

# Sharing information across patient subgroups to draw conclusions from sparse treatment networks

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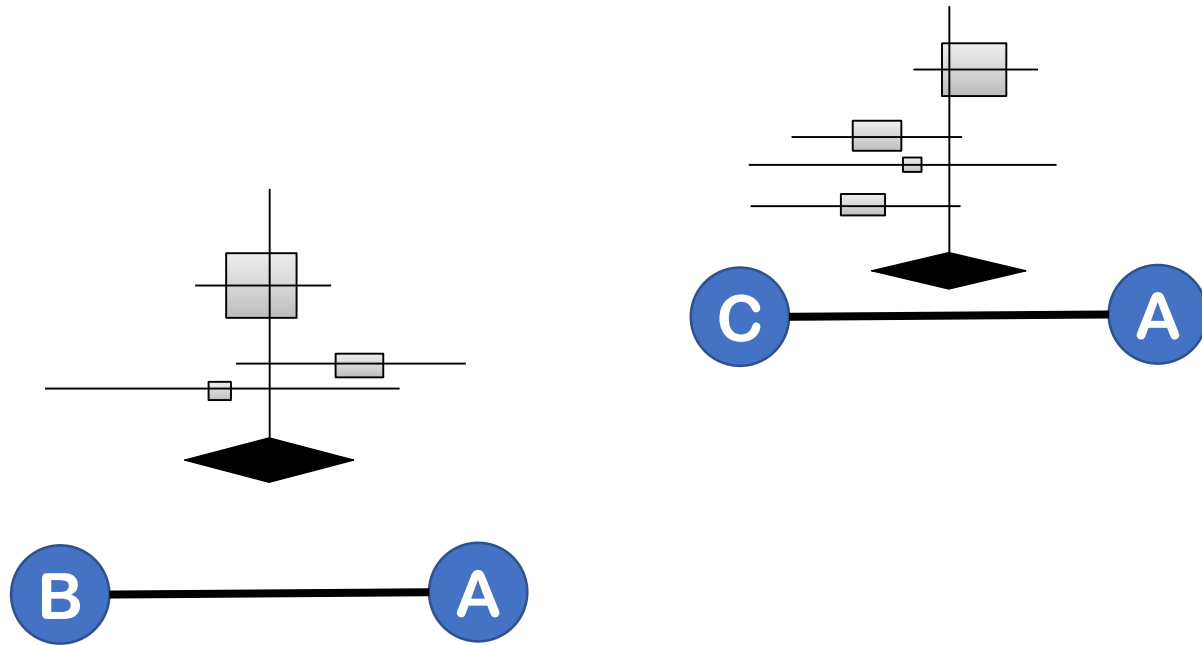
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# Introduction to Network Meta-Analysis (NMA)

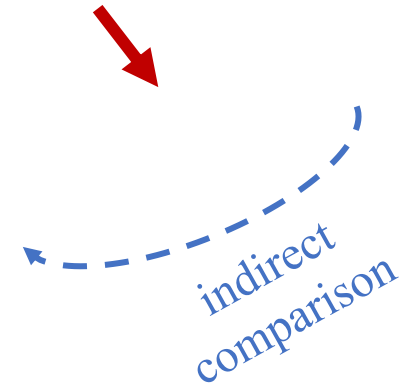


# Introduction to Network Meta-Analysis (NMA)

## Advantages of NMA

- ✓ Allows the comparison of treatments that have never been compared directly in individual studies.
- ✓ Combines both direct and indirect evidence resulting into estimates with highest precision.
- ✓ Allows for a relative ranking of the competing treatments.

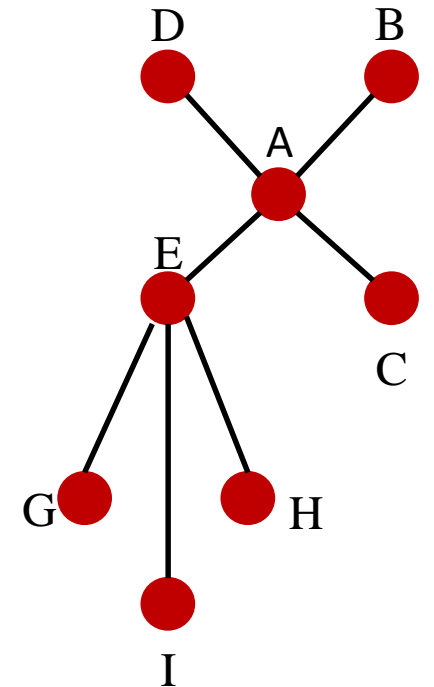
Why to perform a NMA?



