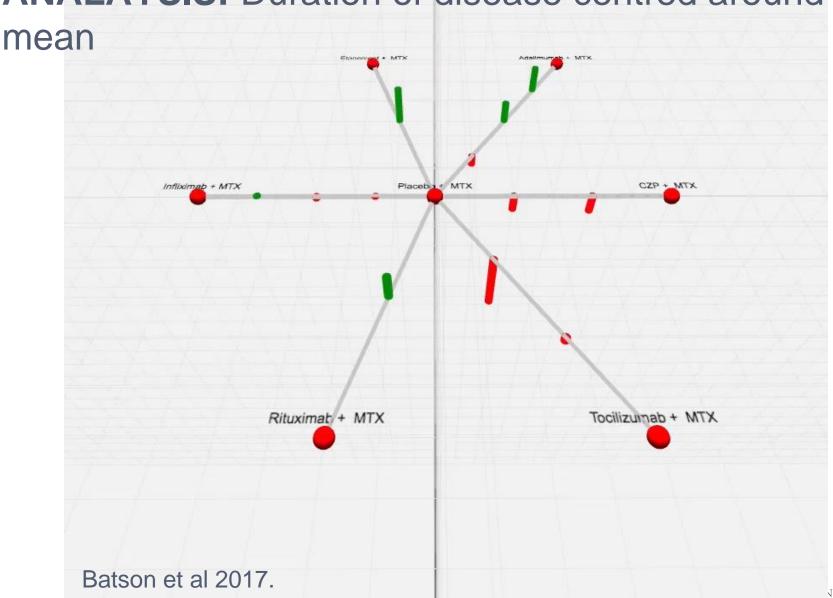


Meta-regression – Network Meta-analysis

 In Network Meta-analysis, a study-level covariate cab be seen as a variable that interacts with the intervention, but these interactions may differ for each intervention.



VISUALISING COVARIATES IN NETWORK META-ANALAYSIS: Duration of disease centred around



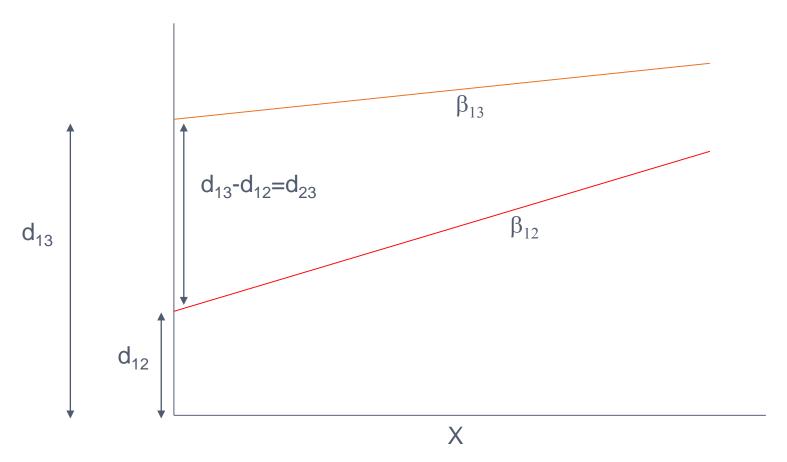
Meta-regression – Network Meta-analysis

- In Network Meta-analysis, a study-level covariate can be seen as a variable that interacts with the intervention, but these interactions may differ for each intervention.
- Large number of different models with different assumptions for the interactions in a multiple intervention framework.
- Three potential models (not an exhaustive list):
 - Independent, intervention-specific interactions
 - Exchangeable, related, intervention-specific interactions:
 - Same interaction effect for all interventions:



Independent, intervention specific interactions

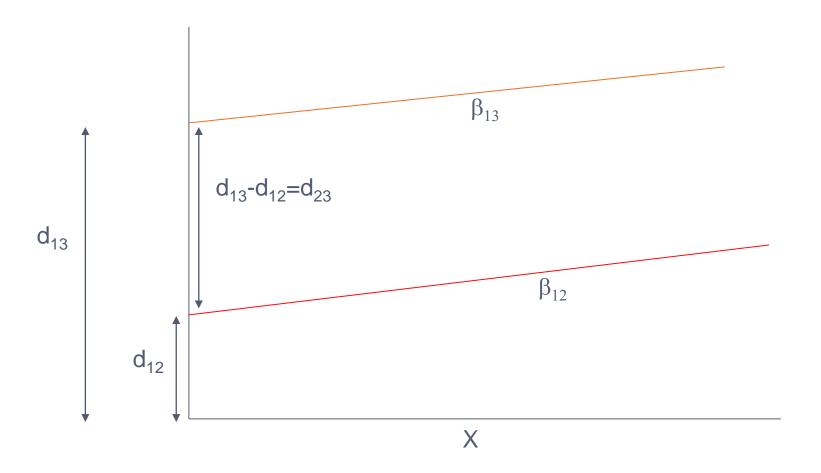
 Independent 'beta' for each intervention x covariate interaction compared to intervention 1 (e.g. placebo)





