

NETWORK META ANALYSIS (NMA)

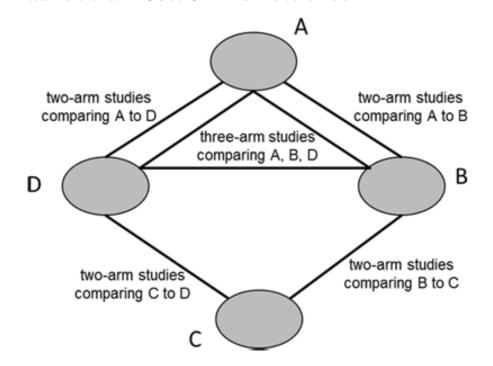
STAT3622
Data Visualization

#### META-ANALYSIS | LIMITATIONS

- ☐ The conventional meta-analysis approach can only
  - o compare **pairs** of interventions at a time
  - o evaluate **direct** treatment effect (interventions A vs B) in **head-to-head** trials (fail to include multi-arm trials)
- Sometimes, only few randomized controlled trials (RCTs) have compared the effects of two interventions **directly**
- ☐ In real cases, usually there would exist **more than two interventions** for one specific disease, and RCTs that simultaneously compare all interventions of interest are almost never available
- ☐ How to compare three or more interventions **simultaneously** in a single analysis?
- ☐ How to incorporate **indirect** evidence? (e.g., A vs B by A vs C and B vs C)

#### NMA | INTRODUCTION

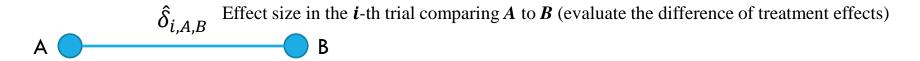
■ Network meta-analysis is a technique for comparing **three or more interventions simultaneously** in a single analysis by combining both **direct** and **indirect** evidence across a **network** of studies



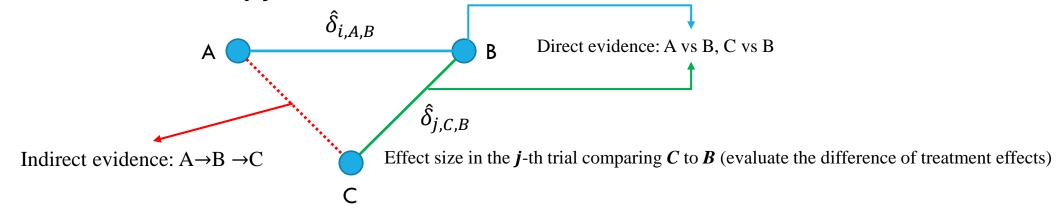
- Evidence of A vs B
  - o Direct: two-arm studies comparing A to B
  - Indirect: loop of evidence, e.g., A to D to B
     (both two-arm studies comparing A to D and three-arm studies comparing A,B,D), A to D to C to B

