Meta-analysis Workshop

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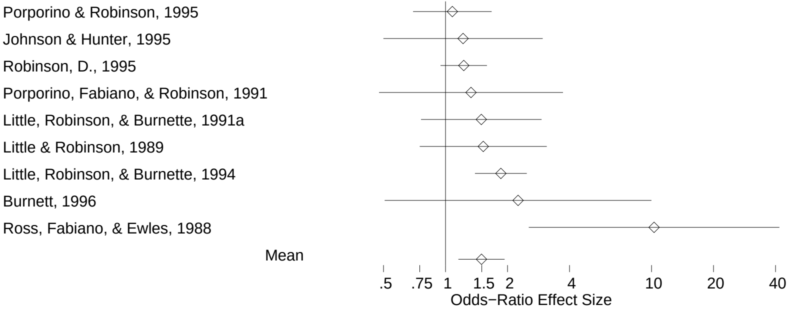
The End-Game

Forest-Plot of Odds-Ratios and 95% Confidence Intervals for the Effects of Cognitive-Behavioral Programs on Recidivism



A Great Debate

- Eysenck 1952: Psychotherapy doesn't work
- Dizzying array of mixed results followed
- Glass (with Smith) average results from 375 studies
- Glass coined the term **meta-analysis**

Deep Roots

- Pearson (1904): averaged correlations between inoculation for typhoid fever and mortality
- Fisher (1944): independent studies individually may not be significant, yet the aggregate seem improbable
- W. G. Cochran (1953): developed methods of averaging means across studies
- A. Wicker (1967) average correlations between attitudes and behavior
- Concurrent with Smith and Glass (1977) were
  - Hunter and Schmidt (1977) *Validity generalization*
  - Rosenthal and Rubin (1978) *Interpersonal expectancy effects*

Why Meta-Analysis?

- Narrative review methods:
  - Focuses on statistical significance
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  - Significant effect is a strong conclusion
  - Non-significant effect is a weak conclusion
  - How do you balance a collection of significant and non-significant effects?

Why Meta-Analysis?

- Narrative review methods:
  - Focuses on statistical significance
  - Lacks transparency and replicability
- Weakness of statistical significance:
  - Significant effect is a strong conclusion
  - Non-significant effect is a weak conclusion
  - How do you balance a collection of significant and non-significant effects?
- Meta-analysis:
  - focuses on **direction** and **magnitude**
  - approaches task as a research endeavor

Overview

- Some preliminaries (searching for studies, etc.)
- Effect Sizes
- Basic aggregation method
- Testing for Homogeneity
- Fixed and Random Effects Models
- Moderator Analysis
  - ANOVA type
  - Regression type
- Publication bias
- Comparison of approaches
  - Hedges and Olkin: Inverse Variance Weight
  - Hunter and Schmidt: Psychometric
- Advanced topics
  - Dependent effect sizes
  - Structural equation models

Some Preliminaries

- A meta-analysis should adopted systematic review methods
  - Comprehensive search for all relevant studies
  - Explicit inclusion/exclusion criteria
  - Systematic and reliable coding

Effect Size

- Encodes relationship of interest into a common index
- Must be:
  - comparable across studies
  - independent of sample size
  - have a computable standard error
- Many different effect size indices
- Multiple methods of computing each
- Most common:
  - Correlation coefficient (r)
  - Standardized mean difference (d)
  - Odds-ratio
  - Risk-ratio

Computing Effect Sizes

- Must compute effect size from information provided
  - Conversions from other statistics
    - t-test
    - p-value
    - descriptive statistics
    - etc.
  - Manipulation of data
    - collapsing across subgroups
    - adding "drop-outs" back into the treatment condition
  - Some conversions better than others (algebraic equivalents; rough approximations)
- Some studies simply do not provide necessary information

Standardized Mean Difference

- Fundamental relationship:
  - Group contrast
  - Continuous dependent variable
- Logic: scaling effects based on standard deviation
- Definitional equation:

$$ES_{sm} = \frac{\overline{X}_1 - \overline{X}_2}{s_{pooled}}$$

- Example: meta-analysis of the effectiveness of cognitive-behavioral therapy in reducing depression

Standardized Mean Difference

- Based on a t-test

$$ES_{sm} = t\sqrt{\frac{n_1+n_2}{n_1 n_2}}$$

- Based on a correlation

$$ES_{sm} = \frac{2r}{\sqrt{1-r^2}}$$

- Based on 2 by 2 table (dichotomous outcome; logit method)

$$ES_{sm} = \ln\left(\frac{ad}{bc}\right)\frac{\sqrt{3}}{\pi}$$

Correlation as Effect Size

- Fundamental relationship:
  - Two inherently continuous constructs
- Correlation "comes" standardized

$$ES_r = r$$

- Example: Relationship between GRE scores and performance in graduate school

Odds-Ratio

- Fundamental relationship:
  - Group contrast
  - Dichotomous dependent variable
- Data can be represented in a 2 by 2 contingency table

