

# Causality: Explanation versus Prediction

Department of Government  
London School of Economics and Political Science

- 1 Brief Review of MT Material
- 2 Causality
- 3 Fundamental Problem of Causal Inference
- 4 Randomized Experiments

# 1 Brief Review of MT Material

## 2 Causality

## 3 Fundamental Problem of Causal Inference

## 4 Randomized Experiments

**What did we learn  
about during MT?**

# New territory...

By the end of today you should be able to:

- Identify what makes for a causal relationship
- Distinguish causation from correlation/association
- Begin to analyse research problems using counterfactual thinking

# The broad story arc for LT

- Causal inference!
  - Generating causal theories and expectations
  - Making comparisons
  - Statistical methods useful for causal inference
  - (Quasi-)Experimentation

# The broad story arc for LT

- Causal inference!
  - Generating causal theories and expectations
  - Making comparisons
  - Statistical methods useful for causal inference
  - (Quasi-)Experimentation
- Developing your research proposals
  - One-on-ones w/ Thomas
  - Literature review
  - Due: 21 March at 5:00pm

1 Brief Review of MT Material

**2 Causality**

3 Fundamental Problem of Causal Inference

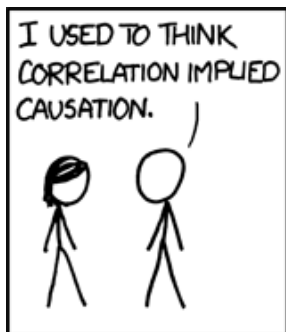
4 Randomized Experiments



**Write for 1 minute**

**What makes  
something a  
*cause*?**





# Physical causality

- Action and reaction
- Features: Observable and deterministic
- Example:
  - Picture a ball resting on top of a hill
  - What happens if I push the ball?

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- Action and reaction
- Features: Observable and deterministic
- Example:
  - Picture a ball resting on top of a hill
  - What happens if I push the ball?
- Physical causality is easy to see

# Correlation I

- Correlation is the non-independence of two variables for a set of observations

# Correlation II

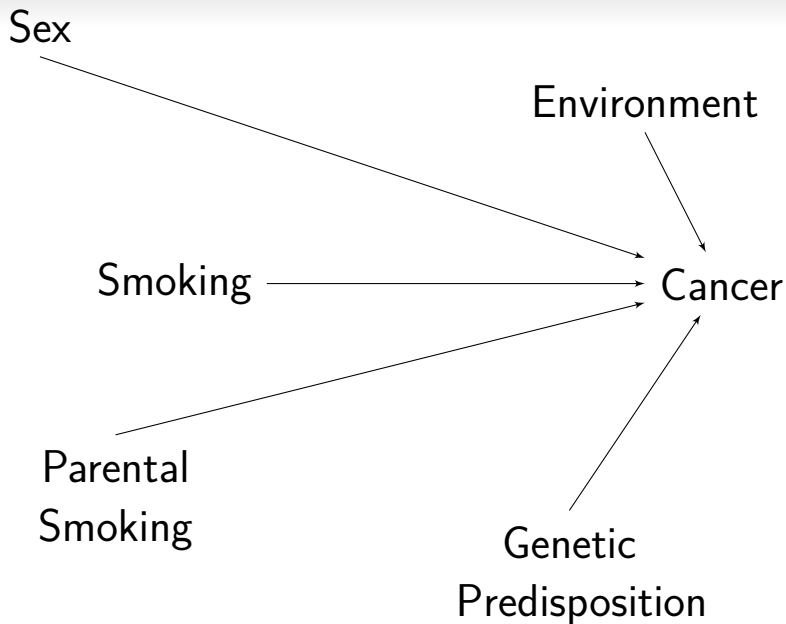
- *Observation*: A case or unit (e.g., person, country)
- *Variable*: A dimension that describes an observation (e.g., income)
- *Independence*: Variables are unrelated to one another
  - Independent: Height and value on a fair dice roll
  - Non-independent: Height and weight