#### NMA | INDIRECT COMPARISON

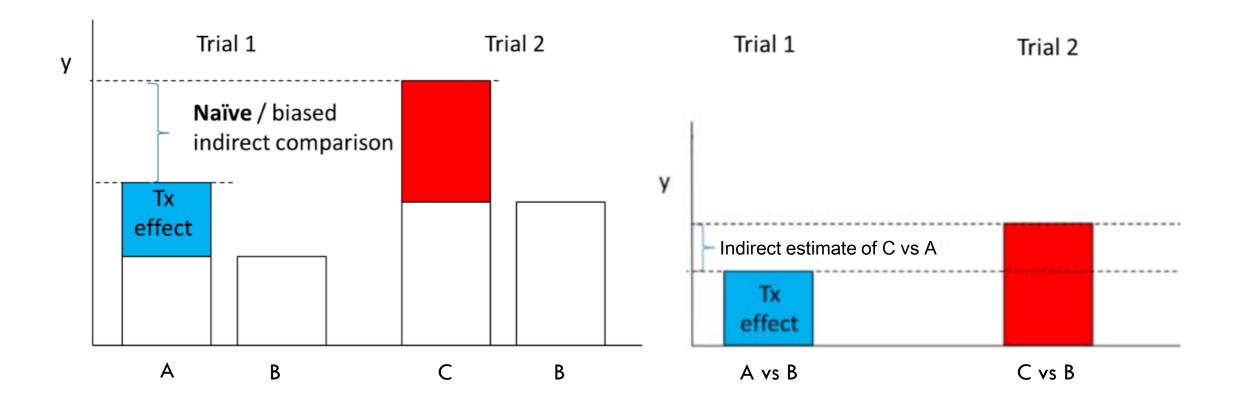
☐ Head-to-head trial *i* for A vs B



☐ Include another study *j* for C vs B

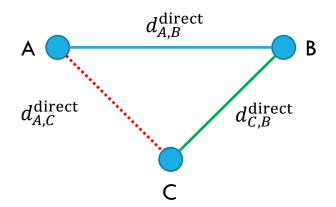


## NMA | INDIRECT COMPARISON



## NMA | INDIRECT COMPARISON

- ☐ Assume that we only have RCTs comparing A to B and C to B (no A to C)
- We can obtain aggregate effect size estimates from direct comparisons as  $d_{A,B}^{\text{direct}}$ ,  $d_{C,B}^{\text{direct}}$
- □ Nodes A and C are indirectly connected by  $A \rightarrow B$ ,  $B \rightarrow C$
- $\square$  Effect between A and C:  $d_{A,C}^{\text{direct}} = d_{A,B}^{\text{direct}} + d_{B,C}^{\text{direct}} = d_{A,B}^{\text{direct}} d_{C,B}^{\text{direct}}$



# NMA | ASSUMPTIONS: TRANSITIVITY

$$d_{A,C}^{\text{direct}} = d_{A,B}^{\text{direct}} + d_{B,C}^{\text{direct}} = d_{A,B}^{\text{direct}} - d_{C,B}^{\text{direct}}$$

- ☐ Transitivity: **validity** of **indirect** evidence
- □ Requirements: we can compare interventions A and C via B
- → there is **no difference in patient and study characteristics** that may **modify treatment effect** in the **direct** comparisons (e.g., A vs B, B vs C) that form the basis for the indirect estimate of effect of the comparison of interest (A vs C)
- ☐ **Imbalance** in the distribution of patient and study characteristics among trials may **bias** treatment effect estimates
- □ For example, if patients included in trials comparing A vs B were all  $\geq$ 50 years and those for B vs C were all  $\leq$ 30 years, then these two direct effect estimates cannot be compared and combined to estimate the indirect effect between A and C

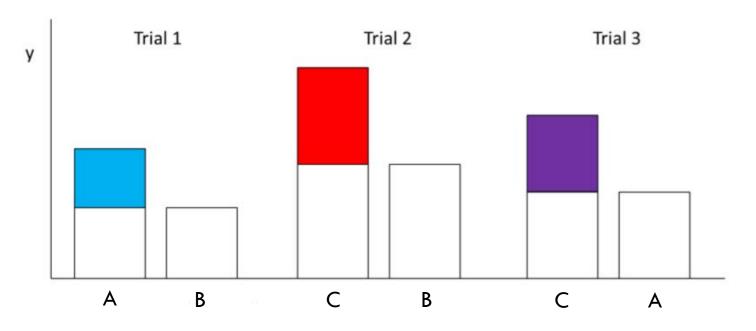
## NMA | ASSUMPTIONS: CONSISTENCY

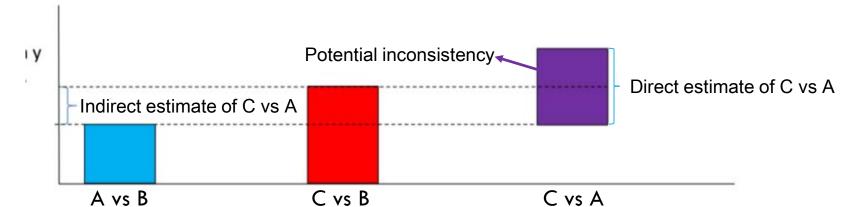
- ☐ In the network meta-analysis, we might obtain both direct (head-to-head comparisons) and indirect (connected by other interventions in the graph) evidence
- ☐ Consistency: the **direct** evidence in a network for the effect size between two treatments (e.g. A vs B) does **not differ** from the **indirect** evidence calculated for that same comparison

