Statistical Methods in Cancer Epidemiology using R

Janne Pitkäniemi

Faculty of Social Sciences, University of Tampere
Finnish Cancer Registry

janne.pitkaniemi@cancer.fi

Lecture 2b

Feb,17 2020

Confounding and effect modification

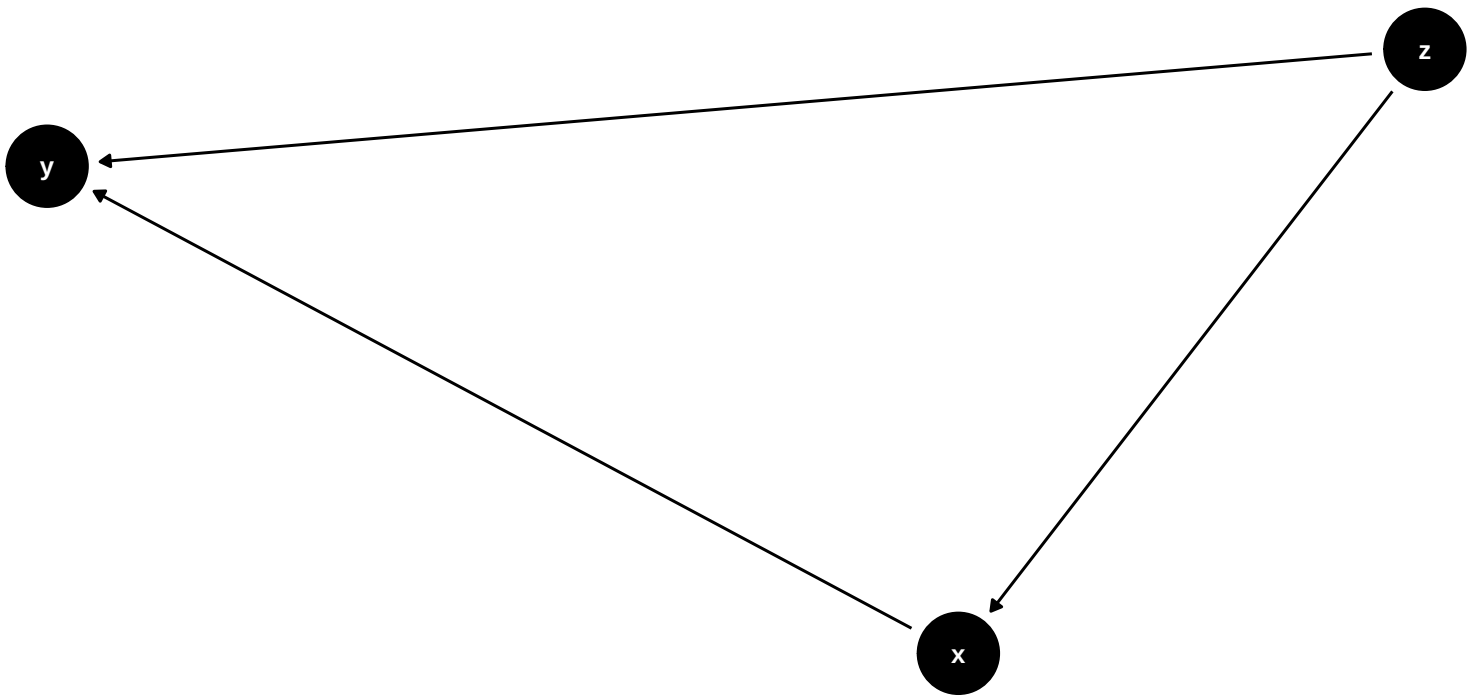
Consider another **factor** Z which is

- also a risk factor of the outcome,
- possibly associated with exposure X in study population,
- not a causal consequence of X.

$\Rightarrow$ Adjustment for possible *confounding* and evaluation of *effect modification* needed.