	Success	Failure
Treatment Group	a	b
Control Group	c	d

- Odds-ratio effect size computed as:

$$ES_{OR} = \frac{ad}{bc}$$

Software for Computing Effect Sizes

- Computing correlation and odds-ratio effect sizes from studies is generally easy
- Computing standardized mean difference effect sizes can get complicated
- Software can be helpful
  - **Effect Size** by Shadish, Robinson, and Lu (`http://assess.com`)
  - **ES Calculator** by Wilson (`http://www.campbellcollaboration.org/resources/effect_size_input.php`)
  - **Comprehensive Meta-analysis** by Biostat (`http://metaanalysis.com`)

Effect Size Computation Exercise

See handout.

Basics of Meta-Analysis

- Goal:
  - Describe the distribution, including its mean
  - Establish a confidence interval around the mean
  - Test that the mean differs from zero
  - Test whether studies tell a consistent story (are homogeneous)
  - Explore the relationship between study features and effect size

Determining the Mean Effect Size

- Problem: some effect sizes are more accurate than others
- What we need is an index of precision
- Standard error is a direct measure of precision
- Hedges and Olkin solution:
  - Weight by the inverse variance
  - Provides a statistical basis for:
    - Standard error of the mean effect size
    - Confidence intervals
    - Homogeneity testing

Some Preliminary Transformations

- Small sample size bias correction for the standardized mean differences:

$$ES'_{sm} = \left(1 - \frac{3}{4N-9}\right) ES_{sm}$$

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Inverse Variance Weights

- Standardized mean difference ES_{sm}:

$$se_{sm} = \sqrt{\frac{n_1+n_2}{n_1 n_2} + \frac{{ES_{sm}}^2}{2(n_1+n_2)}}$$

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$$se_{OR} = \sqrt{\frac{1}{a} + \frac{1}{b} + \frac{1}{c} + \frac{1}{d}}$$

- Inverse variance weight w:

$$w = \frac{1}{se^2}$$

Almost ready

- At this point, we have for each study:
  - An effect size
  - An inverse variance weight
- Problem: statistical models assume independence
- Only include one effect size per study (or independent sample)
- Multiple analyses for different subsets of independent effects
  - Different outcome constructs
  - Different time periods

Inverse Variance Weighted Mean Effect Size

Meta-analytic mean effect size is:

$$\overline{ES} = \frac{\sum w_i ES_i}{\sum w_i}$$

where ES_i is the effect size for each study (i) and w_i is the inverse variance weight

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Standard error of the mean effect size is:

$$se_{\overline{ES}} = \frac{1}{\sum w_i}$$

Some Basic Inferential Statistics

Confidence intervals can be constructed in the usual manner:

$$\overline{ES}_{lower} = \overline{ES} - se_{\overline{ES}} 1.96$$
$$\overline{ES}_{upper} = \overline{ES} + se_{\overline{ES}} 1.96$$

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$$\overline{ES}_{upper} = \overline{ES} + se_{\overline{ES}} 1.96$$

And a z-test can be performed as:

$$z = \frac{\overline{ES}}{se_{\overline{ES}}}$$

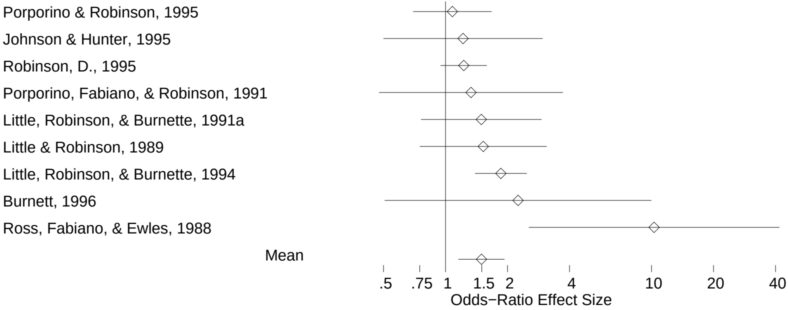
An Example: Group-Based Cognitive-Behavioral Programs for Adult Offenders

Author	Sample Size	Odds-Ratio	Logged OR	w
Burnett, 1996	60	2.25	0.81	1.727
Johnson & Hunter, 1995	98	1.22	0.20	4.843
Little & Robinson, 1989	180	1.52	0.42	7.614
Little et al 1991	152	1.49	0.40	8.466
Little et al 1994	1381	1.86	0.62	45.742
Porporino et al 1991	63	1.33	0.28	3.633
Porporino & Robinson, 1995	757	1.08	0.08	19.919
Robinson, D., 1995	2125	1.25	0.20	56.895
Ross et al 1988	45	10.29	2.33	1.958

Note: These studies are a subset of studies included in Wilson et al. (2005) and represent two specific treatment programs (Moral Reconation and Reasoning and Rehabilitation) and studies that were randomized or used high quality quasi-experimental designs.

