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# What do we mean by cause in public health?

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### Motivation

Work and discussions by colleagues and speaker.

Penrose, R (1989). The emperor's new mind. Oxford.



### **Outline**

- 1. Causal effects: what do we mean?
- 2. Do we do research based on what we mean?
- 3. Challenges to current approach



#### 1. Causal effects: what do we mean?

### Example (a)

#### When we say:

"More women will survive cancer because (thanks to) the newer screening method"

#### we mean:

"if women get screened with the new method, more of them will survive than if the same women get screened with the existing method"



### Example (b)

When we say:

"Hormone replacement therapy (HRT) increases the risk of heart problems in (a group of) women"

we hope we mean:

"the group of women will have more heart problems if they get HRT versus if they do not get HRT"



#### Notes:

By "causal effect", in principle, we mean a comparison of outcomes if the same group of people at the same time were to be given two different treatments, so

a Causal Effect is a result of \ an intervention.

We cannot directly observe a causal effect, although we can estimate it under assumptions/or designs with comparable groups



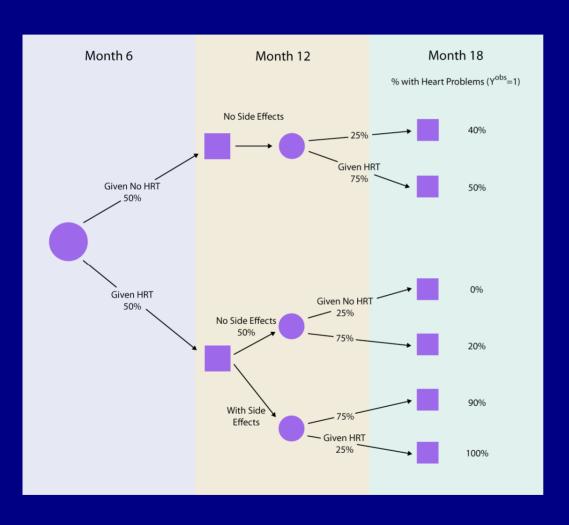
# 2. Does usual statistical research reflect what we mean by causal effects?

We argue that it does not always, and that this impacts, ultimately, whether we really choose the right treatments.

See an example



### Example: a hypothetical 2-phase study on HRT



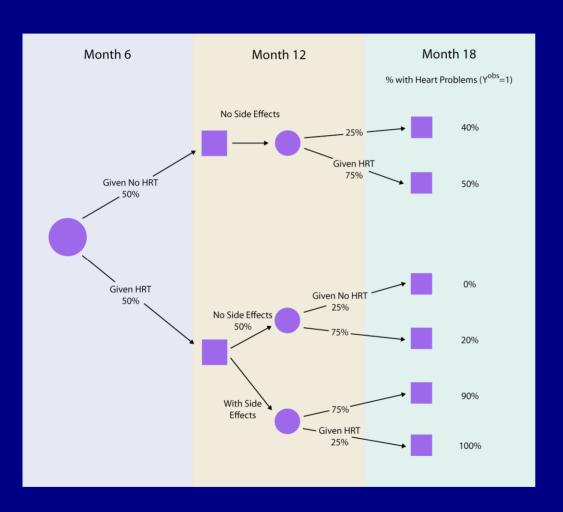
Women in a 2-time study on effect of hormone replacement therapy (HRT) on heart problems

Doctors randomize women to no HRT/ HRT, based on evidence of side-effects

Is sustained HRT better for women, than no HRT?

→ Three comparisons ...





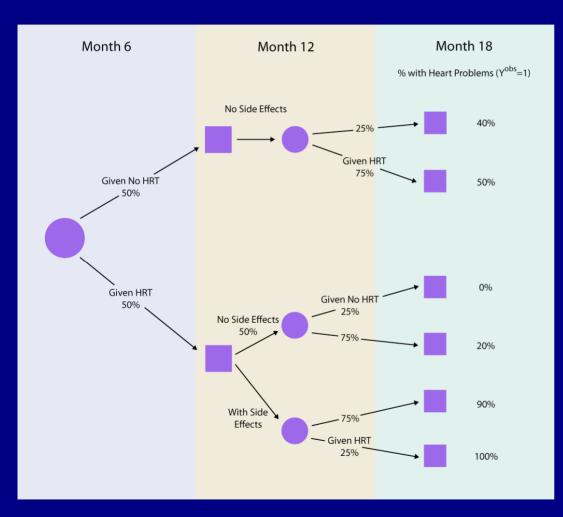
"Correct" comparison : from the data, we can show that :

