

... and how about interactions, etc.?

Håkon K. Gjessing

Professor/Principal Investigator

Centre for Fertility and Health (CeFH)

Norwegian Institute of Public Health, Oslo

and

Department of Global Public Health and Primary Care, University of Bergen

University of Bergen

Wednesday, May 16, 2018

REFER TO PREVIOUS EXAMPLE ON MORTALITY...

$$RD = p_2 - p_1 = 0.093$$

$$RR = \frac{p_2}{p_1} = 1.94$$

$$OR = \frac{p_2/(1-p_2)}{p_1/(1-p_1)} = \frac{p_2}{p_1} \cdot \frac{1-p_1}{1-p_2} = 1.94 \cdot 1.11 = 2.16$$

NOTE:

- RR and OR are very close when prevalence is low (say, less than 10%). This is because both $1 - p_1 \approx 1$ and $1 - p_2 \approx 1$.
- OR always farther away from 1 than RR (whether above or below 1). Here: $\frac{1-p_1}{1-p_2} = 1.11 > 1$

THREE MOST IMPORTANT MEASURES FOR GROUP COMPARISON

1 Risk Difference (RD):

- Intuitive (percentage points difference)
- High public health relevance

2 Relative Risk (RR)

- Intuitive (percentage increase in risk)
- High relevance for risk assessment in research

3 Odds Ratio (OR)

- Percentage increase in odds
- Of high practical utility and relevance in research
- Applicable also in **case-control studies**

HOW DO THEY HANDLE SELECTION?

	Males	Females	Total
X (deaths)	398	188	586
n - X (non-deaths)	1688	1726	3414
n (total)	2086	1914	4000

Select 50% of males:

	Males	Females	Total
X (deaths)	199	188	387
n - X (non-deaths)	844	1726	2570
n (total)	1043	1914	2957

	Before	After
RD	0.093	0.093
RR	1.94	1.94
OR	2.16	2.16

BUT REMEMBER:

- Confidence intervals get wider
- I.e. less significant difference

HOW DO THEY HANDLE SELECTION?

	Males	Females	Total
X (deaths)	398	188	586
n - X (non-deaths)	1688	1726	3414
n (total)	2086	1914	4000

Select 50% of controls (non-deaths):

	Males	Females	Total
X (deaths)	398	188	586
n - X (non-deaths)	844	863	1707
n (total)	1242	1051	2293

	Before	After
RD	0.093	0.14
RR	1.94	1.79
OR	2.16	2.16

THUS:

- OR is unbiased
- RD and RR are biased

FLIP THE COIN

What if we want to compare *survival* probabilities, not death?

	Males	Females	Total
X (deaths)	398	188	586
n - X (non-deaths)	1688	1726	3414
n (total)	2086	1914	4000

Females versus males:

$$RD = (1 - p_1) - (1 - p_2) = \frac{1726}{1914} - \frac{1688}{2086} = 0.093$$

$$RR = \frac{1 - p_1}{1 - p_2} = \frac{1726/1914}{1688/2086} = 1.11$$

$$OR = \frac{(1 - p_1)/p_1}{(1 - p_2)/p_2} = \frac{p_2}{p_1} \cdot \frac{1 - p_1}{1 - p_2} = 1.94 \cdot 1.11 = 2.16$$

RD and OR unaffected!

MYTH I

“For high prevalences, OR cannot be used, only RR is correct”

Wrong!

- For instance, when $p_1 > 0.5$, then $RR = 2$ is mathematically impossible.
- RR gets squeezed down to 1 when p_1 increases, since p_2 hits the roof of 1.
- So for very large p_1 you get $RR = 1.01$ and similarly uninformative results.
- Estimation of the RR with binomial regression becomes increasingly unstable when p_1 increases.

OR handles all this very nicely.

MYTH II

“Using OR is cheating, since it’s bigger than RR”

Wrong!

- If you state that it is the OR, then there’s no cheating.
- The significance is the same (at least for two groups).
- In a case-control study, you would need to use the OR anyway.
- The “true” reason for presenting the RR is usually slight ease of interpretation since “people” are more familiar with risk than odds.

MYTH III

“Additive risk scale is biologically correct”

Wrong!

- There is nothing inherently biological about an additive risk scale.
- However, choice of scale *will* have implications for for instance causal inference, and an additive scale is frequently used.

Figur F001: Sammenhengen mellom samfunnets endringshastighet og omstillingskrav overfor individ og samfunn

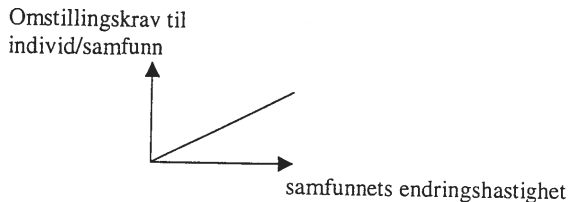


Fig F001: Hypotese: omstillingskravene antas å øke proporsjonalt ved samfunnets endringshastighet

SCALE DEPENDENCE

- Measurement scale dependence pervades all of statistical modeling
- “Problem without solution” (at least no simple, canonical solution)
- Results will depend on measurement scale
- Some methods are robust to monotone scale change, such as methods based on observation rank, i.e. many non-parametric methods.

- 1 Fit a statistical model:
 - Incorporate structural relationships, such as growth curves, additive, linear structures, etc.
 - Take into consideration causal aspects, confounders, interactions etc.
 - Add a stochastic model for random variability (i.e. how randomness is generated)
- 2 Check if model fits to data.
- 3 If model fits, interpret data in light of model.
- 4 Problem:
 - If two different plausible models with different interpretations both fit, what then?
 - Perhaps too little data to distinguish