

Introduction

Methods and issues around heterogeneity

(Remarks on the introduction of I^2 , and related events)

Julian Higgins

THE UNIVERSITY OF READING



Department of Applied Statistics

Exploiting Information in Random Effects Meta-analysis

JULIAN P.T. HIGGINS

Submitted for the degree of PhD

September 1997



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- Study i estimates parameter θ_i
- **Heterogeneity:**
 $\theta_i \neq \theta_j$ for at least one pair
- A test for heterogeneity has poor properties and asks an uninteresting question

- Post doc on Medical Research Council grant (Simon Thompson, Doug Altman, Jon Deeks)
- Included an aim to find a better way to measure heterogeneity
- *Solved?*

$$I^2 = \frac{Q - (k - 1)}{Q} \times 100\%$$

$$I^2 = \frac{\hat{\tau}^2}{\hat{\tau}^2 + \hat{\sigma}^2}$$

(k = number of studies)

- I originally stood for “intraclass”
- (I now say it stands for “inconsistency”)

An alternative to testing for heterogeneity in a meta-analysis

Julian Higgins and Simon Thompson

MRC Biostatistics Unit, Cambridge, UK

Concluding remarks

- The extent of heterogeneity is important for determining **consistency**, and hence **generalizability** of review findings
- The test is a **poor** way of measuring this
- H and I^2 **quantify** the extent of heterogeneity
- **Uncertainty** about the heterogeneity can be described
- **H** and/or **I^2** should be presented in Cochrane reviews in preference to the test
- Clinical aspects of studies and size of treatment effect must also play an important rôle



I^2 was presented (...and misunderstood)

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Quantifying heterogeneity in a meta-analysis

2002 STATISTICS IN MEDICINE

Julian P. T. Higgins, Simon G. Thompson

MRC Biostatistics Unit, Institute of Public Health, Robinson Way, Cambridge CB2 2SR, U.K.

Study heterogeneity Random effects model View More (34+)

The extent of heterogeneity in a meta-analysis partly determines the difficulty in drawing overall conclusions. The extent may be measured by estimating a between-study variance, but interpretation is then specific to a particular treatment effect metric. A test for the existence of heterogeneity e...



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rates

10.9 Meta-analysis of time-to-event outcomes

10.10

Heterogeneity

10.10.1 What is heterogeneity?

10.10.2 Identifying and measuring heterogeneity

10.10.3 Strategies for

Thresholds for the interpretation of the I^2 statistic can be **misleading**, since the importance of inconsistency depends on several factors. A rough guide to interpretation in the context of meta-analyses of **randomized trials** is as follows:

- 0% to 40%: might not be important;
- 30% to 60%: may represent moderate heterogeneity*;
- 50% to 90%: may represent substantial heterogeneity*;
- 75% to 100%: considerable heterogeneity*.

*The importance of the observed value of I^2 depends on (1) **magnitude and direction of effects**, and (2) strength of evidence for heterogeneity (e.g. P value from the χ^2 test, or a confidence interval for I^2 : **uncertainty** in the value of I^2 is substantial when the number of studies is small).

Frank E. Harrell, Kerry L. Lee, Daniel B. Mark
Duke University

**I^2 is not an
heterogeneity**
Larry V. Hedges^c and

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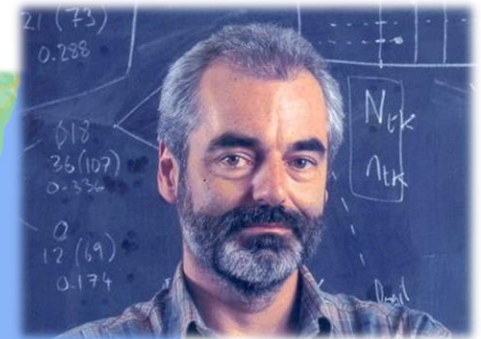
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^aMRC Biostatisti
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Abstract

Objectives:
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Study Design:
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medical area. Pre
directly as informati

Results: Among ou
comparison types, hete
reported for different s
estimate.