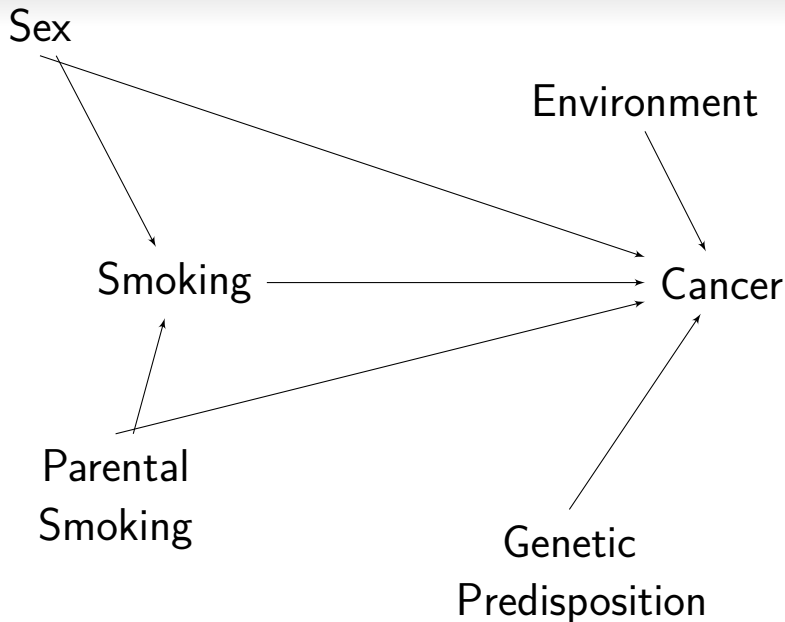
# Correlation III

- Synonyms: correlation, covariation, relationship, association
  - “Effect” is frequently used to mean correlation
  - We’ll reserve that term for a *causal effect*
- Any correlation is a potential cause
  - X might cause Y
  - Y might cause X
  - X and Y might be caused by Z
  - X and Y might cause Z
  - There may be no causal relationship



Smoking → Cancer





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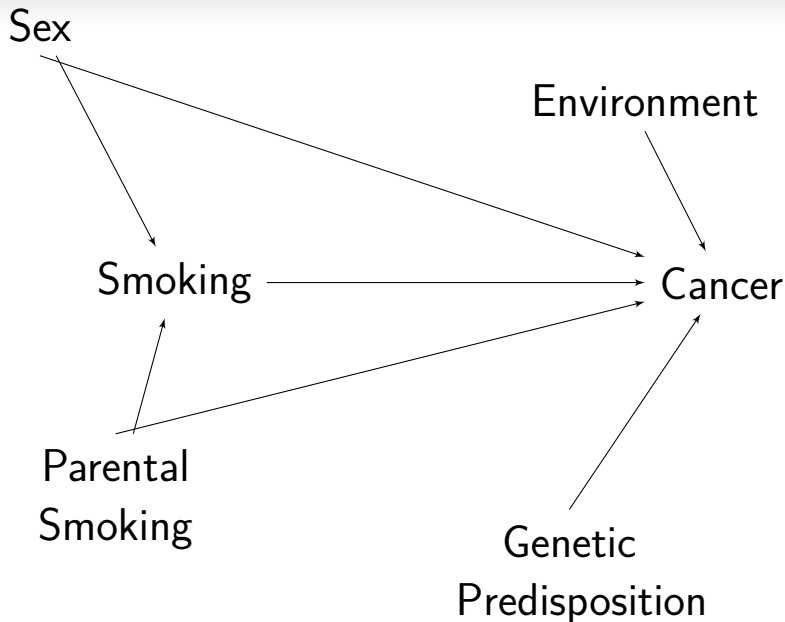
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- Causality flows between variables, which are represented as “nodes”
- Variables are causally linked by arrows
- Causality only flows *forward*
- Nodes creating a “backdoor path” from  $X$  to  $Y$  are confounds

