



Exact meta-analysis for 2×2 tables with rare outcomes

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What's your talk about?

- 2×2 tables, from populations in which relevant odds ratios are heterogeneous
- Avandia! Recall Regina Liu on Tuesday, & see Yi Huang's talk later
- Exact intervals, for inference on the population(s) from whom we have data, a.k.a. *fixed effects* (FE) meta-analysis

Slides, papers and course materials at

tinyurl.com/fixef

Exact FE methods for 2×2 tables: motivation

- In 2007 Nissen & Wolski meta-analyzed data on Avandia (rosiglitazone maleate), looking at myocardial infarction (MI) and cardiovascular-related death (CVD) outcomes
- N&W found a significant effect of Avandia on MI...
- ...leading to many legal cases – see right. Avandia got a **black box warning**
- The N&W analysis used large-sample approximations, with small cell counts. Was that okay? Can it be trusted?



Exact FE methods for 2×2 tables: notation

We denote

		Outcome e.g. CVD		Total
		1	0	
Group	1 e.g. Avandia	X_i	$M_i - X_i$	M_i
	0 e.g. placebo	$T_i - X_i$	$N_i - T_i + X_i$	N_i
Total		T_i	$M_i + N_i - T_i$	$M_i + N_i$

for studies $i = 1, \dots, k$.

- Each group (i.e. M_i, N_i) at least moderate-size, but the bad outcome (side effect) is rare in any group; **expect small and sometimes zero counts**
- No confounding, and trial groups split roughly evenly
- Denote cell probabilities and odds ratio in population i as

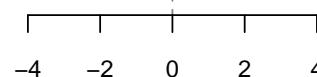
$$\theta_{ij} = \mathbb{P}[\text{Outcome} = j | \text{Group} = i], \quad \psi_i = \frac{\theta_{i1}}{1 - \theta_{i1}} \frac{1 - \theta_{i0}}{\theta_{i0}}$$

Exact FE methods for 2×2 tables: small counts!

MI data

Study # Paper/Abstract*

49653/011	Lebovitz et al (2001)
49653/020	Charbonnel et al (1999)*
49653/024	Phillips et al (2001)
49653/093	Jones et al (2003)
49653/094	Fonseca et al (2000)
100684	
49653/143	Campbell et al (2004)*
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49653/284	Weissman et al (2005)
712753/008	
AVM100264	
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BRL 49653/334	
BRL 49653/347	Hollander et al (2005)*
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49653/080	St John Sutton et al (2002)
49653/082	Raski et al (2001)
49653/085	
49653/095	
49653/097	
49653/125	Vongthavaravat et al (2002)
49653/127	Garber et al (2001)*
49653/128	
49653/134	Jones et al (2001)*
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49653/136	
49653/145	Baksi et al (2004)
49653/147	Barnett et al (2003)
49653/162	Kerenyi et al (2004)
49653/234	Hamann et al (2003)*
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49653/331	Ellis et al (2007)
49653/137	
SB-712753/002	Bailey et al (2005)
SB-712753/003	Stewart et al (2006)
SB-712753/007	
SB-712753/009	Home et al (2007)*
49653/132	Zhu et al (2003)
AVA100193	
DREAM	The DREAM Investigators (2006)
ADOPT	Kahn et al (2007)
49653/044	Collegeville, PA (2001)*
49653/096	
49653/282	Rood et al (2009)*
49653/369	
49653/325	Rosenstock et al (2005)*
797620/004	



log OR estimate

RSG

Ctrl

M_k X_k N_k T_k - X_k

357	2	176	0
391	2	207	1
774	1	185	1
213	0	109	1
232	1	116	0
43	0	47	1
121	1	124	0
110	5	114	2
382	1	384	0
284	1	135	0
294	0	302	1
563	2	142	0
278	2	279	1
418	2	212	0
395	2	198	1
203	1	106	1
104	1	99	2
212	2	107	0
138	3	139	1
196	0	96	0
122	0	120	1
175	0	173	1
56	1	58	0
39	1	38	0
561	0	276	2
116	2	111	3
148	1	143	0
231	1	242	0
89	1	88	0
168	1	172	0
116	0	61	0
1172	1	377	0
706	0	325	0
204	1	185	2
288	1	280	0
254	1	272	0
314	1	154	0
162	0	160	0
442	1	112	0
394	1	124	0
2635	15	2634	9
1456	27	2895	41
101	0	51	0
232	0	115	0
70	0	75	0
25	0	24	0
196	0	195	0
676	0	225	0
797620/004			

