

# Quantitative Bias Analysis in Practice

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With thanks to **Ian Douglas** and **Marleen Bokern** for slides

**Validate study variables to reduce  
misclassification bias: recent tools and research needs**

HYBRID WORKSHOP

27 March 2025 - 14.30-18.30

ARS Toscana - Villa La Quiete, via Pietro Dazzi 1 - Florence, Italy

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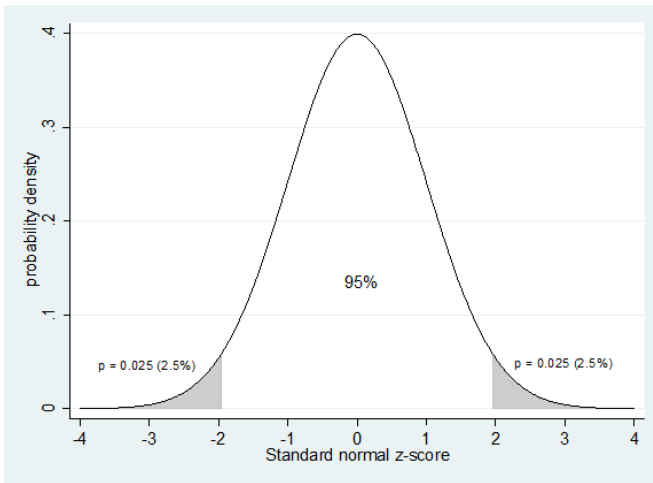
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# How do we handle error in epidemiological studies?

