

Multivariate random-effects meta-analysis for sparse data using `smvmeta`

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Conflicts of interest

I have no conflicts of interest to declare ¹

¹I'm the author of the method and `smvmeta` command I'm talking about today

Multivariate meta-analysis, sparse data, and `smvmeta`

- Meta-analysis

- Multivariate meta-analysis with sparse data

How to use `smvmeta`

- Installing `smvmeta`

- Setting up an analysis

- Performing meta-analysis and making forest plots

How `smvmeta` works

- The model used by `smvmeta`

Why and when you should trust `smvmeta`

- Validation experiments

Summary

Questions?

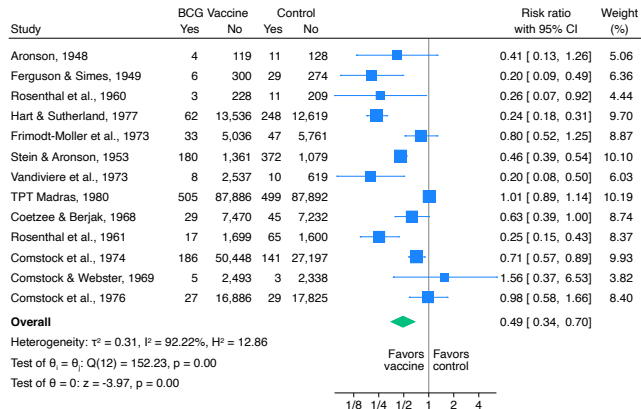
Multivariate meta-analysis, sparse data, and `smvmeta`

Meta-analysis

- Systematic review — identify and synthesize all relevant evidence
- Meta-analysis — “pool” estimates from multiple studies into a single estimate
- Univariate (pairwise) meta-analysis — synthesize multiple estimates of one variate

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- Example using Stata’s bcgset data on efficacy of BCG vaccine for tuberculosis



Random-effects REML model

Note: “effect size” often used in place of variate, estimate, etc.

Heterogeneity and random-effects meta-analysis

- Simplest meta-analysis model assumes all studies share the same estimation target
- However, this is rarely the case in biomedicine and other fields (e.g., some differences between populations, treatments, outcomes, etc.)
- Differences in estimation targets is called *heterogeneity*

Heterogeneity and random-effects meta-analysis

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- Differences in estimation targets is called *heterogeneity*
- Heterogeneity is often dealt with using *random-effects* (RE) meta-analysis
- Estimation target in RE meta-analysis is a *distribution* of study-level targets
- Usually modelled using a normal distribution, $N(\mu, \tau^2)$

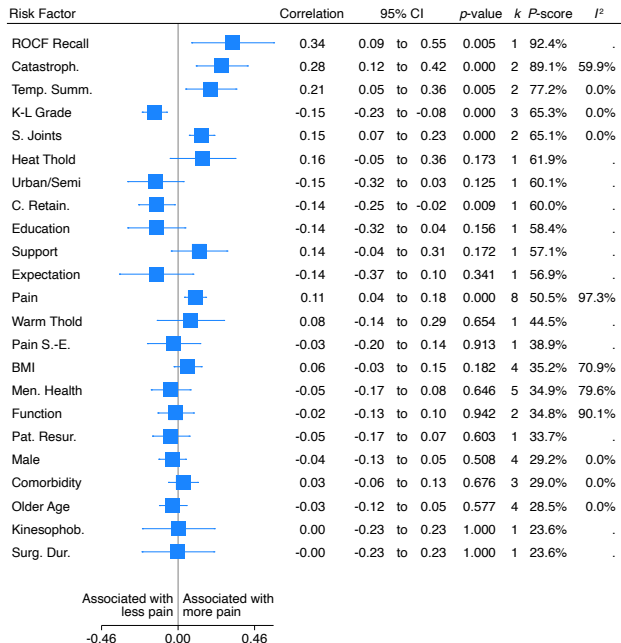
Multivariate meta-analysis

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- Each study can report estimates for between 1 and p variates
- There may be heterogeneity and the variates may be *correlated*
- The classic example is diagnostic test accuracy:
 - the variates are sensitivity and specificity
 - sensitivity and specificity are correlated (increasing one tends to decrease the other)
- Failing to account for correlation → bias
(Riley, 2009; Riley, Thompson, and Abrams, 2008)
- Higher-dimensional applications include the study of risk factors