Forest-Plot

Forest-Plot of Odds-Ratios and 95% Confidence Intervals for the Effects of Cognitive-Behavioral Programs on Recidivism



An Example: Group-Based Cognitive-Behavioral Programs for Adult Offenders

Stata output from "meanes.ado"

```
. meanes lgor [w=w]
(analytic weights assumed)
Version 2005.05.23 of meanes.ado

No. of obs  =       9                                  Homogeneity Analysis
Minimum obs =   .0764                                        Q =      14.19
Maximum obs =   2.331                                       df =          8
Weighted SD =   0.307                                        p =    0.07695
---------------------------------------------------------------------------
                |    Mean    -95%CI    +95%CI        SE         Z         P
----------------+----------------------------------------------------------
Fixed effect    | 0.37107   0.21146   0.53067   0.08143   4.55671   0.00001
Random effect 1 | 0.40218   0.14349   0.66086   0.13198   3.04718   0.00231
Random effect 2 | 0.38438   0.17673   0.59203   0.10595   3.62808   0.00029
-------------------------------------------------------------------------
1 Random effects variance component (method of moments)    = 0.05542
2 Random effects variance component (full information ML) = 0.02054
```

An Example: Group-Based Cognitive-Behavioral Programs for Adult Offenders

Stata output from "meanes.ado"

```
. meanes lgor [w=w], print(exp)
(analytic weights assumed)
Version 2005.05.23 of meanes.ado

No. of obs   =       9                            Homogeneity Analysis
Minimum obs  =    1.08                                 Q =      14.19
Maximum obs  =  10.290                                df =          8
Weighted SD  =       .                                 p =    0.07695
--------------------------------------------------------------------------
                |    Mean    -95%CI    +95%CI        SE          Z        P
----------------+---------------------------------------------------------
Fixed effect    | 1.44928   1.23548   1.70008         .    4.55671  0.00001
Random effect 1 | 1.49507   1.15430   1.93645         .    3.04718  0.00231
Random effect 2 | 1.46870   1.19331   1.80765         .    3.62808  0.00029
------------------------------------------------------------------------
1 Random effects variance component (method of moments)    = 0.05542
2 Random effects variance component (full information ML) = 0.02054
Results are the exponent of computed values (i.e., results are odds-ratios)
```

Homogeneity Testing

- Homogeneity analysis tests whether the assumption that all of the effect sizes are estimating the same population mean is a reasonable assumption.
- If homogeneity is rejected, the distribution of effect sizes is assumed to be heterogeneous.
  - Single mean ES not a good descriptor of the distribution
  - There are real between study differences, that is, studies estimate different population mean effect sizes.
  - Three options:
    - model between study differences
    - fit a random effects model
    - do both

Computation of the Homogeneity Q Statistic

- Q is simply a weighted sums-of-squares:

$$Q = \sum w_i (ES_i - \overline{ES})^2$$

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- There are easier computational formulas:

$$Q = \sum w_i ES_i^2 - \frac{(\sum w_i ES_i)^2}{\sum w_i}$$

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- It is distributed as a chi-square with $k - 1$ degrees of freedom, where k is the number of effect sizes

Alternative to Q

- Q is statistically under-powered when the number of studies is low and when the sample size within the studies is low
- $I^2 = 100\% \times \frac{Q - df}{Q}$
- Larger values of I^2, the more heterogeneity
- 75%: large heterogeneity
- 50%: moderate heterogeneity
- 25%: low heterogeneity

Random versus Fixed Effects Models

- Fixed effects model assume:
  - there is one true population effect that all studies are estimating
  - all of the variability between effect sizes is due to sampling error
- Random effects model assume:
  - there are multiple (i.e., a distribution) of population effects that the studies are estimating
  - variability between effect sizes is due to sampling error + variability in the population of effects

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  - variability between effect sizes is due to sampling error + variability in the population of effects
- Known versus unknown influences of true effects
- Mixture (mixed) models
- Current advise: assume random effects model a priori