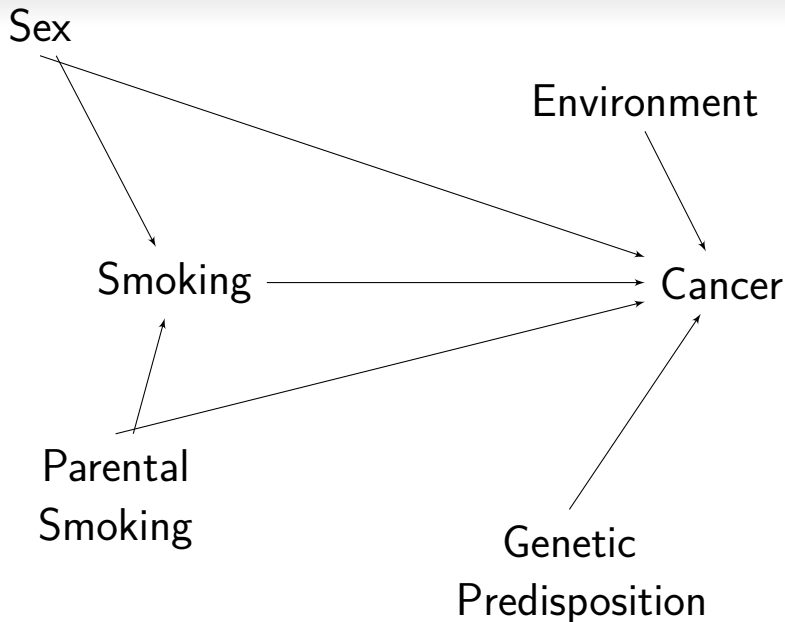




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## 1 Correlation

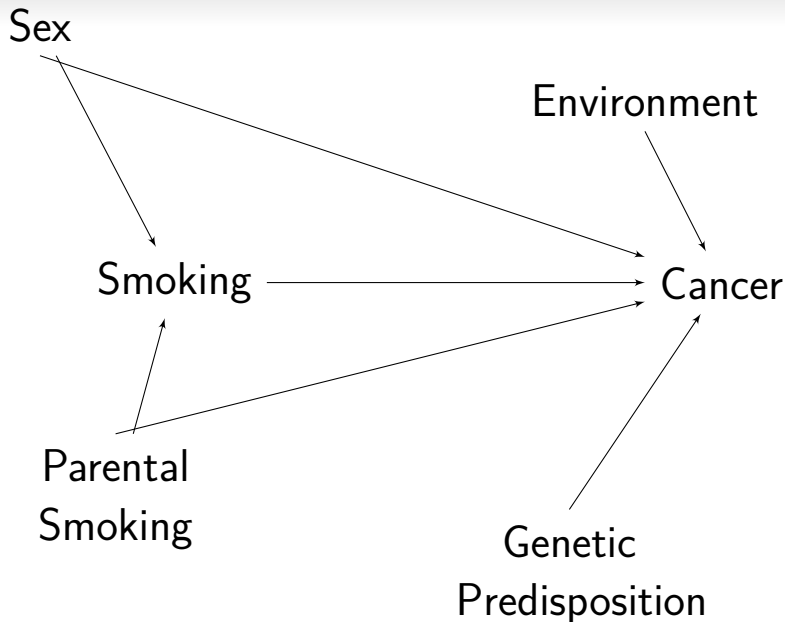


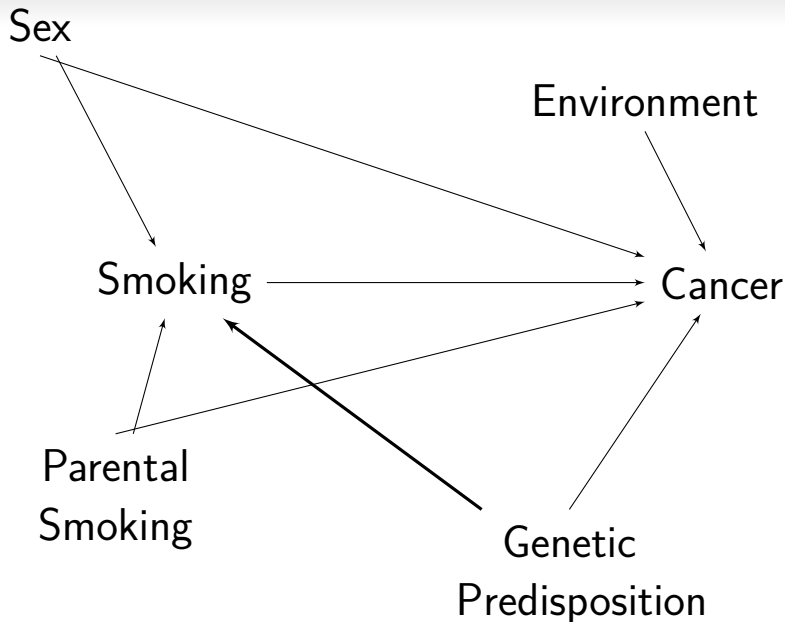
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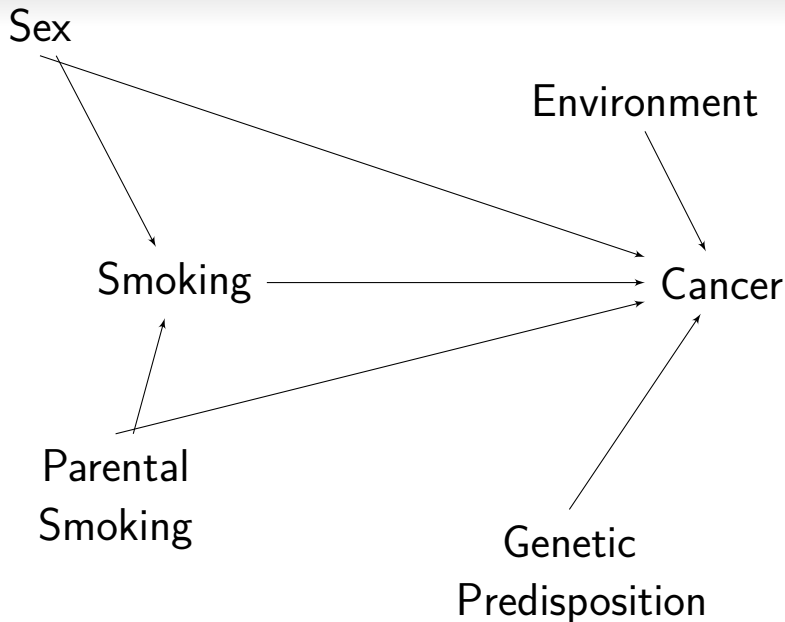