% of women with heart problems, if all were given HRT at both times = 60 % but

% of women with heart problems, if none was given HRT at both times = 40%

So, sustained HRT causes more heart problems



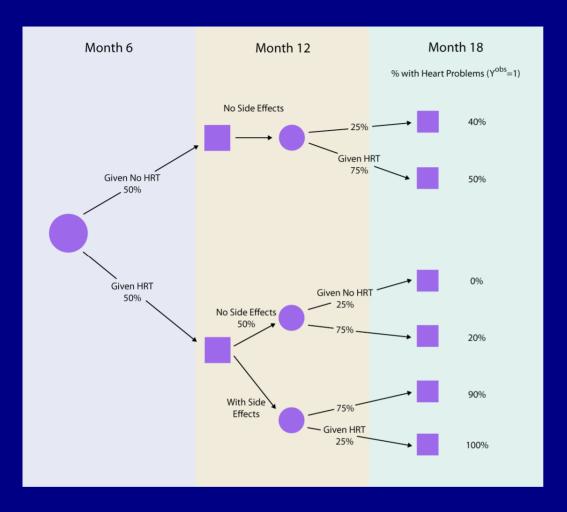


"Crude" comparison

% of women with heart problems, among those who get HRT at both times 40%

% of women with heart problems, among those who get no HRT 40%

So, "crude comparison" gives equal treatments

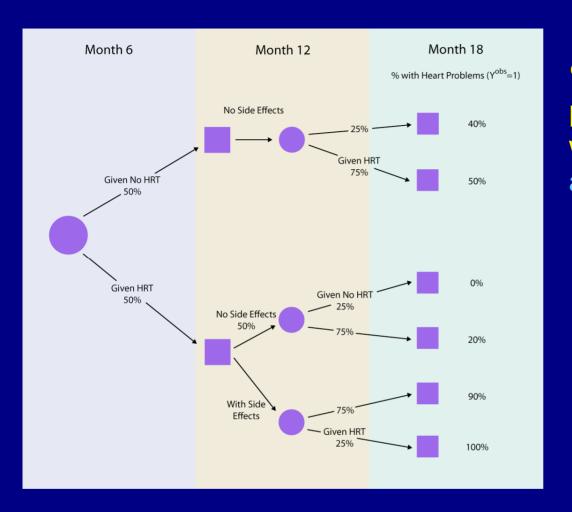


"Adjusting" for side effects

% of women with heart problems, among those who get HRT at both times, and have no side effects: 20%

% of women with heart problems, among those who get no HRT, and have no side effects: 40%

So, "adjustment" favours the worst treatment



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Note: the above "adjustment" as a regression is sometimes represented by:

Y <sub>month 18</sub> ~ side effects <sub>month 12</sub> + treatment <sub>month 6</sub>+ treatment <sub>month 12</sub>



#### How did we get the correct answer?

By using what we mean by causal effect: the comparison of the two clinical outcomes of women, if they were given HRT versus if they were not.

For a particular woman, these two outcomes are called "Potential Outcomes" (Rubin 74).



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It means we use them as <u>unknowns with the (correct) logic</u>, just as we can solve multiple equations with multiple unknowns



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Why does the usual "adjustment" generally fail?

Because the <u>logic</u> operates on the Potential Outcomes, and not directly on the observed data



# 3. Challenges to the meaning of causal effect used in public health

The usual meaning has at least two key characteristics:

Consistency:

 a process evolves the same way whether we observe
 (or otherwise measure) the process or not

2) Temporality: the effect of a cause "happens" after the cause



### On "consistency"

The currently accepted physical theory for the microscopic level is quantum mechanics:

according to quantum mechanics:

a measurement (even if not by observation)
causes a processes to change its values,
but also

a process obeys different rules when not being measured than when it is being measured



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The 2<sup>nd</sup> thermodynamic law does address time flow, saying that systems will evolve to disorder

In this law, <u>cause and effect are reverse in time</u> (teleologic): the <u>cause is the future</u> state of disorder, to which the present system is attracted.

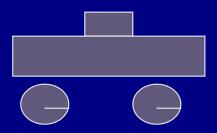




It happens very often!

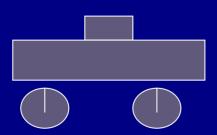


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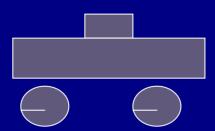


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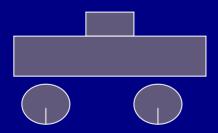


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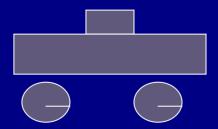


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Think of a child watching a movie of a car going right, and observing its wheels turning counter-clockwise.

The child\* would conclude that: "wheels spinning counter-clockwise" cause "the car to move right"!

\* If the child learns about frequencies, it will understand differently.



### How are these challenges relevant to public health?

Research in public health becomes more focused at the microscopic level

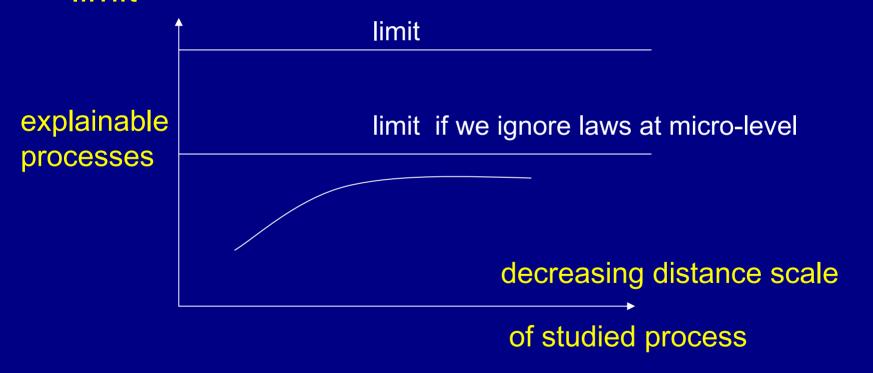
#### Suppose

- a) causality at that level is dominated by teleologic laws, and
- b) we try to explain observations by a usual meaning of causal effects

Then, our prediction abilities (e.g., for processes ultimately causing diseases) will reach a plateau, perhaps long before reaching the humanly explainable limit



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#### Remarks

- 1) By a Causal Effect in public health currently we mean a result of an intervention
- 2) Much of statistics addressing causal effects in public health is not based on what we mean, yet this can be done
- 3) with the focus of public health at the microscopic level, flexible concepts of causal effects, such as stemming from potential outcomes, become increasingly important for understanding and predicting processes