Computing a Random Effects Model

- Fixed effects model: weights are a function of sampling error
- Random effects model: weights are a function of sampling error + study level variability
- Thus, we need a new set of weights
- First, compute τ^2 (random effects variance component):

$$\tau^2 = \frac{Q - df_Q}{\sum w_i - \frac{\sum {w_i}^2}{\sum w_i}}$$

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- Second, re-compute the inverse variance weights:

$$w_i = \frac{1}{{se_i}^2 + \tau^2}$$

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$$w_i = \frac{1}{{se_i}^2 + \tau^2}$$

- Third, re-compute meta-analytic results using new weight

An Example: Effectiveness of Correctional Boot-camps relative to Prison in Reducing Re-offending

Stata output from "meanes.ado"

```
No. of obs   =      55                              Homogeneity Analysis
Minimum obs =    -.58                                    Q =     219.65
Maximum obs =   3.194                                   df =         54
Weighted SD =   0.434                                    p =    0.00000
---------------------------------------------------------------------------
                |    Mean    -95%CI    +95%CI        SE         Z        P
----------------+----------------------------------------------------------
Fixed effect    | 0.44902   0.39160   0.50645   0.02930  15.32515  0.00000
Random effect 1 | 0.50430   0.37920   0.62941   0.06383   7.90050  0.00000
Random effect 2 | 0.50848   0.37654   0.64042   0.06732   7.55340  0.00000
-------------------------------------------------------------------------
1 Random effects variance component (method of moments)   = 0.14711
2 Random effects variance component (full information ML) = 0.17046
```

(Note: effect size is the logged odds-ratio.)

Fixed versus Random: Which to Use?

- Random effects models become fixed-effect models when distributions are homogeneous
- Assumptions of fixed effects model rarely plausible
  - Consequence: standard error that is too small; confidence intervals that are too narrow
- Historically, most meta-analyses in *Psychological Bulletin* have used fixed effects models
- General advise within meta-analytic literature: use random effects models
- Area of active debate and work among statisticians

Moderator Analysis

- Modeling between study variability
  - Categorical models (analogous to a one-way ANOVA)
  - Regression models
- Fixed and random effects versions of each (latter often called "mixed" models)

Analog to the ANOVA

- Useful for a single categorical independent variable
- Produce a separate mean effect size for each category
- Recall that Q is a sum-of-squares
- The total sum-of-squares (Q) can be partitioned
  - Variability between groups ($Q_{between}$)
  - Residual variability within groups (Q_{within})
- $Q_{between}$ analogous to an F-test between means
- Q_{within} assesses whether residual distribution homogeneous
- Note: in a random effects (mixed effects) version of this, the Q_{within} is not meaningful

Analog to the ANOVA Example: Experimental versus Quasi-experimental Studies in the Domestic Violence

Meta-Analytic Analog to the One-way ANOVA, Mixed Effects Model

Source	Q	df	P
Between	0.0072	1	0.93227
Within	15.2630	12	0.22737
Total	15.2702	13	0.29079

Descriptive Fixed Effects Meta-Analytic Results by: random

random	Mean	St. Er.	[95% Conf.	Int.]	z	P>|z|	k
0	.285	.17366	-.05493	.62579	1.6437	0.10025	7
1	.264	.18284	-.09435	.62236	1.4439	0.14876	7
Total	.275	.12591	.02848	.52206	2.1862	0.02880	14

Random effects variance component (via iterative max. likelihood) = .1513908
Standard error of random effects variance component = .0818776

Notes on the Analog to the ANOVA type Analysis

- Random effects variance component estimated based on residual variance, not total variance
- Random (mixed) effects model has low statistical power
- Can only examine one categorical variable at a time

Meta-analytic Regression

- Conceptually identical to multiple regression
  - Effect size is the dependent variable
  - Study moderator variables are the independent variables
- Can handle multiple variables simultaneously
- Don't use standard OLS regression procedures (even if weighted)
  - OLS assumes "iid" data
  - Meta-analytic data independent but not identically distributed
  - Consequence
    - With weighting, you get correct regression coefficients
    - Standard errors and related statistics off
    - Can be corrected by hand
    - No method of computing a random (mixed) model
  - A solution: use available macros, such as mine