# Sparse data in NMA

- The issue refers to **poorly connected** networks with **limited direct comparisons** and **few studies** to inform them
- Statistical challenges in the case of sparse networks
  - large sample approximations fail
  - NMA estimates are expected to be imprecise and biased
  - the formal evaluation of NMA assumptions (transitivity, consistency) is challenging

*An example of a sparse network*

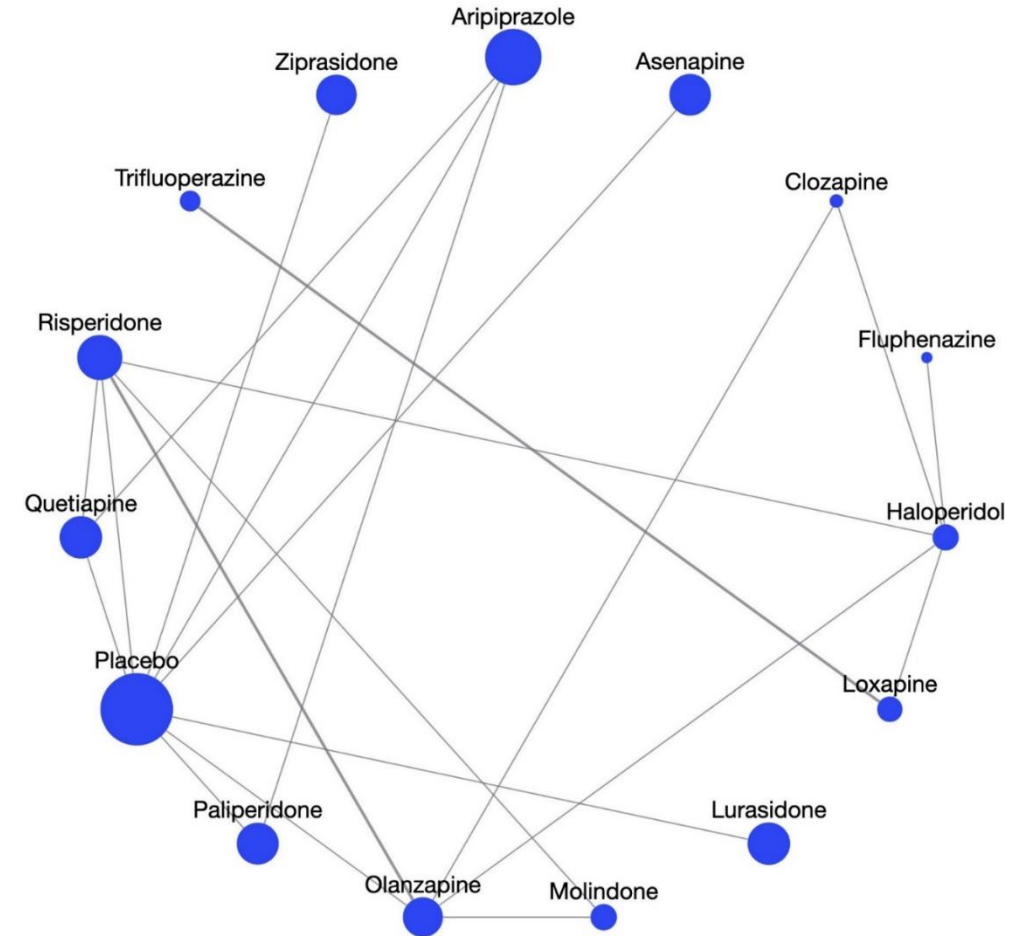


# Aim of our work

- To propose a framework suitable for NMA of sparse networks in order to
  - improve the precision in the estimation
  - increase the reliability of the final NMA estimates
- Our idea is to use external evidence and to construct informative priors for the analysis of the sparse network