CVD mortality data

Study # Paper/Abstract*

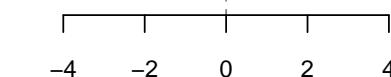
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2635	12	2634	10
1456	2	2895	5
101	0	51	0
232	0	115	0
70	0	75	0
25	0	24	0
196	0	195	0
676	0	225	0



log OR estimate

Exact FE methods for 2×2 tables: what's wrong?

N&W caused trouble!...

...and nerdy excitement, in some UW offices!



As well as MDs/industry/politicians pushing their own agendas:

- Shuster *et al* (2007, *SiM*) assert that random effects are “needed” – they use large- n methods, but exact version given by Gronsbell *et al* (2019, *SiM*)
- Assuming all $\psi_i = \psi$ (*common effect model*) can use **stratified Fisher's exact test**, but Tian *et al* (2009, *Biostatistics*) present exact CIs (also RR, RD)

✓✓✓
Handling
small counts!

XXX
The ψ_i aren't randomly sampled,
nor are they homogeneous.

What to do instead?

- Inference **for the study populations at hand** (just like we use for trials)
- ... on some overall "average" odds ratio

For much more on these, see Rice, Higgins & Lumley ([JRSSA, 2017](#)) – on why/how fixed effect**S** (*plural!*) methods achieve this.

Our approach adapts this for rare events 2×2 tables, and exact inference.

Note: ‘exact’ means ‘not anti-conservative’ e.g. the guarantee that $T1ER \geq \alpha$ in Fisher’s ‘Exact’ Test

What will you estimate/test?

Under homogeneity, it's standard to start with the hypergeometric distribution for each X_i , conditional on the row & column totals:

$$\mathbb{P}[X_i = x | M_i = m, N_i = n, T_i = t] = \frac{\binom{m}{x} \binom{n}{t-x} \psi_i^x}{\sum_{\max(0, t-n) \leq x' \leq \min(t, m)} \binom{m}{x'} \binom{n}{t-x'} \psi_i^{x'}}$$

where ψ_i is the odds ratio for study k .

Very helpfully, this is **exactly** equal to the convolution of a series of non-identical Bernoulli variables ([Kou & Ying, 1996](#)), with success probabilities

$$p_{ij}(\psi) = \frac{1}{1 - \lambda_{ij}/\psi_i},$$

where ψ is the vector of subtable-specific odds ratios and λ_{ij} are roots of subtable-specific hypergeometric polynomials.

What will you estimate/test?

The well-known *conditional maximum likelihood estimator* is the solution to

$$X_i = \sum_j p_{ij}(\hat{\psi}_i), \quad \text{single table}$$

$$\sum_i X_i = \sum_{i,j} p_{ij}(\hat{\psi}_{CMLE}), \quad \text{multiple tables}$$

Under heterogeneity, we **define overall odds ratio** ψ_F as the solution of

$$\sum_{i,j} p_{ij}(\psi_F \mathbf{1}_k) = \sum_{i,j} p_{ij}(\psi)$$

... and $\hat{\psi}_{CMLE}$ estimates ψ_F consistently, as number of subtables k increases.

Big idea: use $\sum_i X_i$ for inference about mean of the p_{ij} ,
and transform this to get inference on ψ_F .

What is the distribution of $\sum_i X_i$?

The point null $\psi_F = \psi_0$ doesn't specify a distribution for $\sum_i X_i$ – it only specifies the mean. But...