Example multivariate meta-analysis



Sparse multivariate random-effects meta-analysis model

Meta-analysis and meta-regression in Stata

- `smvmeta` is a new add-on command for random-effects multivariate meta-analysis: (Rose, C. J., *The Stata Journal* 24:2, 2024)
- Stata already has excellent built-in support for meta-analysis:
 - `meta esize` for computing effect sizes from summaries (e.g., big and little N s)
 - `meta summarize` and `meta forestplot` for meta-analysis
 - `meta regress` for meta-regression
 - `meta meregress` and `meta multilevel` for multilevel meta-regression
 - `meta mvregress` for multivariate meta-regression
- Where does `smvmeta` fit in?

Multivariate meta-analysis with sparse data

- In the most general case, multivariate meta-analysis models are parameterized by:
 - a p -vector of mean effect sizes β
 - a $p \times p$ correlation matrix Φ
 - a $p \times p$ variance-covariance matrix Ψ that models heterogeneity
- Such a model will have $p + p^2$ parameters (note that this is quadratic in p)

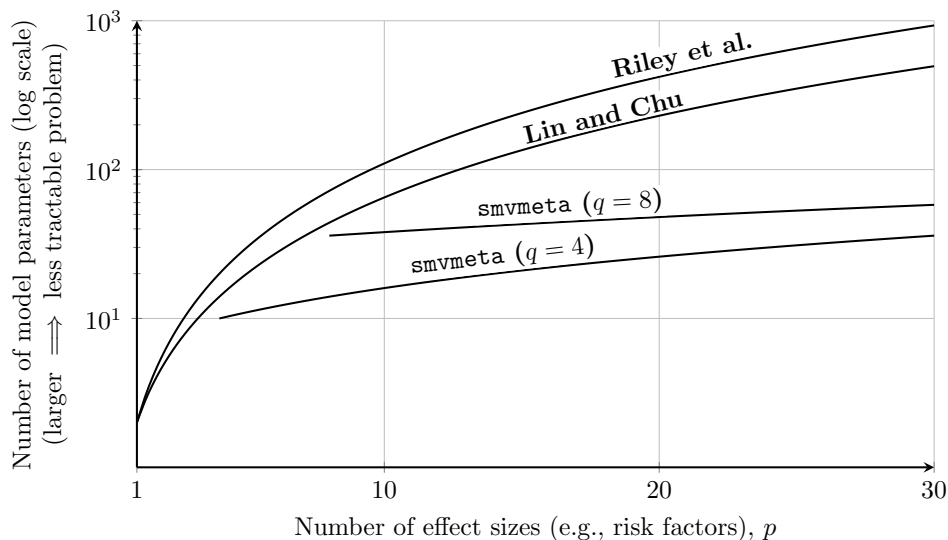
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- We are likely to have far fewer study estimates than parameters
- This is what I mean by sparsity — it makes estimation challenging
- Previous models address this by requiring us to specify or assume how variates are correlated (e.g., using published values or assumed matrix structures)
- Studies typically do not publish correlation estimates; we may be unable or unwilling to make these assumptions — this is where `smvmeta` fits in

Multivariate meta-analysis with sparse data



In previous models (e.g., Riley, Lin and Chu), the number of model parameters scales quadratically with p . The model used by `smvmeta` scales linearly with p .

How to use smvmeta

The pain12 dataset

- Systematic review on risk factors for pain and function after total knee arthroplasty (TKA) (Olsen et al., 2020, 2022, 2023)
- ~ 20% of patients experience pain and poor function after surgery
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- ~ 20% of patients experience pain and poor function after surgery
- Identifying risk factors could lead to better outcomes
- Studies typically estimate associations on a range of metrics (e.g., RRs, ORs, MDs, correlations)
- Meta-analysis must be performed on a common metric:
 1. Extracted the reported estimates
 2. Imputed the corresponding tetrachoric correlations
 3. Fisher z-transformed ² the correlations