Same interaction effect for all interventions

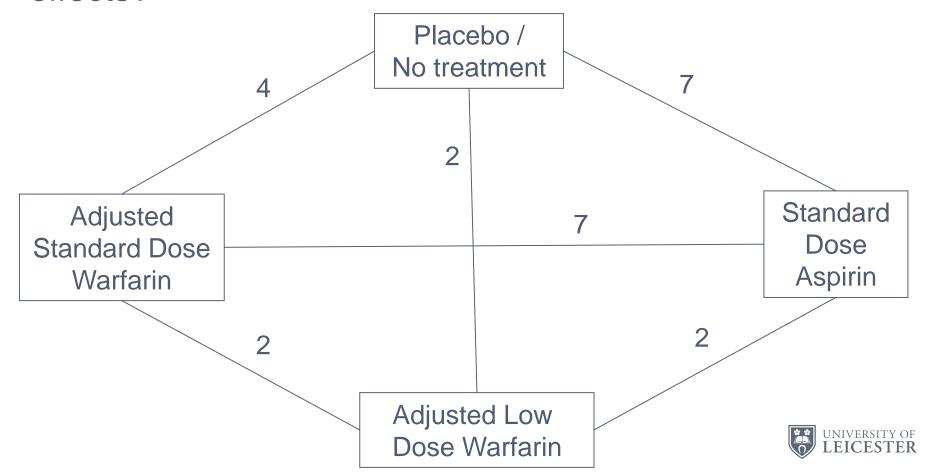
 Common 'beta' for each intervention x covariate interaction compared to intervention 1 (e.g. placebo)



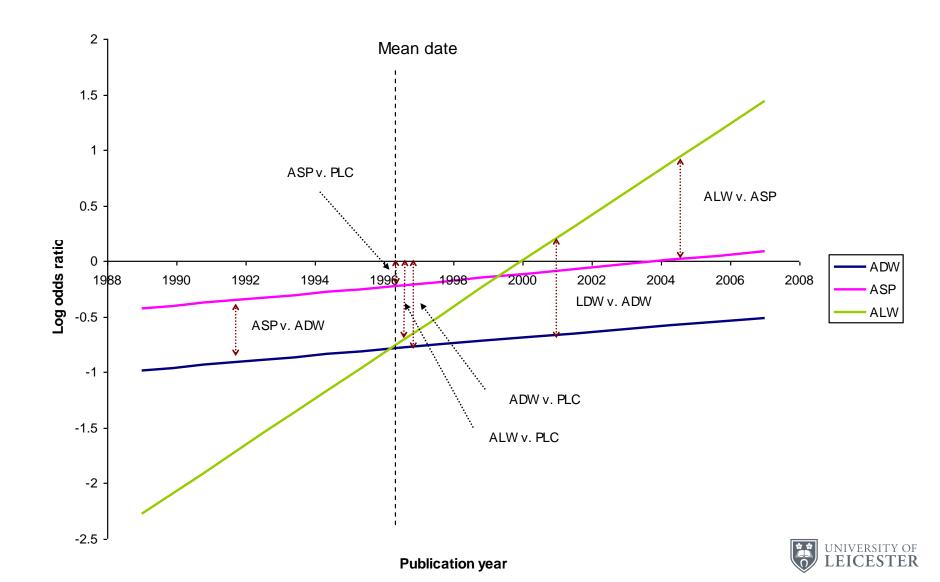


Example: Treatments to prevent stroke in non-rheumatic atrial fibrillation patients