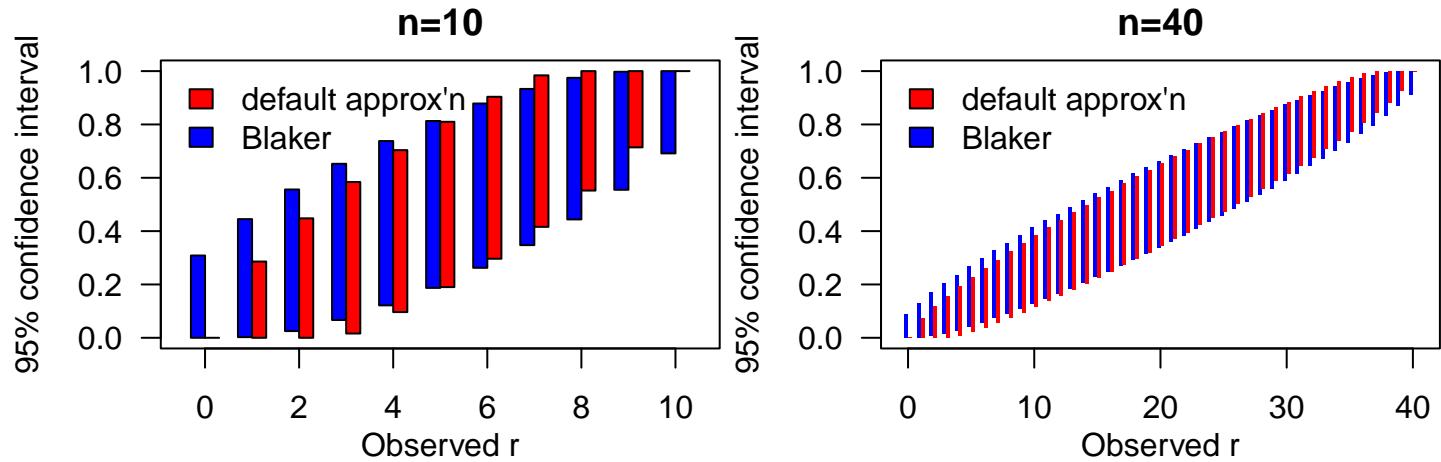
Among **all** convolutions of n Bernoullis with a specific overall mean $n\theta$, the ‘pure’ Binomial(n, θ) has the lightest tails.

Hoeffding ([Annals](#), 1956)

So exact inference using $\sum_i X_i$ for its mean under the Binomial under homogeneous p_{ij} **also** provides exact inference under heterogeneous p_{ij} , we which we get with heterogeneous ψ_i .