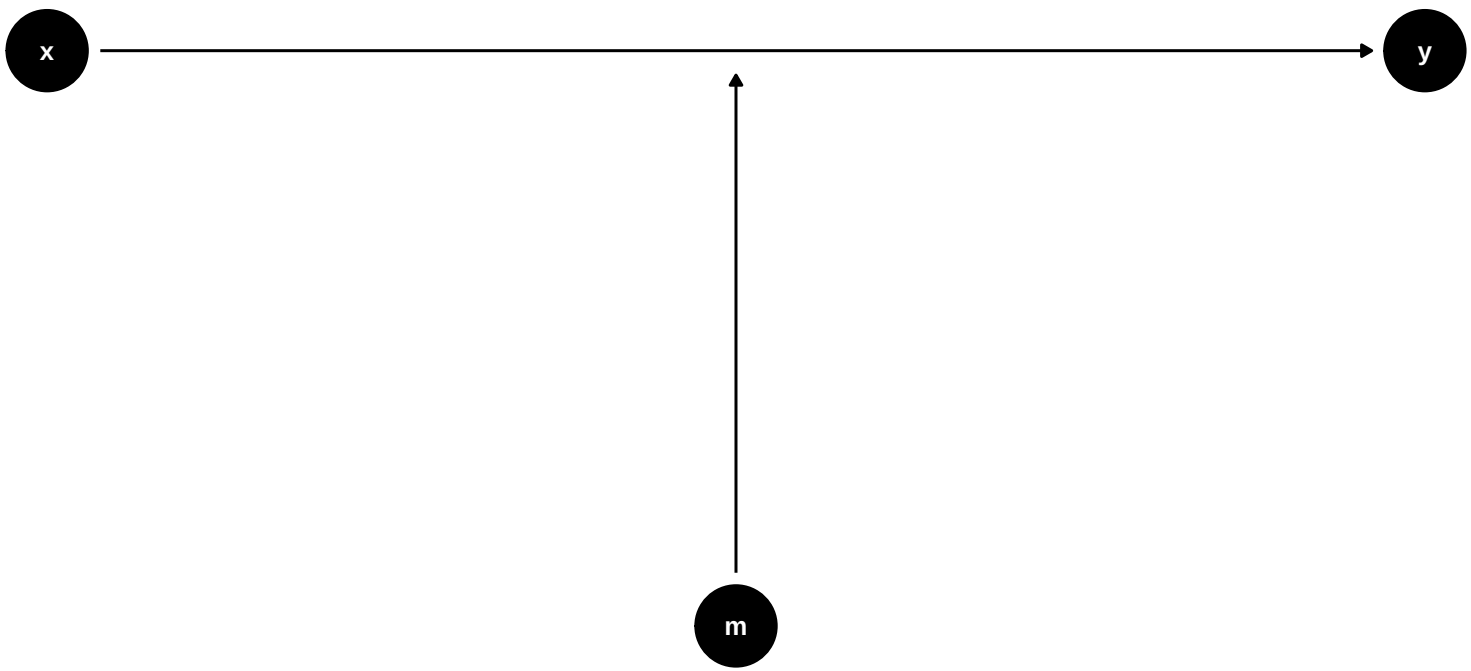
Confounder

- **Confounder**s (Z) are variables that
  - is both an ancestor of the exposure (X)
  - and an ancestor of the outcome (Y) (along a path that does not include the exposure).



Effect modification

- Unfortunately, there's not an agreed upon way to show effect modification/moderation/interaction.
- effects are assumed to be heterogeneous by default in causal models. (JP)



Example: OS vs. PN (cont'd)

Failure of treatment depends also on initial condition of patient, like extent and severity of disease.

Results stratified by initial diameter size of the stone:

Size	Trt	Fails	Npats	Fail-%	**RD(%)**
$<$ 2 cm	OS	6	87	*6.9*	
	PN	35	270	*13.0*	$-$**6.1**
$\geq$ 2 cm	OS	71	263	*27.0*	
	PN	25	80	*31.3*	$-$**4.3**

OS seems more successful in both subgroups, even though overall PN appeared better.

IS THERE A PARADOX?

Confounding

Solution: Treatment groups are not *comparable* w.r.t. initial size. Size of the stone is a *confounder* of the association between operation type and failure risk,because it is

- an *independent determinant* of outcome (failure), based on external knowledge,
- *statistically associated* with operation type in the study population,
- *not causally affected* by operation type.