²Inverse hyperbolic tangent function

Install smvmeta, ancillary files (incl. the pain12 dataset), and list:

```
. net install st0749.pkg , all  
. use pain12, clear  
. list in 1/10
```

	study	factor	z	z_se
1.	Lingard 2007	Men. Health	.0242904	.038518
2.	Papakostidou 2012	Pain	.1760553	.0713318
3.	Papakostidou 2012	Older Age	-.0094856	.0745588
4.	Papakostidou 2012	Male	-.0968132	.0735721
5.	Papakostidou 2012	BMI	-.0395895	.0744007
6.	Papakostidou 2012	Support	.136985	.0725892
7.	Papakostidou 2012	Education	-.1422099	.0724378
8.	Papakostidou 2012	Urban/Semi	-.1482175	.0722573
9.	Sullivan 2011	Male	-.0012088	.0945578
10.	Sullivan 2011	Older Age	-.0012088	.0945578

Use `smvmeta set` to specify generic effect sizes, SEs, and risk factors:

```
. smvmeta set z z_se factor
Meta-analysis setting information
Data
  No. observations: 51
    Sparse: Yes
Effect size
  Type: Generic
  Label: Correlation with pain (Fisher z-transformed)
  Variable: z
  Missing: 0
Precision
  Type: Standard error
  Label: SE on correlation
  Variable: z_se
  Missing: 0
Factor variable
  Label: Risk Factor
  Variable: factor
  Levels: 23
  Missing: 0
Model and method
  Model: Sparse multivariate random-effects meta-analysis (smvmeta)
  Method: Penalized maximum likelihood
```

Perform the meta-analysis using smvmeta estimate:

```
. smvmeta estimate, dim(3) nolog transform(corr) superior(big) sort(_Pscore, descending)
```

```
Sparse multivariate meta-analysis (smvmeta)      Number of obs   =       51
Factor variable label : Risk Factor              Num. factors    =       23
Optimization          : Penalized ML            Dimensions (q)  =        3
```

	Coef.	Eff. SE	P>u	[95% Conf. Int.]	k	P-score	I2
ROCF Recall	0.342	0.126	0.005	0.089 0.554	1	92.4	.
Catastroph.	0.278	0.074	0.000	0.118 0.424	2	89.1	59.9
Temp. Summ.	0.211	0.076	0.005	0.050 0.361	2	77.2	0.0
K-L Grade	-0.154	0.036	0.000	-0.230 -0.075	3	65.3	0.0
S. Joints	0.153	0.032	0.000	0.073 0.230	2	65.1	0.0
Heat Thold	0.159	0.117	0.173	-0.052 0.355	1	61.9	.
Urban/Semi	-0.147	0.097	0.125	-0.318 0.033	1	60.1	.
...							
Comorbidity	0.032	0.077	0.676	-0.063 0.126	3	29.0	0.0
Older Age	-0.035	0.062	0.577	-0.121 0.053	4	28.5	0.0
Kinesophob.	0.001	0.095	1.000	-0.229 0.232	1	23.6	.
Surg. Dur.	-0.001	0.095	1.000	-0.232 0.229	1	23.6	.

Estimates have been tanh-transformed.

Untransformed effect sizes with larger magnitudes are superior.

Use smvmeta forestplot to make the forest plot I showed earlier

How smvmeta works

The smvmeta model

- Recall that in previous models, the number of model parameters is quadratic in p
- The number of parameters in the smvmeta model is *linear* in p , not quadratic:
 - smvmeta does not attempt to decompose correlation and heterogeneity
→ only need to estimate a single covariance matrix Ψ
 - smvmeta reduces the dimensionality of the problem by approximating Ψ in a low-dimensional space using *random projection*

The smvmeta model

- Random projection is similar to principal components analysis (PCA)
 - establish a random (i.e., arbitrary) low-dimensional orthonormal basis in $\mathbb{R}^{q < p}$ (i.e., a random matrix \mathbf{R} of orthogonal unit vectors)
 - let $\mathbf{\Sigma}$ be a $q \times q$ covariance matrix (cf. $p \times p$)
 - approximate $\mathbf{\Psi}$ as $\mathbf{R}\mathbf{\Sigma}\mathbf{R}^\top$ (i.e., project $\mathbf{\Sigma}$ from \mathbb{R}^q up into \mathbb{R}^p)
- Estimate an approximation to the distribution of study-level targets $N(\beta, \mathbf{R}\mathbf{\Sigma}\mathbf{R}^\top)$
- Estimation performed using penalized maximum likelihood (see paper)
- Like PCA, good approximation with small q (e.g., $q \approx 6$ rather than $p \approx 25$)
- Use domain knowledge to choose q , or let smvmeta choose it automatically