# Motivating dataset

- A sparse network of 14 antipsychotics and Placebo
  - **Population of interest**: Children and adolescents (CA)
  - **Outcome of interest**: Reduction in overall schizophrenia symptoms (continuous outcome)
- 21 direct comparisons 19 studies in the network
  - 90% of the direct comparisons are informed by 1 study

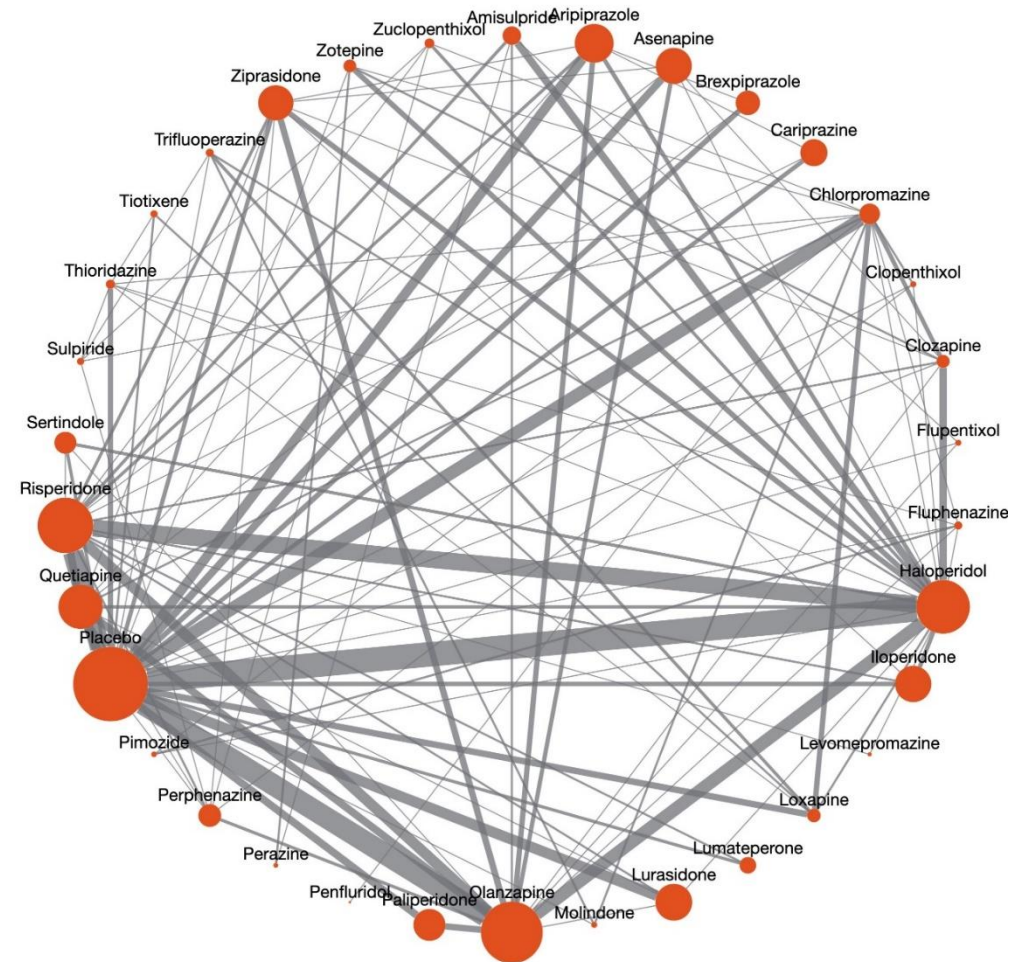


## **Objective:**

Obtain reliable NMA estimates for the effectiveness of the antipsychotics in the population of CA

# The dense network of general patients

- An informative network of 33 antipsychotics and Placebo
  - **Population of interest**: General patients (GP)
  - **Outcome of interest**: Reduction in overall schizophrenia symptoms (continuous outcome)
- 116 direct comparisons and 255 studies in the network
  - No common studies between the two networks