This is an instance of "confounding by indication":

- patient status affects choice of treatment $\rightarrow$ *bias* in comparing treatments.

This bias would be best to avoid in planning:
$\rightarrow$ *randomized allocation* of treatments!

Stratified analysis

Stratification of cohort data with proportions

- at each level k of factor Z results are summarized:

Exposure to risk factor	Number of cases	Number of non-cases	Group size
yes	D_{1k}	C_{1k}	N_{1k}
no	D_{0k}	C_{0k}	N_{0k}
Total	D_{+k}	C_{+k}	N_{+k}

Stratum-specific incidence proportions by exposure group:

$$R_{1k} = \frac{D_{1k}}{N_{1k}}, \qquad R_{0k} = \frac{D_{0k}}{N_{0k}}$$

Adjusted estimation of risk difference

- Let π_{jk} be true risk in exposure group j ($j = 0, 1$) as to X and stratum k ($k = 0, \ldots, K$) of Z. Let also

$$\theta_k = \pi_{1k} - \pi_{0k}$$

  be the risk difference in stratum k.

- Many approaches to combine stratum specific results into one summary estimator that adjusts for confounding.

These are all somehow `weighted averages` of stratum-specific estimators.

- Different weighting principles:
  - Maximum likelihood (ML),
  - Mantel-Haenszel (MH) weights,
  - Standardization either by external standard population or by "indirect" standardization.

Model-based adjustment of risk difference

Define generalized linear model for binary outcome with

- one binary exposure variable X and
- one binary stratifying factor or covariate Z (easily generalized to polytomous factors).

Random part: Number of cases D_{jk} in exposure group j $(j = 0, 1)$ of X and level k $(k = 0, 1)$ of Z is assumed to be binomially distributed

$$D_{jk} \sim \text{Binomial}(N_{jk}; \pi_{jk}),$$

Model-based adjustment of risk difference (cont'd)

Systematic part:

$$\pi_{jk} = \alpha + \beta X_j + \gamma Z_k,$$

where X_j is 0/1-indicator as before, and

- $Z_k = 1$ for level $k = 1$ of Z, otherwise $Z_k = 0$,
- $\alpha = \pi_{00} =$ baseline (''corner cell'') risk,
- $\gamma = \pi_{01} - \pi_{00} = \pi_{11} - \pi_{10}$,
- $\beta = \pi_{10} - \pi_{00} = \theta_0 = \pi_{11} - \pi_{01} = \theta_1$,

How do we read this?

Model-based adjustment of risk difference (cont'd)

Implications of model definition

- the model assumes *homogeneity* of true risk difference θ associated with factor X (exposed vs. unexposed) across levels of Z: $\theta_1 = \theta_0 = \beta$,
- inclusion of Z in the model leads to adjustment of it when estimating the "true" effect θ of X,
- $\gamma =$ risk difference between levels 1 and 0 of Z; this is same in both exposure groups ($j = 0, 1$)
  $\Rightarrow$ homogeneity of the effect of Z is assumed, too.

Example. Treatment of renal calculi (cont'd)

- Define new variable
  `size` = initial stone size (0 for `small`, 1 for `large`)
- Extended data matrix comprises four observational units (rows) and four variables (columns):

size	trt	fails	npats
0	1	6	87
0	0	35	270
1	1	71	263
1	0	25	80

- These may be read in as before, *e.g.*

```
library(Epi)
size <- c( 0, 0, 1, 1) ; trt <- c( 1, 0, 1, 0)
fails <- c( 6, 35, 71, 25)
npats <- c( 87, 270, 263, 80)
props <- fails/npats
```

Fitting model for adjusted risk difference

As before, but model formula supplemented by `+ size`

```
RDmod2 <- glm( props ~ trt + size,
      fam = binomial(link='identity'), w = npats)
round( ci.lin(RDmod2), 3)
```

```
             Estimate StdErr      z     P   2.5% 97.5%
(Intercept)     0.128  0.019  6.596 0.000  0.090 0.166
trt            -0.056  0.030 -1.888 0.059 -0.114 0.002
size            0.195  0.032  6.106 0.000  0.132 0.258
```

Reading the results:

- $\widehat{\alpha}$ $=$ **0.128** $= \widehat{\pi}_{00}$, fitted baseline risk,
- $\widehat{\gamma}$ $=$ **0.195**, RD between large and small stones,
- $\widehat{\beta}$ $=-$ **0.0561** [$-$ **0.114**, **0.002**], estimated common treatment effect $\widehat{\theta}$ for OS *vs.* PN.
  $=$ Weighted average of $\widehat{\theta}_0 = -0.061$ and $\widehat{\theta}_1 = -0.043$.