Why and when you should trust smvmeta

Simulation-based validation

- Some studies may not report estimates for all variates
- An estimate for a particular variate may be missing from a study:
 - completely at random (MCAR)
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Simulation-based validation

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 - completely at random (MCAR)
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- We may have — or lack — domain knowledge for choosing q
- Simulated a large number of systematic reviews with known groundtruth to
 - estimate empirical coverage of `smvmeta`'s 95% CIs
 - compare `smvmeta`'s bias and precision to random-effects meta-regression

under 3 scenarios:

Scenario	Missingness mechanism	Is ρ known?
1	MCAR	No
2	MCAR	Yes
3	MNAR	No

Summary of validation experiment results

- Results for the 3 scenarios are very similar
- Empirical coverage of 95% CIs is 94.4% (95% CI 94.1% to 94.7%)
- Bias is 1.03 (95% CI 1.02 to 1.04) times larger for `smvmeta` compared to meta-regression (but negligible in absolute terms)
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- `smvmeta`'s estimates are more precise than for meta-regression (e.g., 95% CIs are about 90% as wide)
- `smvmeta` tends to perform better as p increases:
 - confidence intervals tend to get shorter compared to meta-regression
 - bias can be very high if p is small ($p \approx 10$)
 - not surprising, given `smvmeta` is based on random projection
- The method appears to be robust to the MNAR scenario
- Recommend `smvmeta` for sparse problems with $p \geq 15$ variates







Summary

Summary

- Introduced multivariate meta-analysis and the problem of sparsity
- Explained how to use `smvmeta` for multivariate random-effects meta-analysis
- Outlined how the method works (see the paper for more details)
- Summarized the results of simulation-based validation experiments

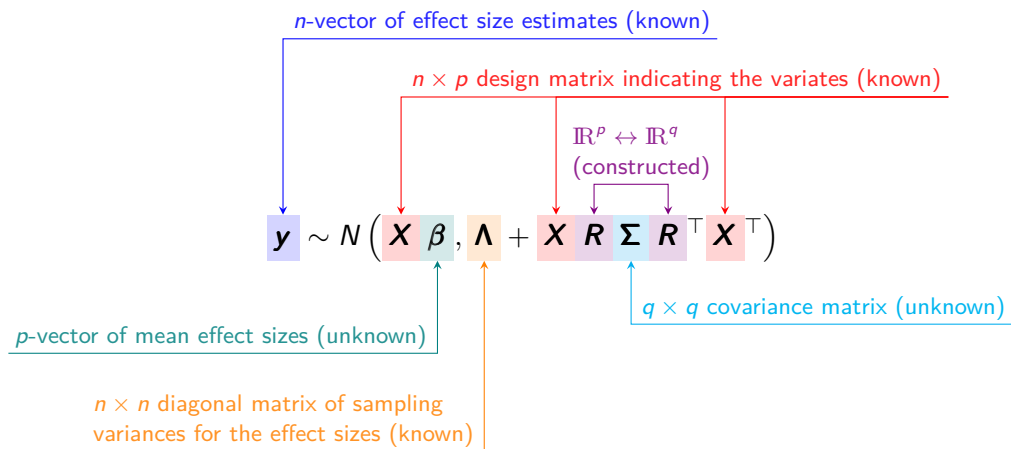
Thanks for listening

References

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Questions?

The smvmeta model



- \mathbf{X} could include covariates for meta-regression (not yet implemented)
- β and Σ are estimated using penalized maximum likelihood (inverse-Wishart penalty applied to Σ to prevent trivial solutions; see paper)

Assessing superiority

- Natural research questions include “Which risk factor is most important?” and “Which treatment is best?” (superiority)
- `smvmeta` assesses superiority using P -scores (Rücker and Schwarzer, 2015)
 - measures the mean extent of certainty that a given effect size is superior to all others
 - P -scores are distinct from p -values
- Some preferable properties over posterior probabilities of superiority (e.g., `pbest()` option of `mvmeta`; see paper)
 - particularly useful for meta-analyses of correlations
 - can be computed almost instantaneously (no MCMC needed)
- `smvmeta` provides an option to specify what superiority means in your meta-analysis