$$d_{A,B}^{\text{indirect}} = d_{A,B}^{\text{direct}}$$

☐ Global and local statistical approaches to check consistency

## NMA | ASSUMPTIONS: CONSISTENCY





- ☐ Assume that data consist of **only two-arm studies**
- $\square$  Suppose that NMA includes n interventions and K two-arm trials
- $\square$  For the *i*-th trial, we observe the treatment difference estimate  $\hat{\delta}_{i,a_i,b_i}$  comparing intervention  $a_i$  to  $b_i$  and its standard error  $s_{i,a_i,b_i}$ , i=1,...,K.
- ☐ For arm-level data, we can choose a summary measure and calculate the treatment differences as well as their standard errors.
- □ We use a  $n \times 1$  vector  $\boldsymbol{\theta} = (\theta_1, ..., \theta_n)$  to denote the treatment effect of n interventions
- The fixed effects model has the form,

$$\hat{\delta}_{i,a_i,b_i} \sim N(\theta_{a_i} - \theta_{b_i}, s_{i,a_i,b_i}^2), i = 1, \dots, n$$

☐ In the matrix form,

$$\widehat{\delta} = X\theta + \epsilon$$

- $\square$  X is a  $K \times n$  design matrix for which the rows represent treatment comparisons with  $X_{i,a_i} = 1$ ,  $X_{i,b_i} = -1$
- $\square \epsilon \sim N(0, \Sigma), \Sigma = \operatorname{diag}(s_{1,a_1,b_1}^2, ..., s_{K,a_K,b_K}^2)$

$$\widehat{\delta} = X\theta + \epsilon$$

- $\square$  The design matrix X might not be of full rank => Its inverse does not exist
- $\square$  A weighted least squares approach can be utilized to estimate  $\theta$ ,

$$L = X^{T}WX,$$

$$W = \operatorname{diag}\left(\frac{1}{s_{1,a_{1},b_{1}}^{2}}, \dots, \frac{1}{s_{K,a_{K},b_{K}}^{2}}\right)$$

$$L^{+} = \left(L - \frac{J_{n}}{n}\right)^{-1} + \frac{J_{n}}{n}$$

$$\widehat{\boldsymbol{\theta}}^{nma} = L^{+}X^{T}W\widehat{\boldsymbol{\delta}}$$

where  $J_n$  is the  $n \times n$  matrix whose elements are all one,  $L^+$  is the Moore–Penrose pseudoinverse of L (L is not invertible).

☐ Predicted values of observed treatment difference:

$$\widehat{\boldsymbol{\delta}}^{\text{nma}} = \boldsymbol{X} \boldsymbol{L}^{+} \boldsymbol{X}^{T} \boldsymbol{W} \widehat{\boldsymbol{\delta}}$$

$$\operatorname{Var}(\widehat{\boldsymbol{\delta}}^{\operatorname{nma}}) = \boldsymbol{X}\boldsymbol{L}^{+}\boldsymbol{X}^{T}$$

The predicted values  $\widehat{\boldsymbol{\delta}}^{nma}$  are linear combinations of the elements of  $\widehat{\boldsymbol{\delta}}$ 

 $\square$  Variance of the treatment difference comparing intervention i to j

$$V_{ij} = L_{ii}^+ + L_{jj}^+ - 2L_{ij}^+$$

## NMA | MULTI-ARM STUDY

- Multi-arm studies can be included in the NMA as a series of two-arm comparisons
- $\square$  For a p-arm trial, there are p(p-1)/2 possible comparisons
- ☐ The comparisons within a multi-arm study are **correlated**
- We need to **adjust the standard error** of each two-arm comparison for the existence of **correlation**
- Rücker and Schwarzer (2014) **inflated** the standard errors for comparisons within each multi-arm study by back-calculation.