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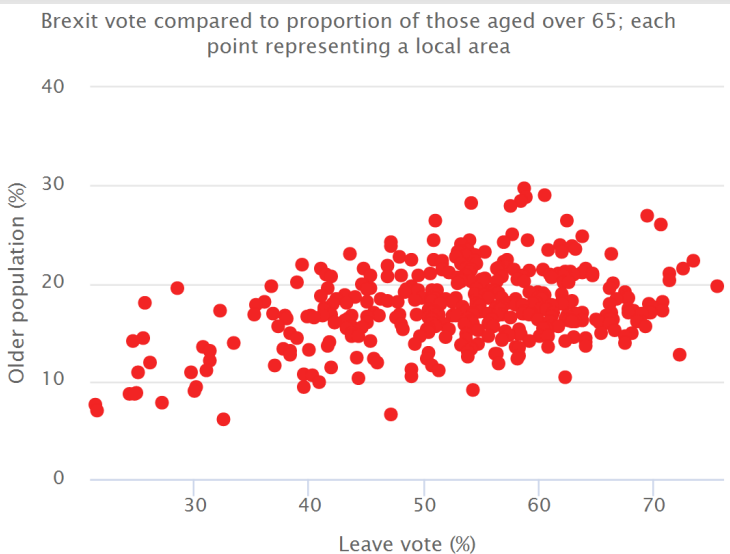


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- 1 Correlation
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- 3 Direction (“temporal precedence”)
- 4 Mechanism
- 5 (Appropriate level of analysis)



Source: ONS

Source: *The Telegraph*. 27 June 2016. <http://www.telegraph.co.uk/news/2016/06/24/eu-referendum-how-the-results-compare-to-the-uks-educated-old-an/>

# Questions?

- 1 Brief Review of MT Material
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# Counterfactual Thinking

- Causal inference involves inferring *what would have happened* in a counterfactual reality *where the potential cause took on a different value*
- *Counterfactual*: relating to what has not happened or is not the case

# “A Christmas Carol”

- 1843 novel by Charles Dickens
- Ebenezer Scrooge is shown his own future by the “Ghost of Christmas Yet to Come”
- Has the choice to either:
  - stay on current path (one counterfactual), or
  - change his ways (take a different counterfactual)

# Dickensian Causal Inference

- *Causal effect*: The difference between two “potential outcomes”
  - The outcome that occurs if  $X = x_1$
  - The outcome that occurs if  $X = x_2$
- The causal effect of Scrooge's lifestyle is seen in the *difference(s)* between two potential futures

# Fundamental problem of causal inference

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We can only observe any given unit in one reality!

# Two solutions!<sup>1</sup>

## 1 Scientific Solution

- All units are identical
- Each can provide a perfect counterfactual
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## 2 Statistical Solution

- Units are not identical
- Random exposure to a potential cause
- Effects measured on average across units
- Known as the “Experimental ideal”

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<sup>1</sup>From Holland

# Mill's methods<sup>2</sup>

- Agreement
- Difference
- Agreement and Difference
- Residue
- Concomitant variations

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<sup>2</sup>Discussed in Holland



## Mill's Method of Difference

If an instance in which the phenomenon under investigation occurs, and an instance in which it does not occur, have every circumstance save one in common, that one occurring only in the former; the circumstance in which alone the two instances differ, is the effect, or cause, or an necessary part of the cause, of the phenomenon.