## Main goal

**Borrow strength from the network of GP to analyze the network of CA**

# How to borrow strength?

Naïve ~~synthesis~~:

1. Analyze the 2 populations together, or
2. Use **directly** NMA estimates of GP as prior information for CA

Assu~~ptions~~

- We assume no population difference
- We assume that they are equivalent sources



**implausible assumptions**

**We use a two stage approach:**

- ✓ At the first stage we extrapolate the results of the dense network of GP to CA
- ✓ At the second stage we use the predictions of the extrapolations to form informative priors and we analyze the network of CA



# Notation and general settings

- Let  $y_{ik}$  denote the observed mean for the treatment  $k$  in study  $i$

**Within-studies assumption:**  $y_{ik} \sim N(\theta_{ik}, sd_{ik}^2)$

- Let  $\delta_{i,1k} = \frac{\theta_{ik} - \theta_{i1}}{sd_i^{pooled}}$  denote the SMD between treatment  $k$  versus the baseline treatment 1 in study  $i$

**Across-studies assumption:**

$$\delta_i \sim N_{K_i-1}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

# arms in study  $i$

matrix structure:  $\tau^2$  in the diagonal,  $\frac{\tau^2}{2}$  in the off diagonal

- Under the consistency assumption,  $\mu_{kl} = \mu_{bl} - \mu_{bk}$

# 1<sup>st</sup> stage: Extrapolating GP results to the CA

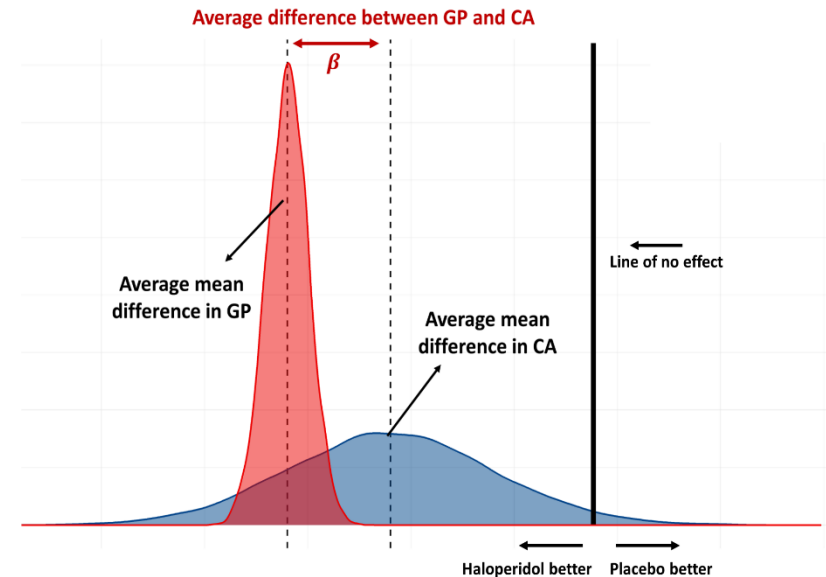
- At this stage we only analyze the network of GP
  - we reduce the network to include only the 15 interventions that exists for CA
  - we use a modified NMA model to analyze GP
- We add a **scale parameter**  $w$  at the within-studies assumption that inflates the variance of per study mean in GP

## NMA assumptions:

$$y_{ik} \sim N(\theta_{ik}, sd_{ik}^2) \quad y_{ik} \sim N\left(\theta_{ik}, \frac{sd_{ik}^2}{w_i}\right), w_i \in (0,1]$$

- We add a **location parameter**  $\beta$  that aims to shift the original distribution of the SMD's in GP towards the distribution of CA

$$\delta_i \sim N_{K_i-1}(\mu, \Sigma) \quad \delta_i \sim N_{K_i-1}(\mu - \beta, \Sigma)$$