Effect modification

Homogeneity assumption – true differences were put equal:

$$\theta_k = \pi_{1k} - \pi_{0k} = \theta$$

across all levels k of covariate Z. *Is this realistic?*

Example. Is the true risk difference for treatment failure between OS and PN similar for small and big stones?

Empirical differences of failure proportions were

small stone: $\widehat{\theta}_0 = 0.069$ - $0.130 =$ **-0.061**
large stones: $\widehat{\theta}_1 = 0.270$ - $0.313 =$ **-0.043**

Is the contrast $-0.043 - (-0.061) = 0.018$ between these differences due to chance only, or is there essential *effect modification* present?

Modelling modification of risk difference

The random part is the same, but the systematic part is

$$\pi_{jk} = \alpha + \beta X_j + \gamma Z_k + \tau U_{jk}.$$

- $U_{jk} = X_j \times Z_k$, product of values of X and Z,
- $\alpha = \pi_{00} =$ baseline (''corner cell'') risk,
- $\beta = \pi_{10} - \pi_{00} = \theta_0, \qquad \gamma = \pi_{01} - \pi_{00},$
- $\tau = \theta_1 - \theta_0 = (\pi_{11} - \pi_{01}) - (\pi_{10} - \pi_{00})$, *interaction parameter*

τ describes, how much greater is the risk difference between levels 1 and 0 of risk factor X among those at level 1 of factor Z than in those at level 0.

Fitting model with modification

- Generation of an interaction of *product term*:
- trtsize = size*treat
- Expanded and rearranged data matrix:

fails	npats	size	trt	trtsize
35	270	0	0	0
6	87	0	1	0
25	80	1	0	0
71	263	1	1	1

```
size <- c( 0, 0, 1, 1) ;
trt <- c( 0, 1, 0, 1);
trtsize <- c(0,0,0,1)
fails <- c( 35, 6, 25, 71)
npats <- c( 270, 87, 80, 263)
props <- fails/npats
```

Fitting model with modification (cont'd)

Fitting the model including the product term:

```
RDmod3 <- glm(props ~ trt + size + trtsize,
              fam = binomial(link='identity'), w = npats)
```

Results and interpretation:

```
round( ci.lin(RDmod3)[ , -(3:4)], 4)
```

```
             Estimate StdErr    2.5%  97.5%
(Intercept)    0.1296 0.0204  0.0896 0.1697
trt           -0.0607 0.0340 -0.1273 0.0060
size           0.1829 0.0557  0.0737 0.2921
trtsize        0.0181 0.0678 -0.1147 0.1509
```

- $\widehat{\beta} = -0.061 = \widehat{\theta}_0 =$ RD for OS *vs.* PN in small stones,
- $\widehat{\gamma} = -0.183 =$ RD btw large and small stones for OS.
- estimate [95 % CI] of the interaction parameter:

$$\widehat{\tau} = \mathbf{0.0181}[-\mathbf{0.115}, \mathbf{0.151}]$$

Final comments

- When risk ratio ϕ or odds ratio ψ is the parameter of interest, adjustment for confounding and evaluation of modification can be done by fitting an analogous binomial GLM with relevant link function.
- Modelling can easily be extended to cover one or more polytomous and/or continuous covariates. Flexible functional forms may be specified to describe the effects of the latter type of variables.
- Binomial models are not limited to grouped data but may be fitted on individual data with binary outcomes, too.
- With more complicated models, especially involving continuous variables, the identity link (sometimes log link, too) violates the basic range restriction:\ outcome probabilities π must remain within 0 and 1.