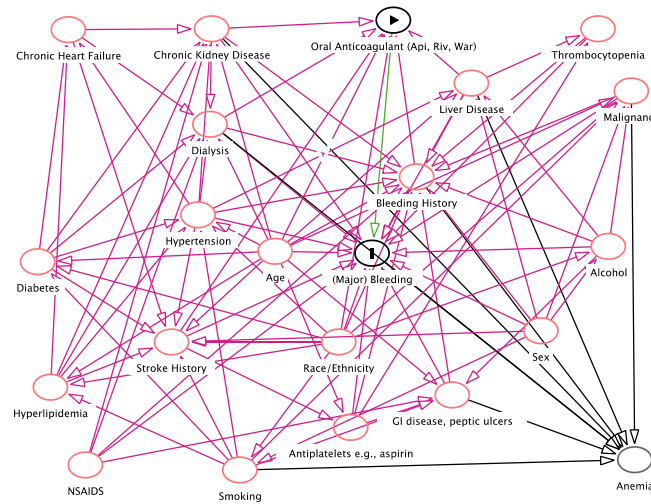
## Random Error

Quantitative assessments  
Confidence intervals, p-values



## Confounding

Careful adjustment  
Often sensitivity analyses



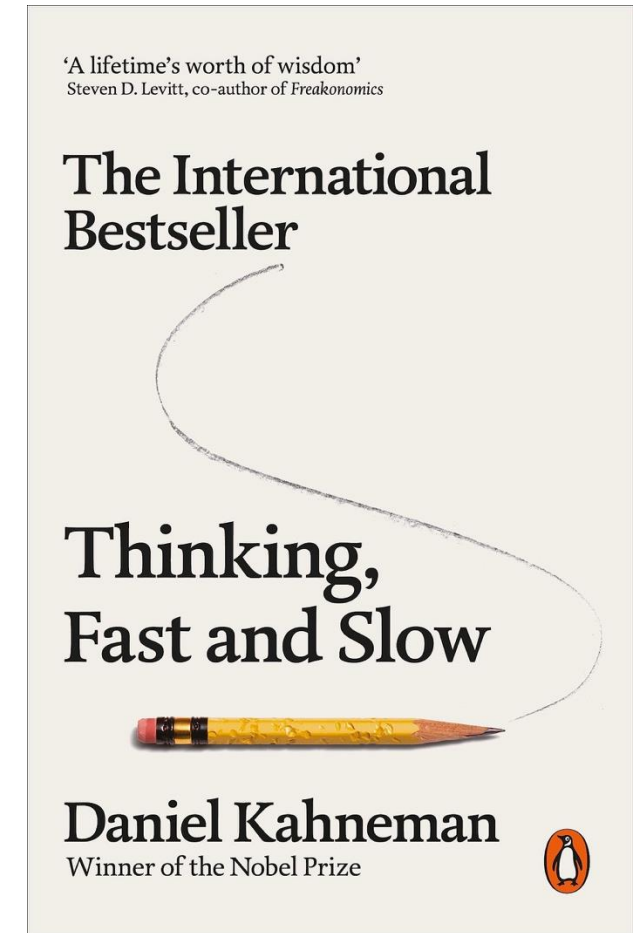
## Misclassification

“blah blah ... bias towards the null”



# The status quo needs improving

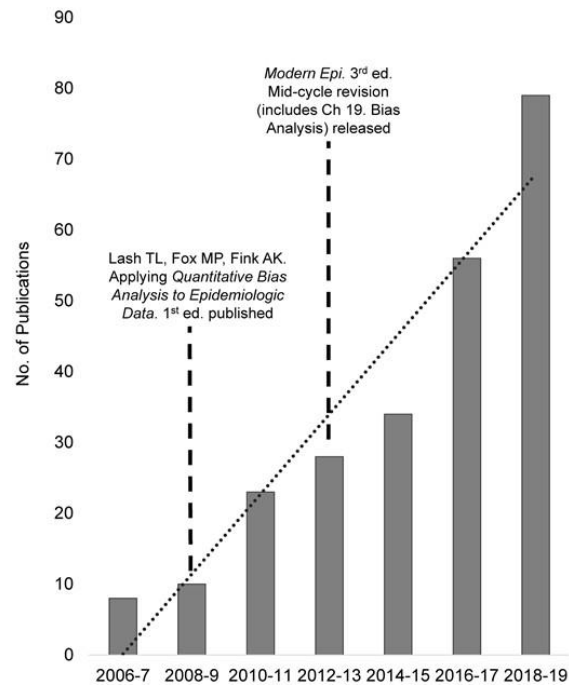
- "Non-differential misclassification biases towards the null", **except...**
  - **Chance:** bias towards null in expectation, not always
  - **More than 2 categories:** may bias away from null
  - **Dependency of 2 misclassified variables:** hard to predict
  - **Outcome misclassification with 100% specificity:** no bias
  - **Misclassification of a confounder:** direction of confounding
- The extent of bias matters
  - RR = 1.5 vs. RR = 1.6 vs. RR = 55
  - We are bad at intuiting the extent of bias



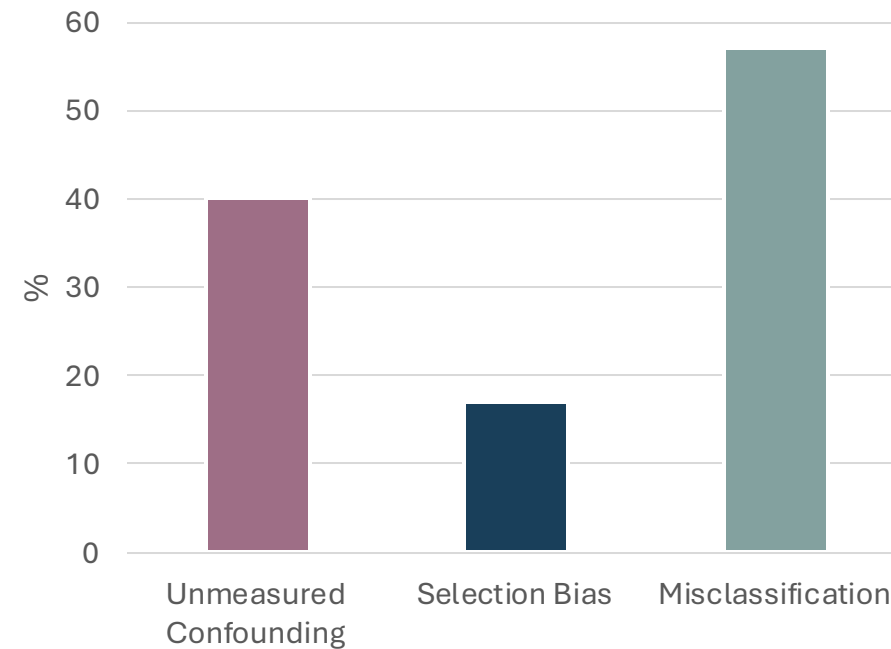
# Quantitative Bias Analysis (QBA)