# Informing the location and the scale parameters

- For the **location parameter**  $\beta$  we consider two approaches
- A data based approach
  - the differences  $d_{1k} = \xi_{1k}^{GP} - \xi_{1k}^{CA}$  is used as prior for  $\beta_{1k}$ ,  $\beta_{1k} \sim N(\hat{d}_{1k}, var(\hat{d}_{1k}))$ 
    - ↓
    - ↓
    - Pooled result for comparison k vs 1 in GP**      **Pooled result for comparison k vs 1 in CA**
- Prior elicitation from expert opinion
  - we gave to the experts estimates for the GP and we asked them to provide estimates for the CA
  - they were also asked to give some uncertainty around their responses
- For the **scale parameter**  $w$  the prior distribution is related to the amount of downweight that we want to apply according to a specific criterion (e.g. high risk of bias)
  - usual choices of priors are the  $Beta(\varepsilon_1, \varepsilon_2)$  or the  $Unif(\varepsilon_1, \varepsilon_2)$

## 2<sup>nd</sup> stage: NMA for CA using informative priors

- By fitting the modified NMA model we will obtain extrapolated SMD estimates
- The **predictive distributions** of the extrapolated SMD's are used as informative prior distributions for CA
- We compare our approach to the standard NMA model which places **non-informative priors** for  $\mu$ 's

# Results for CA

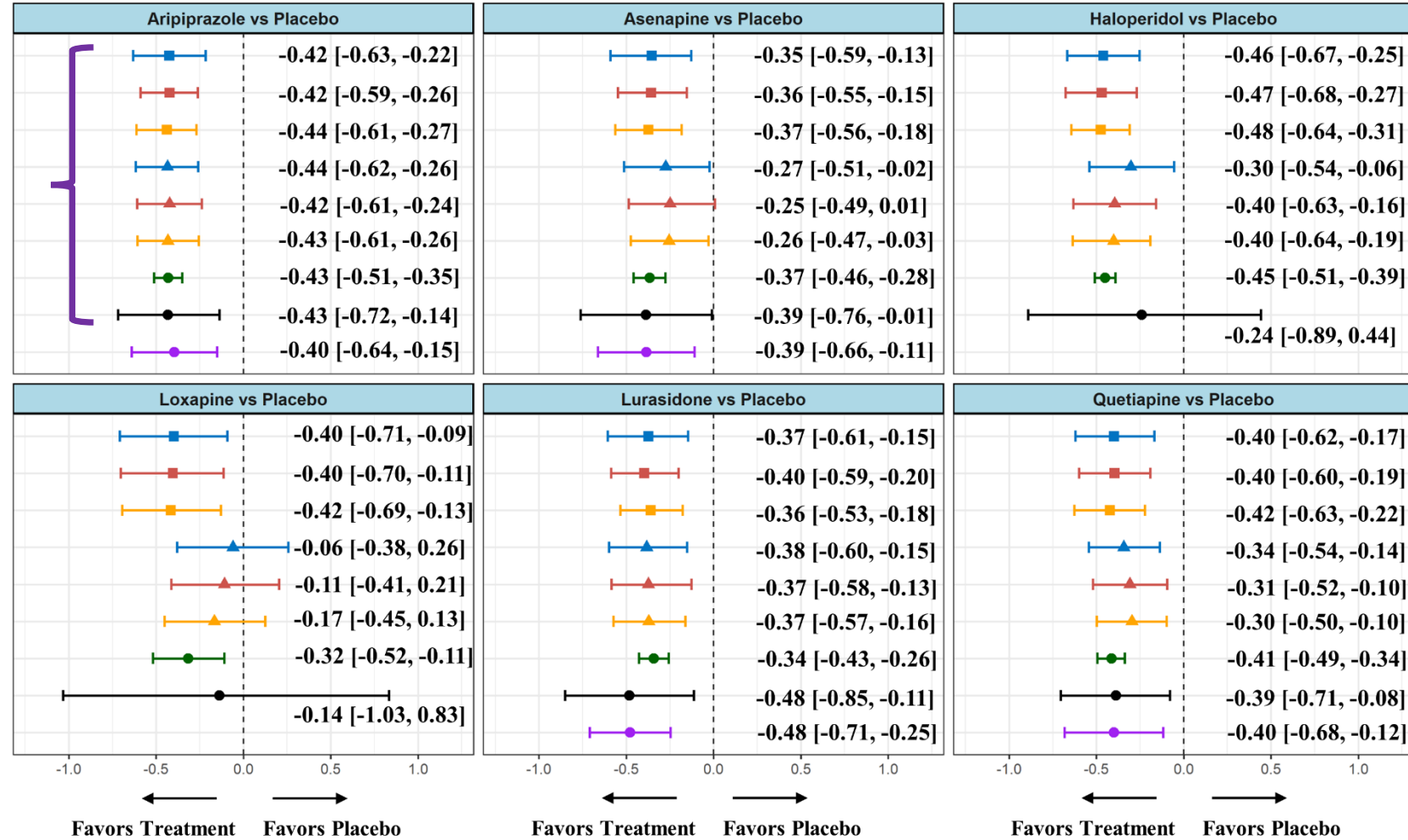
-  Data based  $\beta$  – No DW
-  Data based  $\beta$  – RoB DW
-  Data based  $\beta$  – NCT DW
-  Expert opinion based  $\beta$  – No DW
-  Expert opinion based  $\beta$  – RoB DW
-  Expert opinion based  $\beta$  – NCT DW
-  Naïve pooling
-  NMA with non-informative priors
-  Direct comparison