Exact inference for binomial mixtures

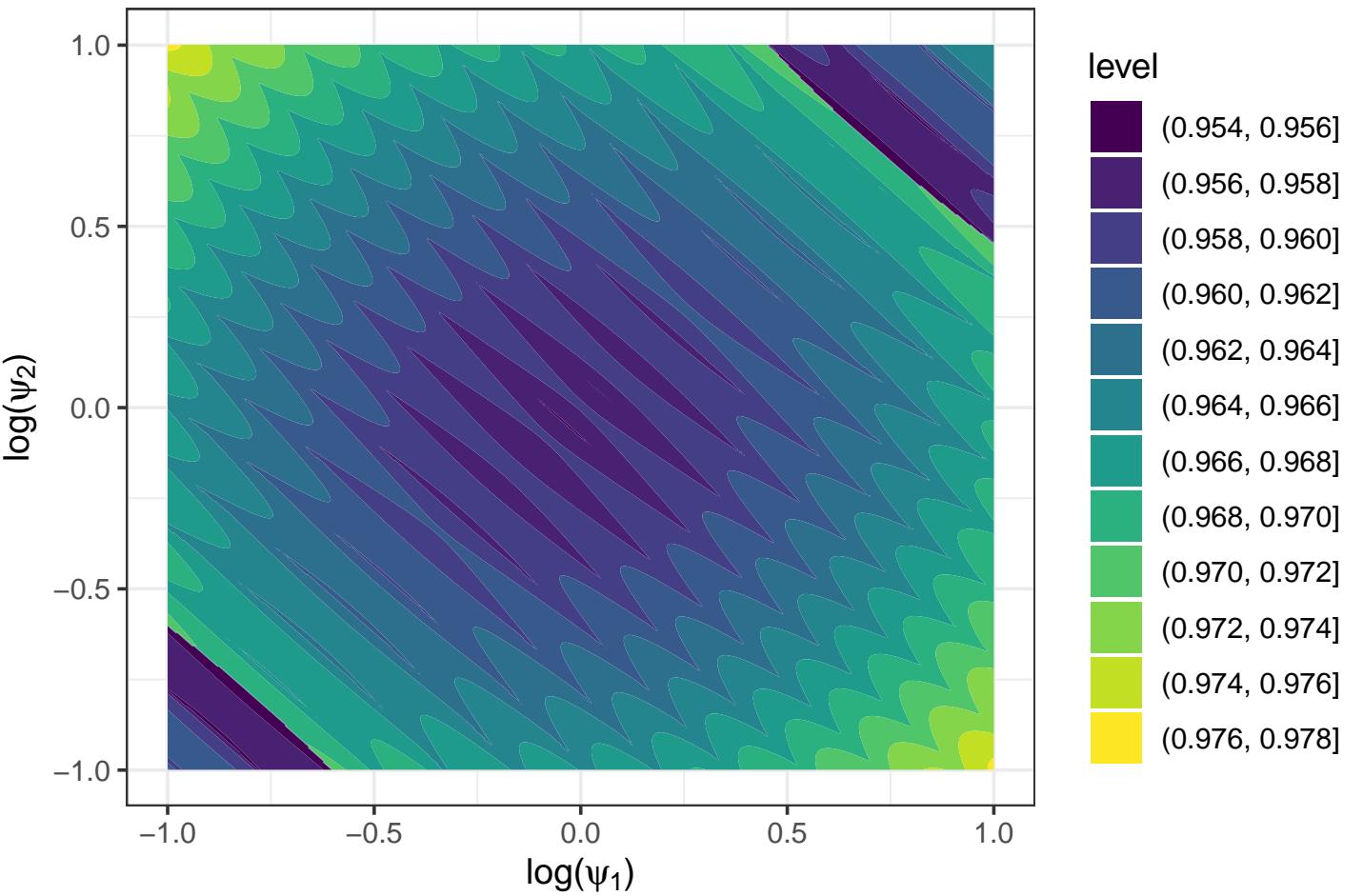
Based on earlier work,
the Blaker approaches
(for r successes out of n)
work well for exact tests
and confidence intervals



- We use a Blaker interval around $\sum_i X_i / \sum_i M_i + N_i$, which is exact when all p_{ij} are identical
- By Hoeffding, it is conservative as a statement of $\sum X_i$'s extremity under any ψ **that have the same overall** ψ_F
- Hence, after transformation to the ψ_F scale, gives exact inference for ψ_F

Does it work? (Yes! Of course!)

- Here we consider $k = 2$ 2×2 tables, each with $M_i = N_i = (500, 500)$ and $T_i = (25, 25)$
- For each $\{\psi_1, \psi_2\}$, coverage rate is for ψ_F , the solution to
$$\sum_{i,j} p_{ij}(\psi_F) = \sum_{i,j} p_{ij}(\psi_i)$$
- Calculations use complete enumeration



'Exact' means a bit conservative: but how much?

Can learn about this comparing the variance of $\sum X_i$ (i.e. $\sum_{ij} p_{ij}(\psi_i)(1 - p_{ij}(\psi_i))$) to the pure binomial variance.