- Methods which quantify the **direction**, **magnitude** and **uncertainty** of systematic error

## QBA is increasingly used



## Most often for misclassification



# QBA for misclassification

- **Aim:** correct an effect estimate, and its uncertainty, for misclassification
- Assumptions - bias parameters : sensitivity, specificity, NPV or PPV
  - Internal validation **29%**
  - External validation (assuming transportability) **48%**
  - Educated guess **24%**
- Different methods
  - Simple / Multidimensional **36%**
  - Probabilistic **57%**

# Simple QBA

## Expected Truth – corrected for outcome misclassification

		Exposure	
		E +	E -
Outcome	Outcome	$A = \frac{a - (a + c)(1 - Sp)}{Se - (1 - Sp)}$	$B = \frac{b - (b + d)(1 - Sp)}{Se - (1 - Sp)}$
	No outcome	$C = (a + c) - A$	$D = (b + d) - B$
		$a + c = A + C$	$b + d = B + D$

# Probabilistic Bias Analysis (PBA)

Uses Monte Carlo sampling methods to generate a distribution of bias-adjusted effect estimates

- 1) Assign probability distributions to bias parameters
- 2) Sample from this distribution
- 3) Use the sampled values to correct 2x2 table
  - a. *Estimate prevalence of outcome in each exposure group*
  - b. *Use prevalence, SE and SP to calculate PPV and NPV*
  - c. *Correct 2x table using PPV and NPV*
  - d. *Calculate corrected OR*
- 4) Repeat many times