Prior for downweight parameter  $w$ :  $w \sim \text{Beta}(3, 3)$










*No-DW*: No downweight

*RoB-DW*: Risk of bias downweight

*NCT*: Non common treatment downweight



# Results for CA

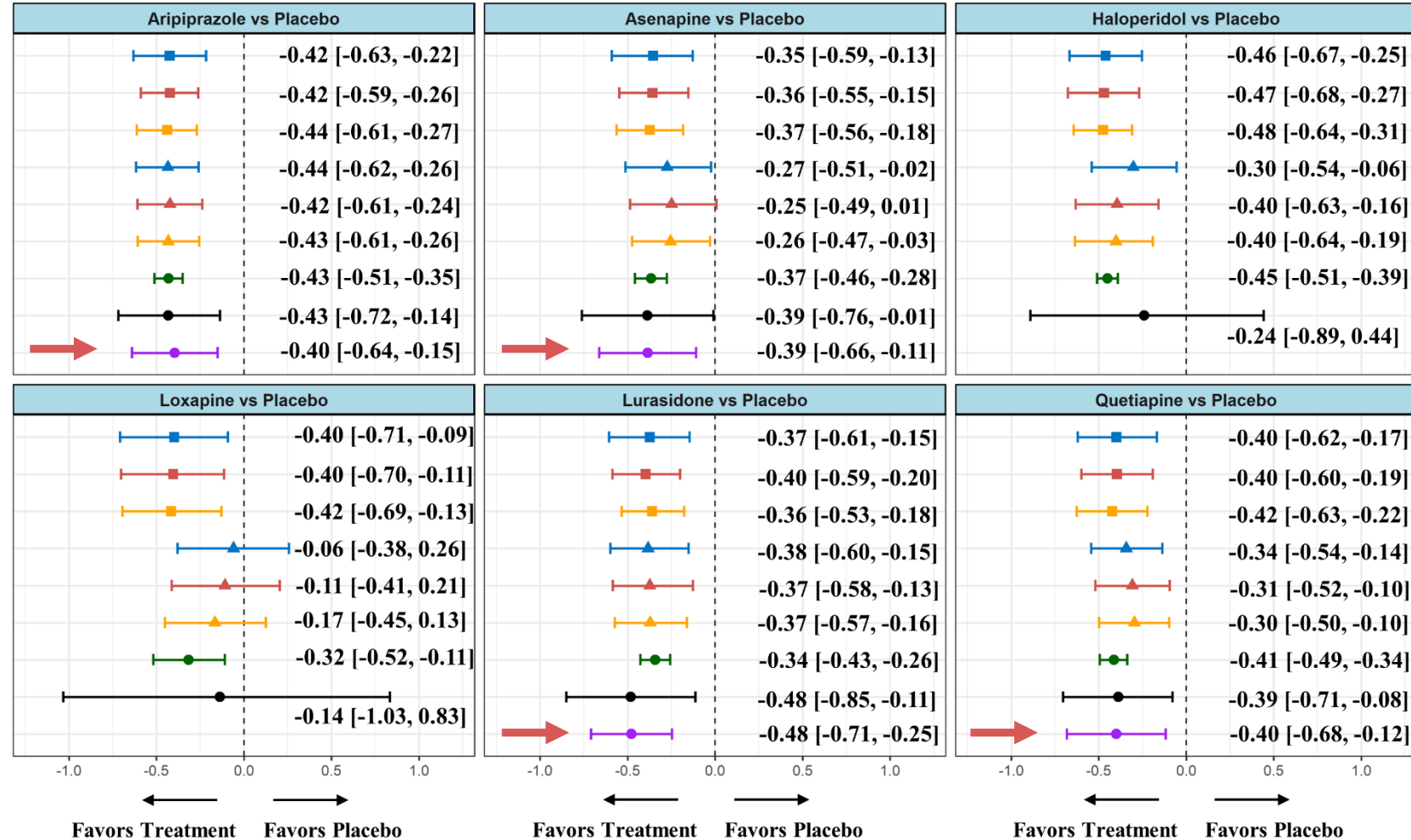
-  Data based  $\beta$  – No DW
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# Discussion