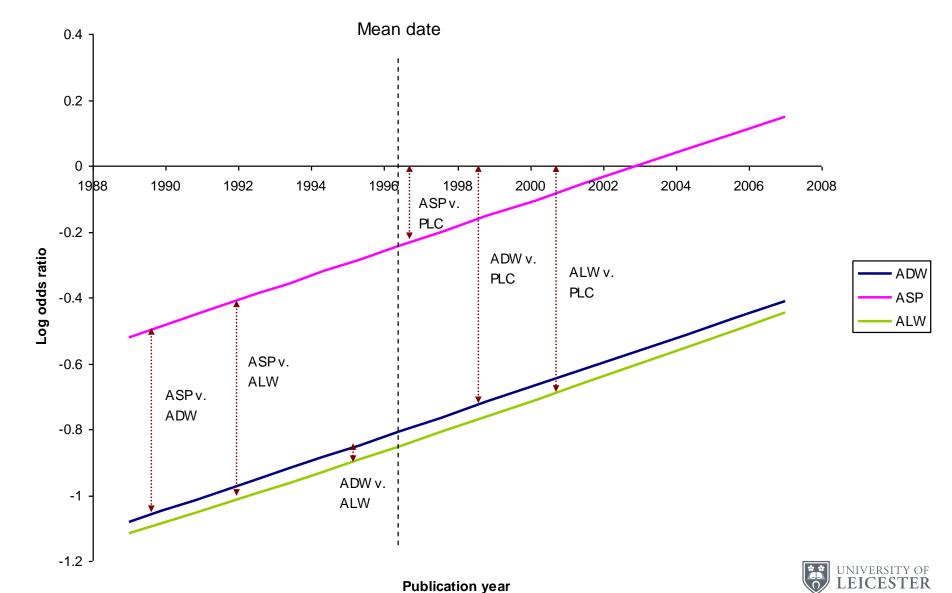
Does date of publication (proxy for factors relating to change in clinical practice over time) affect treatment effects?



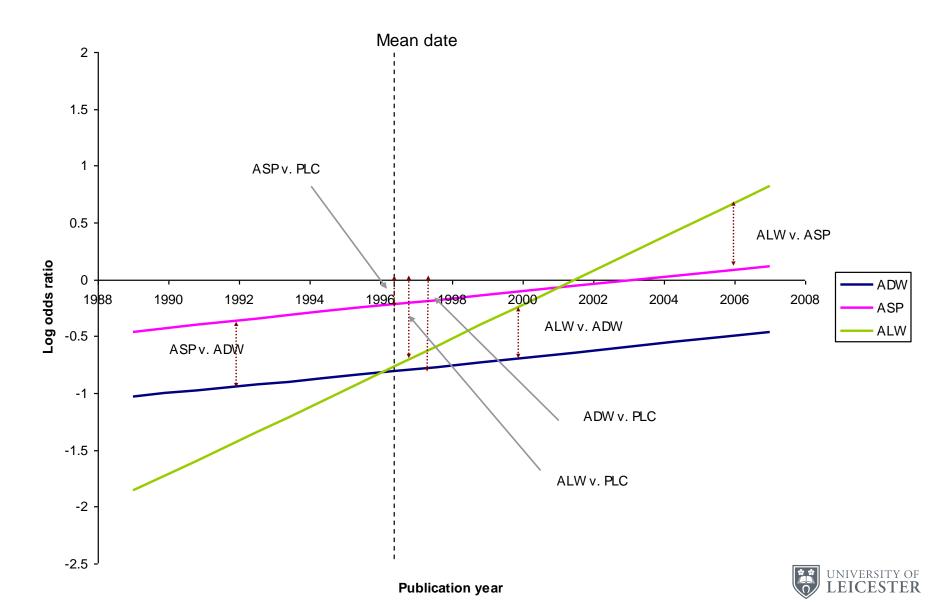
Example: Independent 'beta' for each *treatment x* covariate interaction compared to placebo



Example: Common 'beta' for *treatment x covariate* interactions compared to placebo



Example: Exchangeable 'betas' for *treatment x* covariate interactions compared to placebo



Adjusting for Baseline Risk

- Special kind of covariate, Baseline risk is often defined as a proxy for underlying patient-level covariates thought to modify the intervention effect, but which cannot be accounted for directly in the model (i.e. unmeasured or unknown e.g. medical history, co-morbidities, etc.).
 - That is, reflects the risk of an event for a patient under the reference intervention
- Need to take into account the correlation between the intervention effect and baseline risk.
 - Methods for including baseline risk as a covariate have been extended to Network Meta-analysis (*Dias et al. 2011, Achana et al. 2013*)



Summary

- Focused on using Meta-regression with aggregate data; however, often too few studies resulting in insufficient data to detect intervention x covariate interactions (Lambert et al., 2002)
- If Individual Patient Data (IPD) available, alternative strategy to relate intervention effect to individual patient characteristics to investigate heterogeneity
 - More powerful than average effect vs. average covariate value meta-regression
 - Few examples of IPD meta-regression with network meta-analysis (Veroniki et al. 2016)
- Other analyses
 - Component network meta-analysis for complex interventions (Welton et al. 2009, Freeman et al. 2018)
 - Multiple outcomes (Riley et al. 2017)



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