  Research Article

  Research Article

Received 24 August 2013,

Accepted 26 May 2014

Published online 18 June 2014 in Wiley Online Library

(wileyonlinelibrary.com) DOI: 10.1002/sim.6236

Reduce dimension or reduce weights? Comparing two approaches to multi-arm studies in network meta-analysis

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## NMA | HETEROGENEITY

☐ Generalized Cochran's Q

$$Q_{\text{total}} = (\widehat{\boldsymbol{\delta}} - \widehat{\boldsymbol{\delta}}^{\text{nma}})^T \boldsymbol{W} (\widehat{\boldsymbol{\delta}} - \widehat{\boldsymbol{\delta}}^{\text{nma}})$$

- $\square$  Each *p*-arm study contributes p-1 degrees of freedom to  $Q_{\text{total}}$
- $\square$  Generalized Higgin's & Thompson's  $I^2$

$$I^2 = \max\left\{0, \frac{Q_{\text{total}} - df}{Q_{\text{total}}}\right\}$$

## NMA | RANDOM EFFECTS MODEL

☐ The random effects model has the form,

$$\hat{\delta}_{i,a_i,b_i} \sim N(d_{i,a_i,b_i}, s_{i,a_i,b_i}^2)$$

$$d_{i,a_i,b_i} \sim N(\theta_{a_i} - \theta_{b_i}, \tau^2), i = 1, \dots, n$$

- $\Box$  The estimated heterogeneity  $\hat{\tau}^2$  is added to the variances of each comparison  $i: s_{i,a_i,b_i}^2 + \hat{\tau}^2$
- $\square$  The generalized DerSimonian–Laird estimator can be used to estimate  $\tau^2$

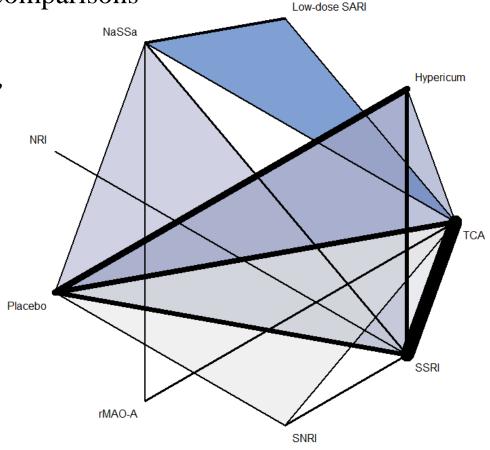
$$\hat{\tau}^2 = \max\left(\frac{Q_{total} - df}{tr((I - XL^+X^TW)UW)}, 0\right)$$

where U is a block diagonal matrix from  $XX^T/2$  by selecting the diagonal  $p_k \times p_k$  block for k = 1, ... K.

#### LINDE2015 | NETWORK PLOT

- ☐ The observations of a network-meta analysis can be viewed as a graph
- □ Nodes are treatments, edges are head-to-head comparisons

- ☐ The width of edges is proportional to the number of studies ←
- ☐ Multi-arm studies are represented as colored polygon (triangles for Linde2015 because it contains only two-arm and three-arm studies)



#### LINDE2015 | FOREST PLOT

Fixed effects model Comparison: other vs 'Placebo' Treatment OR OR [95%-CI] (Fixed Effect Model) (Placebo as reference) Hypericum 1.97 1.97 [1.62; 2.39] Low-dose SARI 1.74 1.74 [1.22; 2.47] forest (Linde. net, 1.16 1.16 [0.87; 1.54] NaSSa NRI 1.41 1.41 [0.98; 2.03] reference.group = 'Placebo', Placebo 1.00 1.00 pool ed = 'fixed', rMAO-A 1.03 1.03 [0.72; 1.47] leftcols = c('studlab', SNRI 1.71 1.71 [1.30; 2.24] 'effect', 'effect.ci'), SSRI 1.67 1.67 [1.45; 1.94] TCA 1.68 1.68 [1.43; 1.97] rightcols = F) 0.5