# Probabilistic Bias Analysis (PBA)

## Summary Level

- Calculated on 2x2 table
- No confounder adjustment

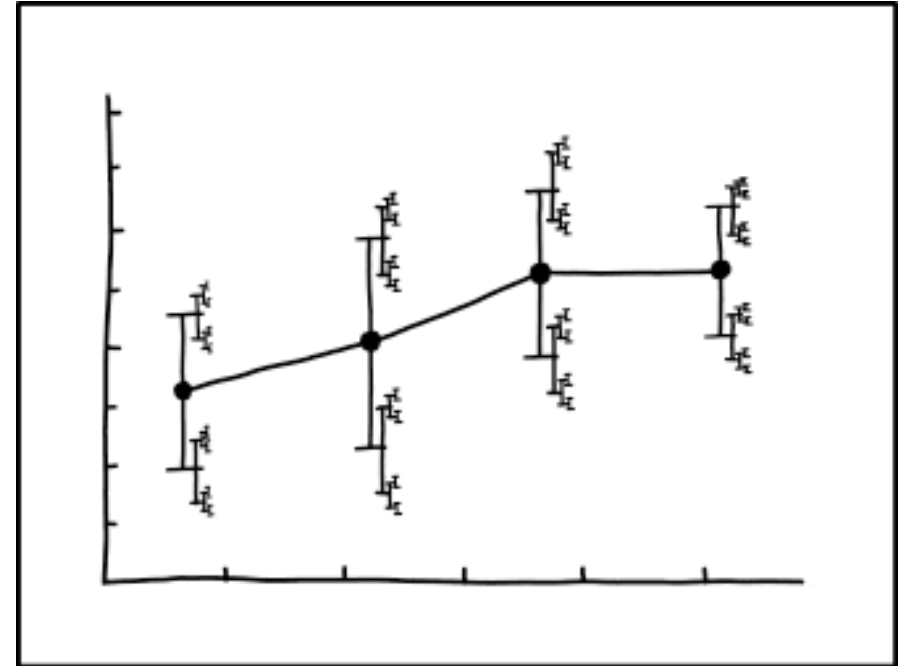
## Record Level

- Simulated outcome for each record
- Full analytical flexibility



# Incorporating uncertainty

- Want to quantify **both** random and systematic error
- Simple bias analysis:
  - Cannot calculate 95%CI directly from the corrected cell counts --> separate formulas
- Probabilistic bias analysis:
  - Simple approximate method
  - Simulates random error around bias adjusted estimate
  - Summarize the resulting distribution as median and simulation interval (2.5th to 97.5th percentile)
  - ‘total error’ - both systematic and random



I DON'T KNOW HOW TO PROPAGATE  
ERROR CORRECTLY, SO I JUST PUT  
ERROR BARS ON ALL MY ERROR BARS.

# Example: COVID-19 drug studies



- First lockdown
- Lots of interest in how drugs impact covid risk
- Extreme time pressure
- ICS proposed as potential repurposing candidate
- Original study (Schultze et al, 2020) → harm
  - Later RCTs → null, or possible protection
- Marleen Bokern PhD:
  - explore impact of different errors
  - how can we do better next time?

# Inhaled corticosteroids (ICS) and risk of COVID death

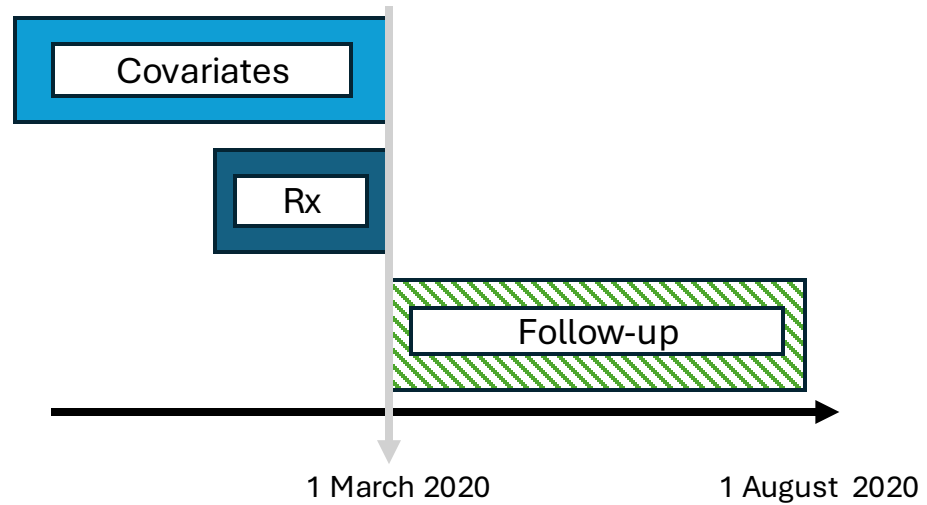


People with COPD in CPRD  
ICS compared to LABA/LAMA



National death registration (ONS)  
ICD-10 codes (U07.1, U07.2)