Meta-analytic Regression: Example

```
 *****  Inverse Variance Weighted Regression  *****
 *****  Random Intercept, Fixed Slopes Model  *****

------- Descriptives -------
      Mean ES     R-Square           k
        .1483        .2225     38.0000

------- Homogeneity Analysis -------
                   Q          df           p
Model        14.7731      3.0000       .0020
Residual     51.6274     34.0000       .0269
Total        66.4005     37.0000       .0021

------- Regression Coefficients -------
                 B        SE  -95% CI  +95% CI        Z        P     Beta
Constant    -.6752     .2392  -1.1439   -.2065  -2.8233    .0048    .0000
RANDOM       .0729     .0834   -.0905    .2363    .8746    .3818    .1107
TXVAR1       .3790     .1438    .0972    .6608   2.6364    .0084    .3264
TXVAR2       .1986     .0821    .0378    .3595   2.4204    .0155    .3091

------- Method of Moments Random Effects Variance Component -------
v       =    .04715
```

Publication Selection Bias

- Statistically significant effects are more likely to be published than nonsignificant effects
- Important threat to the validity of meta-analysis (and any other method of reviewing studies)
- Search for and included unpublished studies that meet eligibility criteria
- Examine difference between published and unpublished studies
- Statistic approaches to assessing publication bias
    - Funnel plot: Scatterplot of effect size against standard error of effect size
    - Trim-and-fill method (Tweedie and Duvall)

Comparison of Approaches

- Discussion so far has focused on the inverse variance approach (Hedges and Olkin)
  - HO approach is dominant in medicine and treatment/intervention focused areas of psychology and education
  - Focus is on the observed effect across studies
- Hunter and Schmidt method differs
  - Evolved within I/O psychology (psychometric research)
  - Dominant approach within I/O and social psychology
  - Adjusts for methodological artifacts
  - Focused on estimating the underlying strength of the relationship (results given perfect research)

Statistically Dependent Effect Sizes

- Studies often report multiple effect sizes
- Only one effect size per study (or sample) is allowed using basic methods
- Sometimes important to include multiple effect sizes in single analysis, such as
  - Multiple end-points
  - Multiple treatments with a single control group
- Gleser and Olkin (1994) *Handbook of Research Synthesis* provide a method

Statistically Dependent Effect Sizes

Weights as a matrix rather than a vector

$$ES = \begin{pmatrix} .23 \\ .12 \\ .52 \\ .81 \\ .32 \end{pmatrix} \quad w = \begin{pmatrix} 1.23 & 0 & 0 & 0 & 0 \\ 0 & 2.92 & 0 & 0 & 0 \\ 0 & 0 & 4.27 & 0 & 0 \\ 0 & 0 & 0 & 3.83 & 0 \\ 0 & 0 & 0 & 0 & 1.77 \end{pmatrix}$$

The zeros in the off-diagonals reflects the assumption of independent

Statistically Dependent Effect Sizes

Incorporate estimates of the covariances between effect sizes

$$ES = \begin{pmatrix} .23 \\ .12 \\ .52 \\ .81 \\ .32 \end{pmatrix} \quad w = \begin{pmatrix} 1.23 & .25 & 0 & 0 & 0 \\ .25 & 2.92 & 0 & 0 & 0 \\ 0 & 0 & 4.27 & .41 & .38 \\ 0 & 0 & .41 & 3.83 & .49 \\ 0 & 0 & .38 & .49 & 1.77 \end{pmatrix}$$

Re-run the meta-analysis with the new weight matrix. (Note: this is a fixed effects model.)

Statistically Dependent Effect Sizes

- Multiply experimental conditions contrasted with a single control condition
- Same outcome, multiple end-points
- Different measures of same construct
- Existing model is fixed effects
- Active area of research; a new random effect approach is being developed by Hedges

Meta-analysis and SEM

- Some relevant publications:
  - Cheung and Chan (2005) *Psychological Methods*
  - Schmidt, Hunter, and Outerbridge (1986) *Journal of Applied Psychology*
  - Becker and Schram (1994) *Handbook of Research Synthesis*
- General approach:
  - Synthesis individual bivariate correlations of desired matrix
  - Use synthesized correlation matrix to estimate SEM model
- Challenges
  - Determining appropriate sample size
  - Non-positive definite matrix
  - Ignoring heterogeneity across studies
  - Using a correlation matrix instead of a covariance matrix

Meta-analysis and SEM

- GLS alternative (based on Becker's work)
  - Use GLS to pool correlation matrix in one step
  - Analogous to Gleser and Olkin method for dependent effect sizes
- Two Stage SEM alternative (Cheung and Chan)
  - Use multi-group CFA to test homogeneity of matrices across studies
  - Can handle "missing" paths in some groups
  - If homogeneous, SEM pooled correlation matrix can be used for SEM analyses (as with above)

Final Comments

- Methods continue to advance
- Publication selection-bias an important area of active research
- Analyzing dependent effect sizes also actively advancing
- Methodological quality
- Confounding of study features
- Meta-analysis' role in identifying "gaps" in literature

Questions?