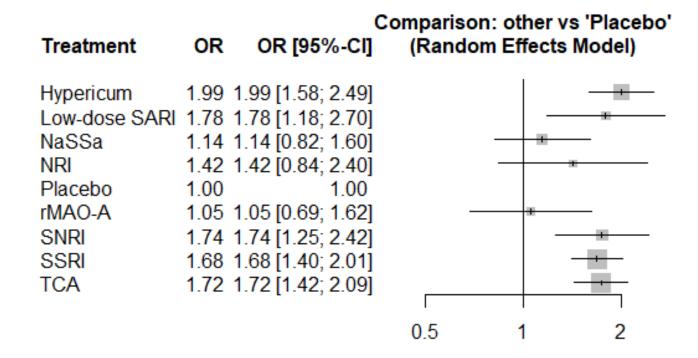
■ Each row in the forest plot represents the NMA estimates of treatment effect comparing the specific treatment to placebo

#### LINDE2015 | FOREST PLOT

Random effects model
(Placebo as reference)

forest(Li nde. net,
 reference. group = 'Placebo',
 pool ed = 'random',
 leftcols = c('studlab',
 'effect', 'effect.ci'),

rightcols = F)



Comparison	Number of Studies	Direct Evidence	Fixed effect model	OR 95%-CI	NaSSa:Placebo Direct estimate Indirect estimate Network estimate	2	0.40	*	1.20 [0.76; 1.88] 1.14 [0.79; 1.64] 1.16 [0.87; 1.54]
Hypericum:Plac Direct estimate Indirect estimate Network estimate	9	0.58	- <del></del>	1.93 [1.50; 2.49] 2.01 [1.49; 2.72] 1.97 [1.62; 2.39]	NaSSa:rMAO-A Direct estimate Indirect estimate Network estimate	1	0.25		1.07 [0.49; 2.34] 1.15 [0.73; 1.81] 1.13 [0.76; 1.67]
Hypericum:SSR Direct estimate Indirect estimate Network estimate	6	0.59	*	1.14 [0.90; 1.45] 1.22 [0.92; 1.63] 1.17 [0.98; 1.41]	NaSSa:SSRI Direct estimate Indirect estimate Network estimate	3	0.54		0.99 [0.68; 1.43] 0.46 [0.31; 0.68] 0.69 [0.53; 0.91]
Hypericum:TCA Direct estimate Indirect estimate Network estimate	2	0.23		1.15 [0.76; 1.75] 1.18 [0.94; 1.47] 1.17 [0.96; 1.43]	NaSSa:TCA Direct estimate Indirect estimate Network estimate	1	0.11	***	0.26 [0.11; 0.60] 0.78 [0.58; 1.04] 0.69 [0.52; 0.91]
Low-dose SARI Direct estimate Indirect estimate Network estimate	4	0.62	<del>-</del> _	2.11 [1.37; 3.25] 0.86 [0.49; 1.49] 1.50 [1.07; 2.11]	SNRI:Placebo Direct estimate Indirect estimate Network estimate	1	0.15	- <del>*</del> -	1.94 [0.96; 3.93] 1.67 [1.24; 2.24] 1.71 [1.30; 2.24]
Low-dose SARI Direct estimate Indirect estimate Network estimate	2	0.69		0.74 [0.50; 1.10] 2.17 [1.21; 3.91] 1.03 [0.74; 1.44]	SSRI:Placebo Direct estimate Indirect estimate Network estimate	7	0.63		1.57 [1.31; 1.89] 1.87 [1.47; 2.37] 1.67 [1.45; 1.94]