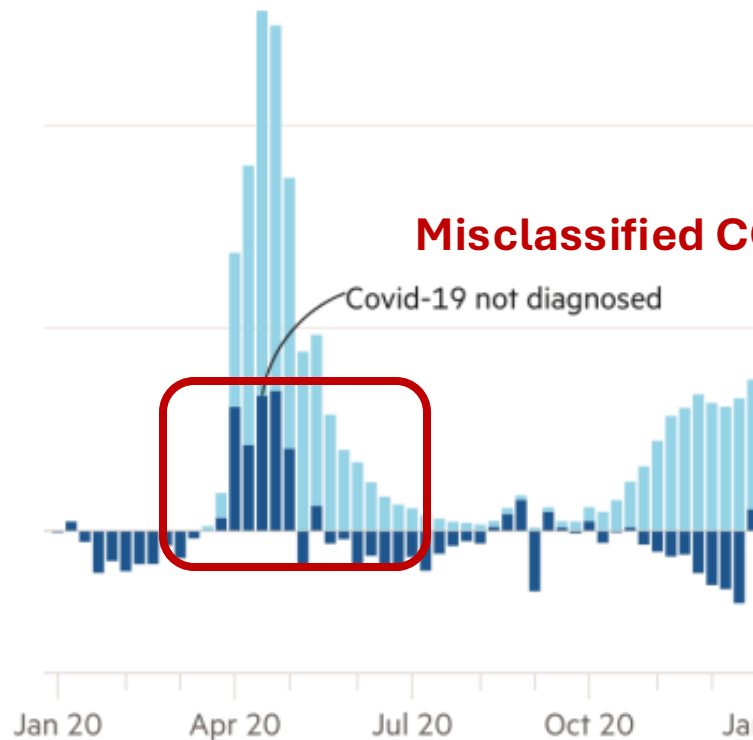
# The basic study design



# COVID-19 outcome misclassification

Deaths in the UK (Sum equals excess deaths)

■ Excess deaths non-Covid    ■ Covid deaths



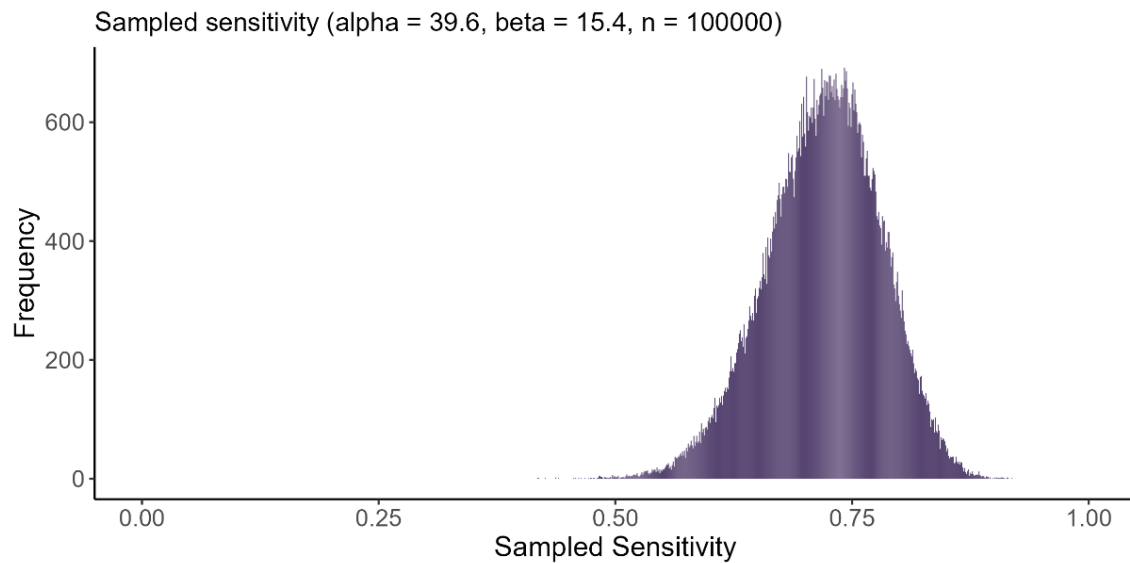
Source: UK statistical agencies, FT calculations

© FT

- Low sensitivity - > 20% of COVID deaths misclassified
- Reduced specificity - limited testing capacity
- Misclassification of cause
  - **why** – not whether – someone died
- Was this an issue?