Conclusion: Hetero
derived for each specifi
few studies. © 2015

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Keywords: Meta-analysis; Heterogeneity; Intervention stu



Original Article

Journal of
of heterogeneity in
Statistics
in Medicine

ed online 30 August 2016 in Wiley Online Library

Informative priors for
analysis using
pseudo data

White,^a Ian R. White,^a
and Julian P. T. Higgins^c

udies, a situation in which the between-study
died. Bayesian meta-analysis allows incorpor
for more robust inference on the effect size
analysis using data augmentation, in which we
nce by pseudo data and use meta-regression
distributions for the between-study variance
heterogeneity in new meta-analyses. In a simu

ulation study, we compare approximate Bayesian methods using meta-regression and pseudo data against fully Bayesian approaches based on importance sampling techniques and Markov chain Monte Carlo (MCMC). We compare the frequentist properties of these Bayesian methods with those of the commonly used frequentist DerSimonian and Laird procedure. The method is implemented in standard statistical software and provides a less complex alternative to standard MCMC approaches. An importance sampling approach produces almost identical results to standard MCMC approaches, and results obtained through meta-regression and pseudo data are very similar. On average, data augmentation provides closer results to MCMC, if implemented using restricted maximum likelihood estimation rather than DerSimonian and Laird or maximum likelihood estimation. The methods are applied to real datasets, and an extension to network meta-analysis is described. The proposed method facilitates Bayesian meta-analysis in a way that is accessible to applied researchers. © 2016 The Authors. *Statistics in Medicine* Published by John Wiley & Sons Ltd.

Keywords: meta-analysis; heterogeneity; informative priors; meta-regression; data augmentation

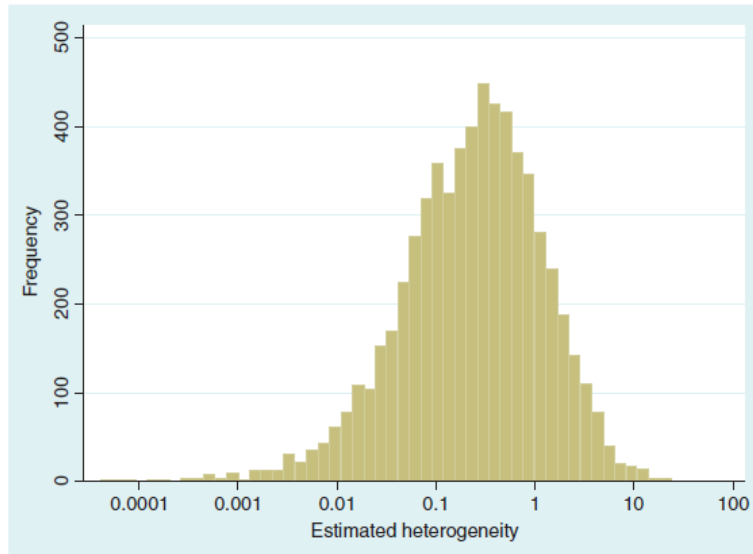


Figure 1 Distribution of non-zero estimates for between-study heterogeneity variance (τ^2), plotted on log scale

meta-analysis, the pred
median 40% and 95% C
odds ratios and log rel
meta-analyses using me
The empirical evidence
consistent in particular
heterogeneity. © 2015 T

Keywords: meta-analys

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estimation allows external ev
The aim of this paper is to
two methods for implementi
techniques. Based on 14 886
derive a novel set of predicti
on the outcomes assessed an
future meta-analyses.

The two methods are impl
to standard but more compl
distributions for the between-
scale. The methods are applic
as prior distributions for bet

We have provided resourc
which allow relevant prior in
Statistics in Medicine published by John Wiley & Sons Ltd.

Keywords: meta-analysis; Bayesian methods; heterogeneity; prior distributions

ely measured outcome, the pre-
y is a log-normal $(-2.13, 1.58^2)$

- I owe particular debts to
 - the MRC
 - Simon Thompson
 - Doug Altman and Jon Deeks
 - David Spiegelhalter
 - Anne Whitehead
 - Ian White
 - Cochrane