- In this work we proposed a framework for analyzing sparse networks by using informative priors
  - the precision and the reliability of the estimates is improved as they consider multiple source of evidence
  - our method can applied for sharing information between any dense network  $P_2$  and a sparse network  $P_1$
- There are limitations in our work
  - the heterogeneity estimation is still based on the data coming from the sparse network
- To conclude sharing of information seems to facilitate the estimation of treatment effects in sparse networks
  - Extensive sensitivity analysis across different choices of prior distributions should always take place to investigate the robustness of the results across different analysis schemes

# References

1. Chaimani A, Caldwell DM, Li T, Higgins JP, Salanti G. Undertaking network meta-analyses. In: Cochrane Handbook for Systematic Reviews of Interventions. John Wiley & Sons, Ltd; 2019:285-320. doi:10.1002/9781119536604.ch11
2. Krause M, Zhu Y, Huhn M, et al. Efficacy, acceptability, and tolerability of antipsychotics in children and adolescents with schizophrenia: A network meta-analysis. *Eur Neuropsychopharmacol J Eur Coll Neuropsychopharmacol*. 2018;28(6):659-674. doi:10.1016/j.euroneuro.2018.03.008
3. Huhn M, Nikolakopoulou A, Schneider-Thoma J, et al. Comparative efficacy and tolerability of 32 oral antipsychotics for the acute treatment of adults with multi-episode schizophrenia: a systematic review and network meta-analysis. *Lancet Lond Engl*. 2019;394(10202):939-951. doi:10.1016/S0140-6736(19)31135-3
4. Yoon JH, Dias S, Hahn S. A method for assessing robustness of the results of a star-shaped network meta-analysis under the unidentifiable consistency assumption. *BMC Med Res Methodol*. 2021;21(1):113. doi:10.1186/s12874-021-01290-1
5. Nikolakopoulou A et al. (2014) Characteristics of Networks of Interventions: A Description of a Database of 186 Published Networks. <https://doi.org/10.1371/journal.pone.0086754>
6. Ibrahim, J. G., Chen, M.-H., Gwon, Y., and Chen, F. (2015) The power prior: theory and applications. *Statist. Med.*, 34: 3724–3749. doi: 10.1002/sim.6728.
7. Dias S, Sutton AJ, Ades AE, Welton NJ. Evidence synthesis for decision making 2: a generalized linear modeling framework for pairwise and network meta-analysis of randomized controlled trials. *Med Decis Making*. 2013;33(5):607-617.
8. Schmitz, S., Adams, R. and Walsh, C. (2013), Incorporating data from various trial designs into a mixed treatment comparison model. *Statist. Med.*, 32: 2935-2949. <https://doi.org/10.1002/sim.5764>
9. Turner, RM, Domínguez-Islas, CP, Jackson, D, Rhodes, KM, White, IR. Incorporating external evidence on between-trial heterogeneity in network meta-analysis. *Statistics in Medicine*. 2019; 38: 1321– 1335. <https://doi.org/10.1002/sim.8044>



THANK YOU!

QUESTIONS?