# Bias parameters & assumptions

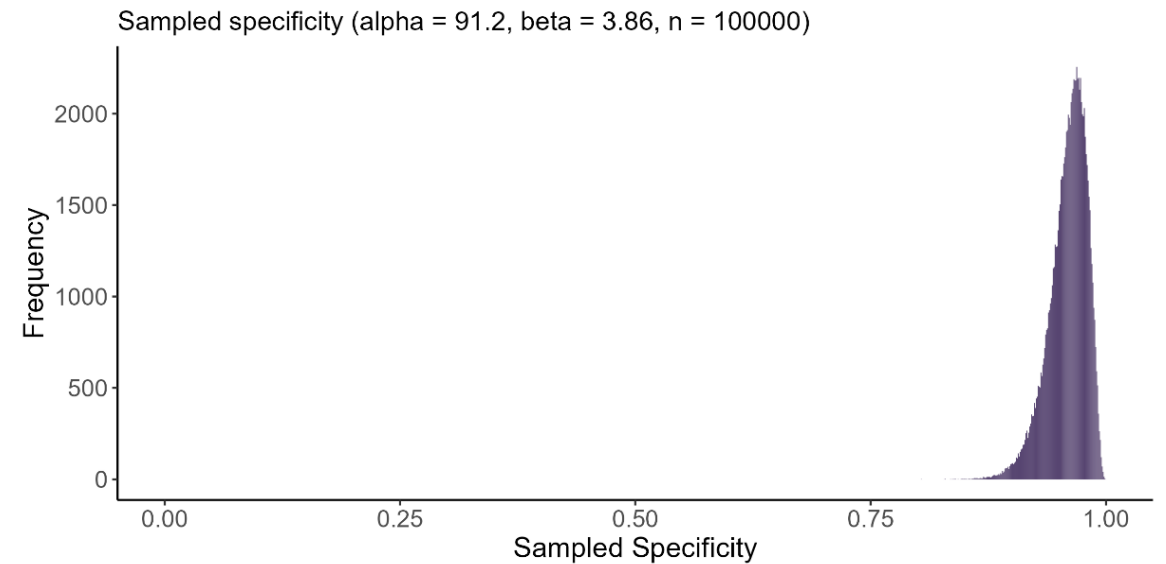
- No validation study
- Solution : use three sources of death information
  - Excess deaths estimates, ONS death registrations and UKHSA (deaths among those with + test)
  - Assume excess deaths were all due to COVID-19