##Results truncated

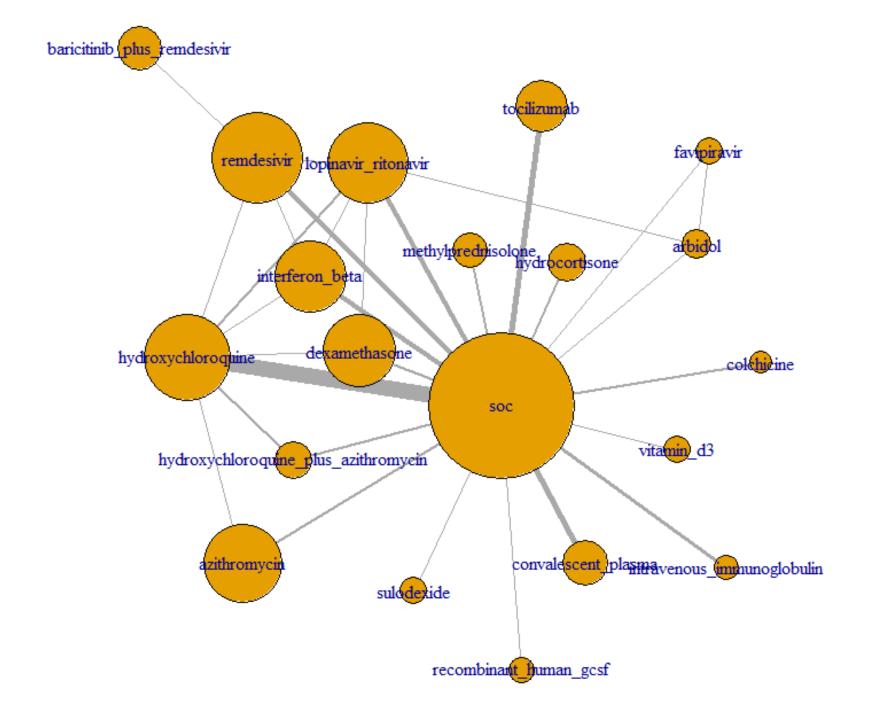
Comparison		Direct Evidence	Random effects model	OR	95%-CI	NaSSa:Placebo Direct estimate Indirect estimate Network estimate	2	0.38	*	1.21 [0.70; 2.08] 1.10 [0.72; 1.69] 1.14 [0.82; 1.60]
Hypericum:Place Direct estimate Indirect estimate Network estimate	9	0.61	*** ***	2.02	[1.47; 2.62] [1.40; 2.91] [1.58; 2.49]	NaSSa:rMAO-A Direct estimate Indirect estimate Network estimate	1	0.29	*	1.07 [0.45; 2.54] 1.09 [0.63; 1.88] 1.08 [0.68; 1.72]
Direct estimate Indirect estimate Network estimate	6	0.58	*	1.25	[0.85; 1.52] [0.89; 1.75] [0.95; 1.47]	NaSSa:SSRI Direct estimate Indirect estimate Network estimate	3	0.52		0.98 [0.63; 1.52] 0.46 [0.29; 0.73] 0.68 [0.50; 0.93]
Hypericum:TCA Direct estimate Indirect estimate Network estimate		0.23	**************************************	1.15	[0.70; 1.88] [0.88; 1.51] [0.91; 1.46]	NaSSa:TCA Direct estimate Indirect estimate Network estimate	1	0.13 —	**************************************	0.26 [0.11; 0.65] 0.76 [0.54; 1.07] 0.66 [0.48; 0.91]
Low-dose SARI: Direct estimate Indirect estimate Network estimate	4	0.67		0.87	[1.30; 3.36] [0.44; 1.70] [1.06; 2.30]	SNRI:Placebo Direct estimate Indirect estimate Network estimate	1	0.17	*	1.94 [0.88; 4.30] 1.70 [1.18; 2.45] 1.74 [1.25; 2.42]
Low-dose SARI: Direct estimate Indirect estimate Network estimate	2	0.66		2.09	[0.45; 1.16] [1.07; 4.07] [0.70; 1.52]	SSRI:Placebo Direct estimate Indirect estimate Network estimate	7	0.59	<del></del>	1.56 [1.23; 1.97] 1.86 [1.41; 2.46] 1.68 [1.40; 2.01]

##Results truncated

## COVID19 | NETWORK PLOT

```
Function plot.mtc.network generates a network plot.
We can directly call plot function and use the mtc.network object as the input
# Network plot
vertex. si ze = aggregate(mortality.network$data.ab$sampleSi ze,
                            by = list(mortality.network$data.ab$treatment),
                                                        Use Davidson-Harel algorithm for the network plot.
                            FUN = sum
                                                        This algorithm has some randomness
plot(mortality.network, layout=igraph::layout.davidson.harel,
      use. description = T, vertex. size = 1.8*(vertex. size $x)**(1/3)
                               The size of the node is proportional to the cubic root of the
      vertex.label.cex = 1)
                               overall number of patients in the treatment group
                               represented by the node
```