The critical quantity is

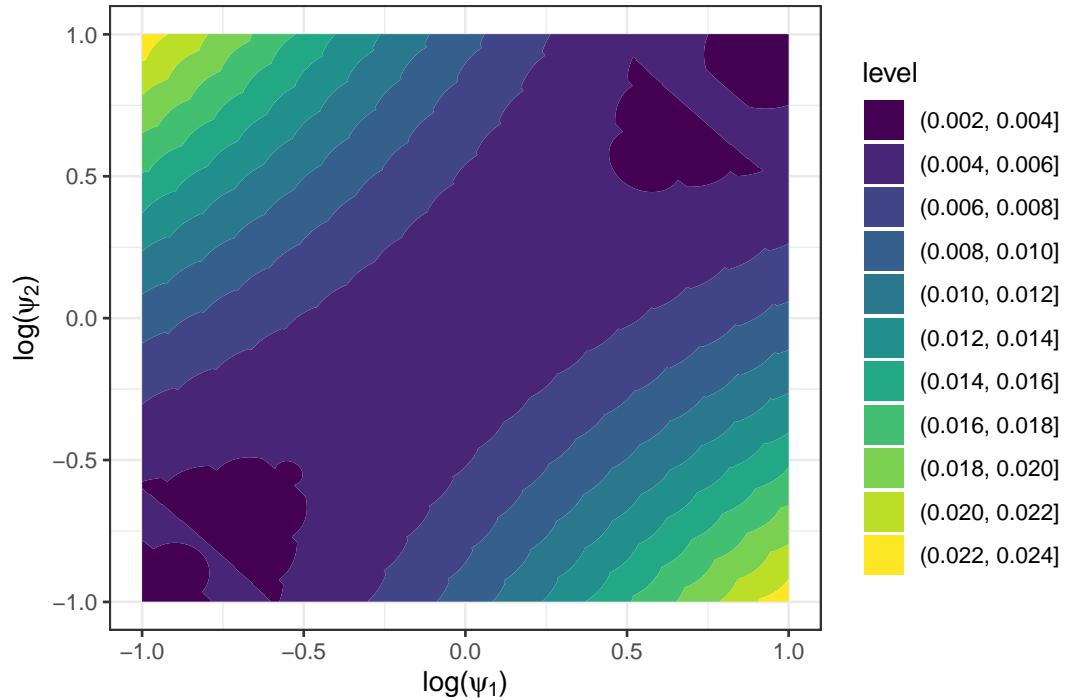
$$\delta^2 = \sum_{i,j} \frac{1}{\sum_i U_i} \left(p_{ji}(\psi_i) - \frac{\sum_{k,j} p_{ji}(\psi_F)}{\sum_i U_i} \right)^2, \text{ where } U_i = \min(T_i, M_i).$$

- δ indicates **approximately** how much bigger the intervals are than they need to be – conservatism due to using pure binomial case **and** due to ψ_i being heterogeneous
- Doesn't describe conservatism (under pure binomial) because we want exact intervals from a discrete sample space – but can simply compute that, with complete enumeration.

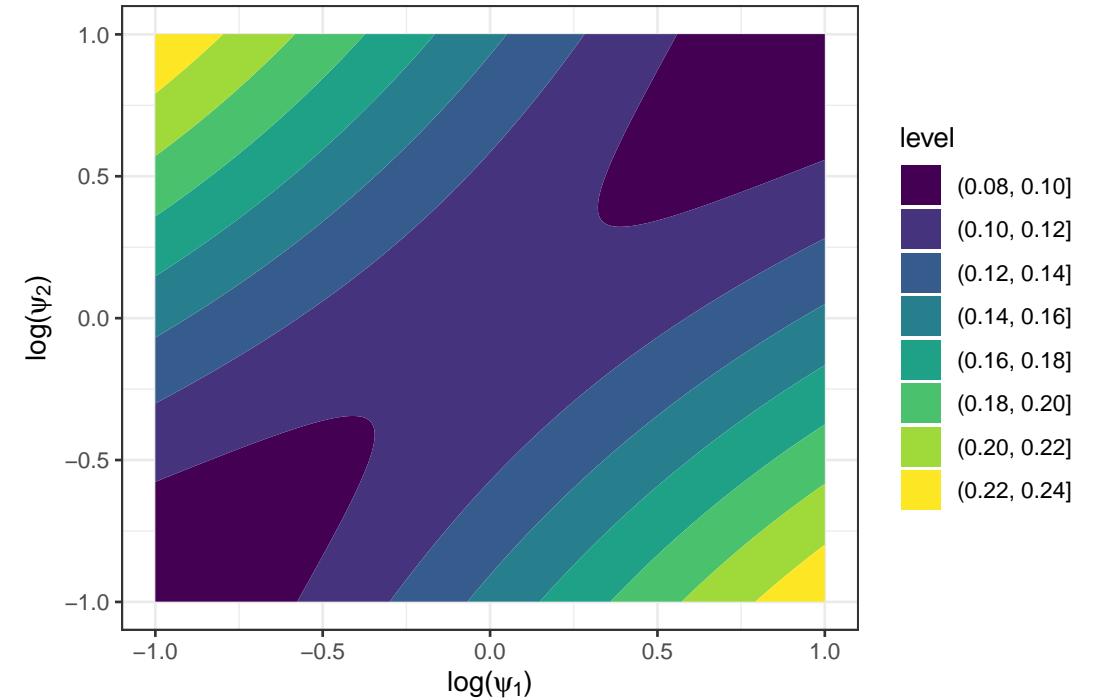
'Exact' means a bit conservative: but how much?