**median = 0.72**

2.5th%-ile = 0.60

97.5th%-ile = 0.83



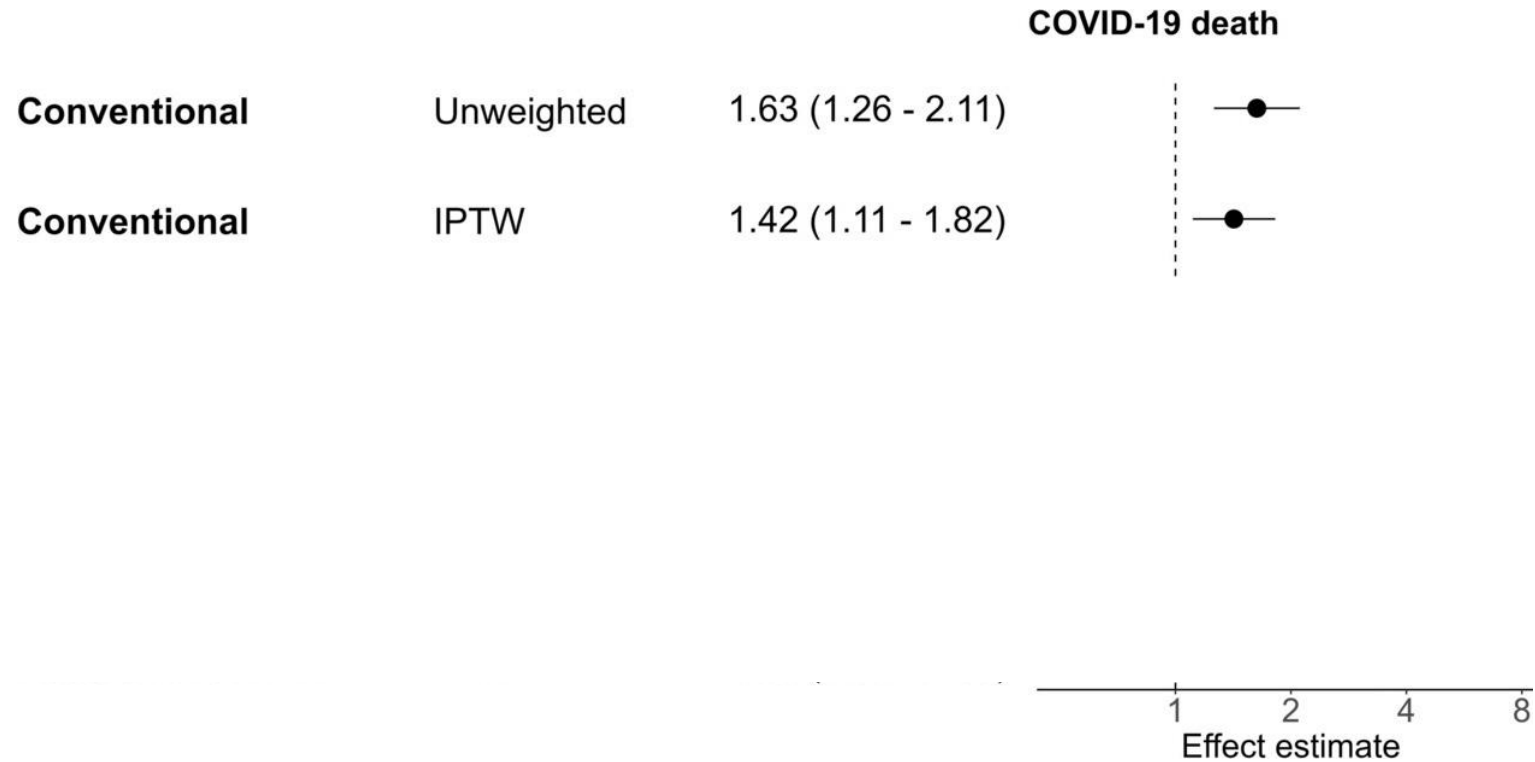
**median = 0.96**

2.5th%-ile = 0.91

97.5th%-ile = 0.99

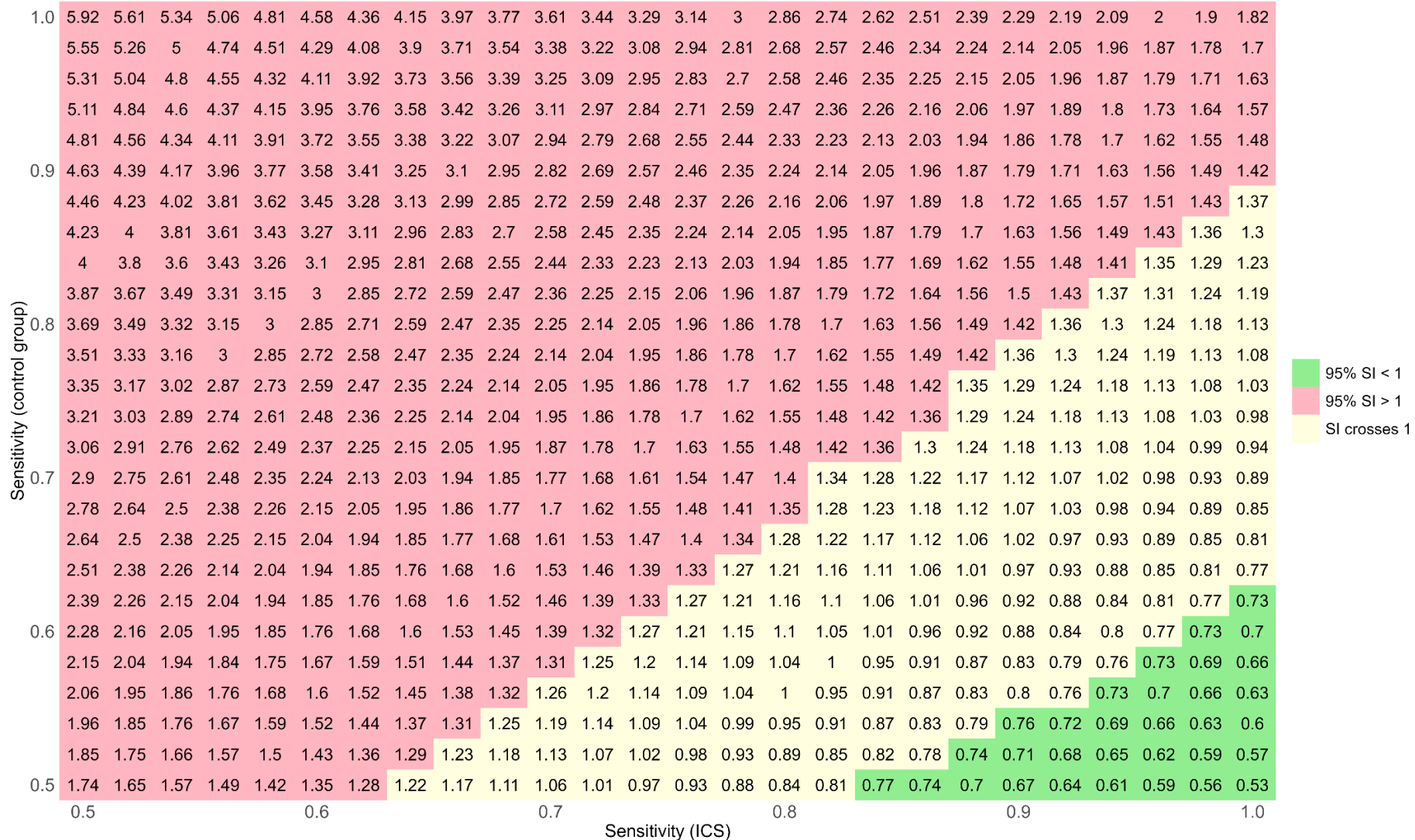
# Results – non-differential sensitivity