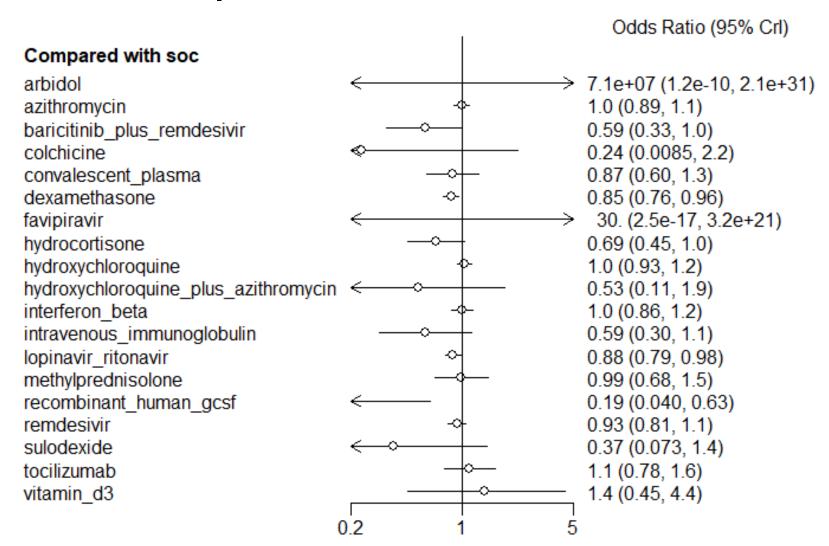
The width of edge between nodes is proportional to the number of head-to-head comparison in the dataset (default setting)

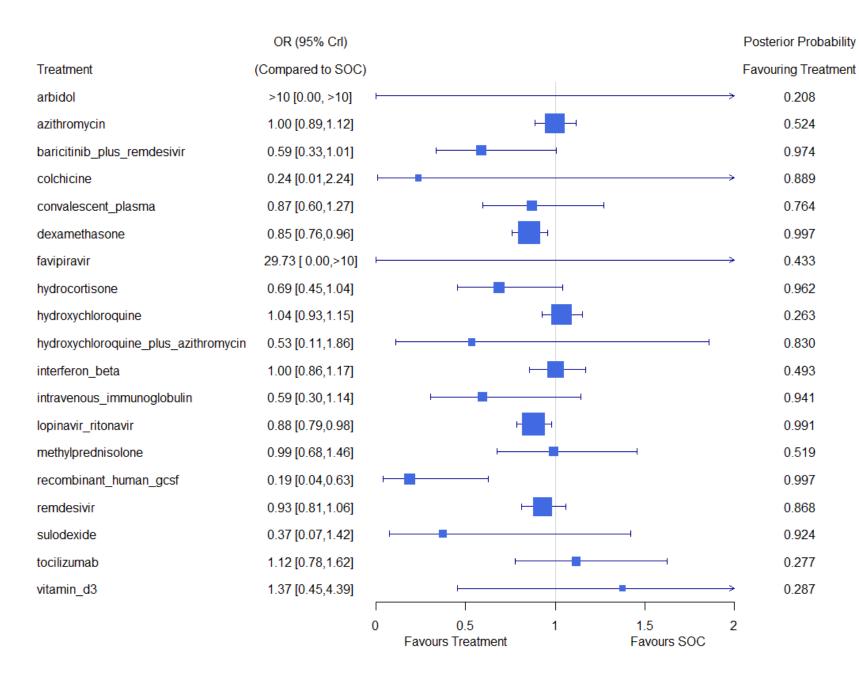


#### forest(mortality.re,

## COVID19 | FOREST PLOT

xlim = c(log(0.2), log(5)),digits = 2)





Or you can generate forest plot by the function *forestplot* in package *forestplot*. See the provided R codes for details.