Again for $k=2$, $M_i=N_i=(500,500)$, $T_i=(25,25)$, showing how δ tracks excess coverage:

Excess coverage



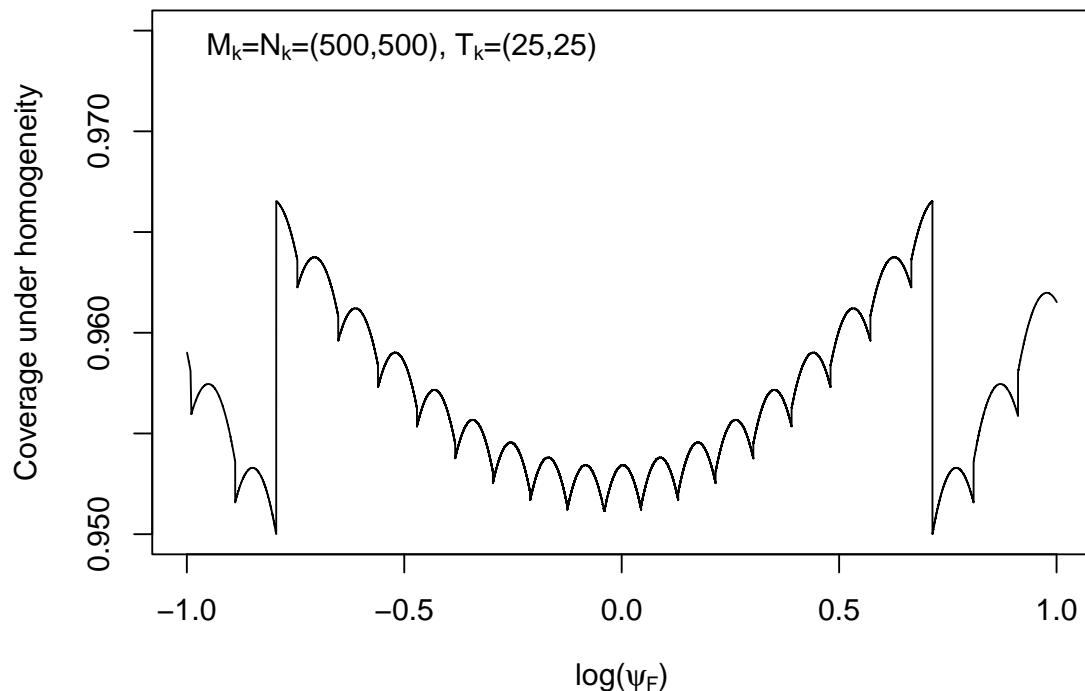
δ



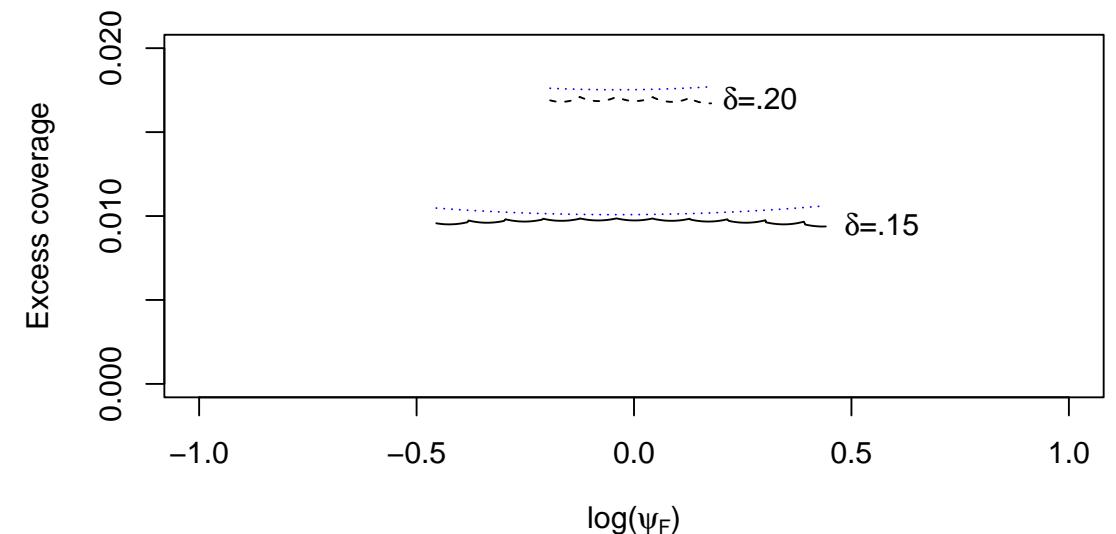
'Exact' means a bit conservative: but how much?

Turning δ 's excess width into approximate excess coverage, beyond what we get from pure binomial:

Coverage under pure binomial



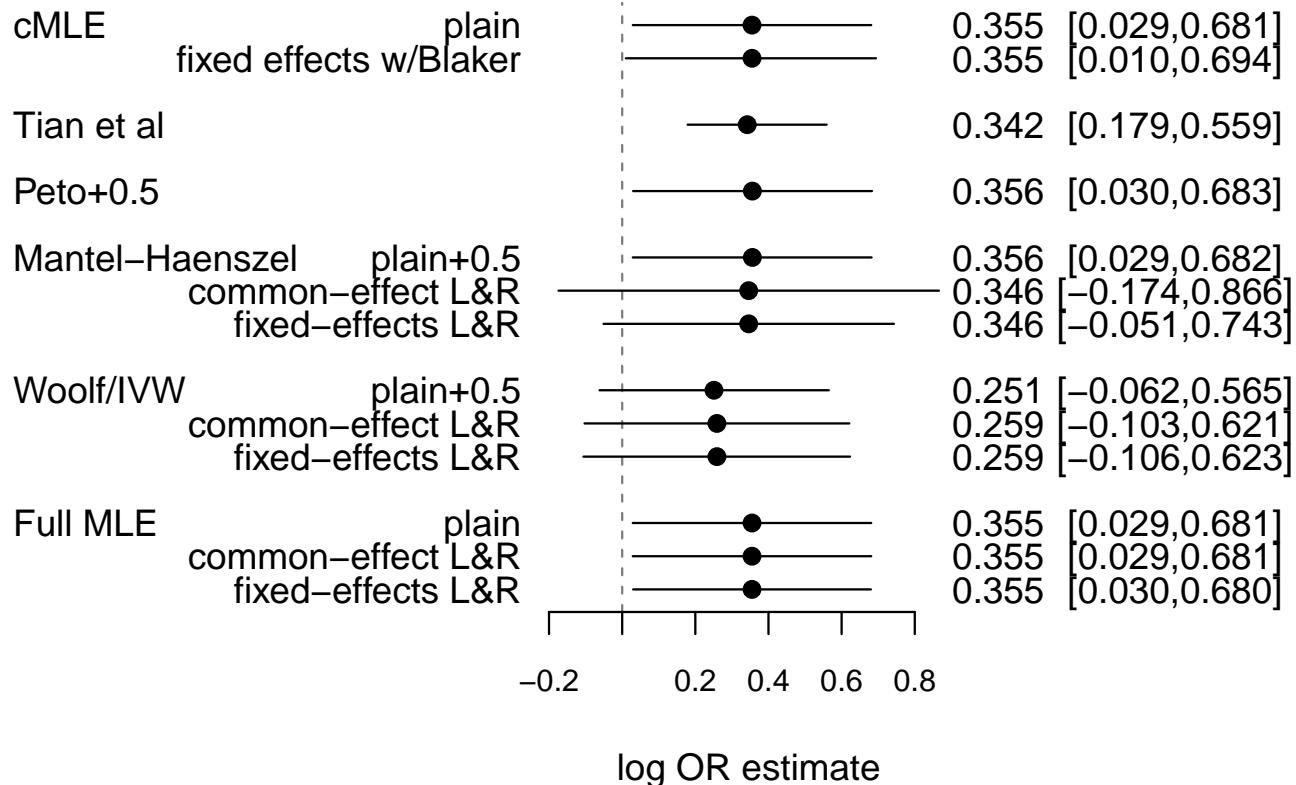
Actual/approximate excess coverage



Weren't you talking about Avandia?

Comparing the exact method (cMLE fixed effects w/Blaker) to others:

MI data: Method



$\hat{\delta} = 0.18, 0.14$ under homogeneous ψ_i , suggests 96.4% (95.9%) coverage

Weren't you talking about Avandia?

Same comparisons for the other endpoint:

CVD mortality data: Method

cMLE plain
fixed effects w/Blaker

Tian et al

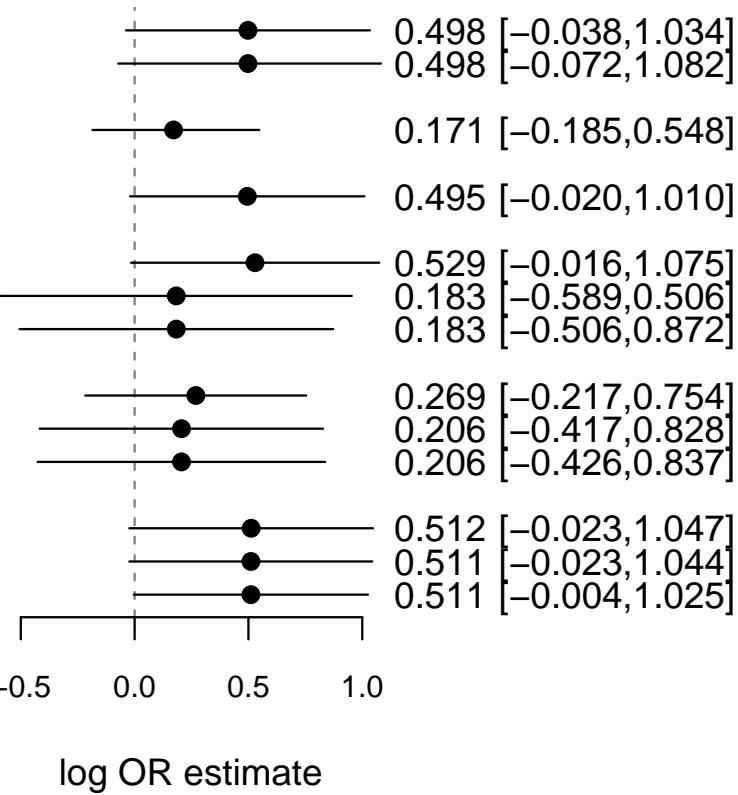
Peto+0.5

Mantel-Haenszel plain+0.5
common-effect L&R
fixed-effects L&R

Woolf/IVW plain+0.5
common-effect L&R
fixed-effects L&R

Full MLE plain
common-effect L&R
fixed-effects L&R

estimate 95% CI



$\hat{\delta} = 0.18, 0.10$ under homogeneous ψ_i , suggests 96.5% (95.6%) coverage

Are you going to stop now?

In summary:

- Nissen & Wolski analysis was fine - for FE inference on ORs
- Hansen & Rice ([SiM 2023](#)) gives exact methods for meta-analysis of 2×2 contingency tables, for inference on the conditional MLE odds ratio ψ_F
- The conservatism of the exact inference can be usefully approximated via δ^2
- Method is appropriate for any application where events are rare and heterogeneity is plausible. (For *common* events, can be very conservative)
- Method is specific to ORs, for which double-zero tables don't contribute

Thank you! (Particularly Yong, and Spencer)

tinyurl.com/fixef