Odds ratios and 95% confidence or simulation intervals for COVID-19 hospitalisations and deaths, comparing ICS/LABA ( $\pm$  LAMA) users to LABA/LAMA users



# Results – differential sensitivity

Point estimates under a range of scenarios



100,000 simulations were run per combination of sensitivity values. Specificity was set at 0.97. SI = simulation interval



# Interpretation

- We missed a lot of COVID-19 deaths, but in the context of high specificity non-differential reduction in sensitivity did not matter
  - Small shift away from null driven by reduced specificity
  - ***Increased uncertainty***
- The extent of differential misclassification needed for us to ‘miss’ a protective effect would need to be substantial
  - Unlikely in context of active comparator
- Importance of considering multiple sources of error
  - Confounding!!

# Recommendations to Xabi

- If you are doing a validation study, report validity measures by exposure / outcome
- Pre-specify when you will run a QBA, and how you will define the bias parameters
  - If your main results are very imprecise, QBA may not be informative
  - Very important to ensure bias parameters are reasonable for your target population
    - If large number of negative cell counts, implies bias parameters not supported by data
- To incorporate uncertainty → probabilistic bias analysis (either summary or record-level)
- If you are doing a distributed analysis, summary-level PBA may be easier to implement
  - Could be run on summary data by a single analyst
  - Record level is more computationally intensive
- If confounding has a large impact, record-level PBA likely preferable
  - If PS-weighting, might be able to apply summary-level PBA to weighted 2x2 summary tables

# Recommendations to Ersilia / Robert

- How do we best use QBA in more complex scenarios?
  - Bias parameters vary with values of one or more (unmeasured) confounders
  - Bias parameters vary over time
  - Time to event outcomes, where time is also misclassified
- When is it okay to ‘transport’ validity measures (SE, SP?) between populations?
- How does QBA compare to alternative methods to handle misclassification?
  - Multiple imputation
- How can interpretation of QBA be improved?
  - Tendency for QBA to ‘*not substantially change conclusions*’ (Petersen, 2021)
  - Should interpretation be pre-specified?
- Why is QBA not more widely used by researchers and regulators?
  - Many tools / resources are available : so what are the barriers?

Thank you!

Any questions?



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