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- Causal inference is meant to help “explain” the world
  - Other notions of explain (e.g., description)
  - Explanation may or may not involve mechanistic claims (see LT Week 5)
- Causation is deterministic at the unit level!
- Counterfactual approaches to causal inference are “forward” in nature

Prediction is not causation.  
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Why are these distinct?



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# The Experimental Ideal

A randomized experiment, or randomized control trial is:

*The observation of units after, and possibly before, a randomly assigned intervention in a controlled setting, which tests one or more precise causal expectations*

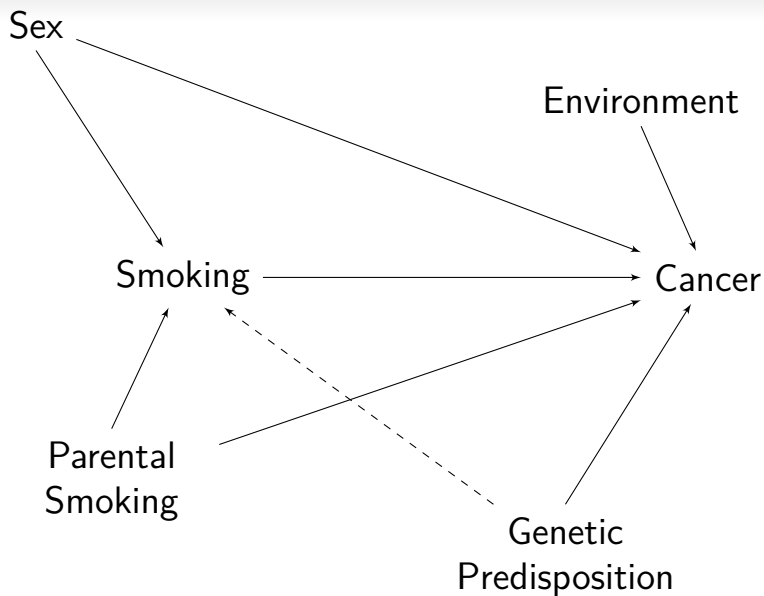
This is Holland's "statistical solution" to the fundamental problem of causal inference

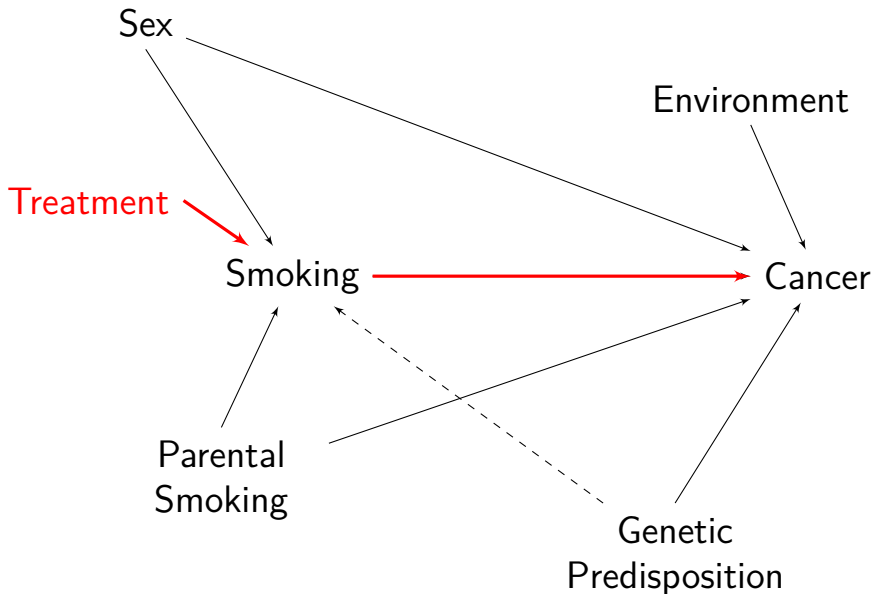
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  - Units only take value of  $X = x$  because of assignment
- This means:
  - Treatment groups, on average, provide in sight into counterfactual “potential” outcomes
  - Randomization means potential outcomes are balanced between groups, so no confounding





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- Each unit has multiple *potential* outcomes ( $Y_{0i}, Y_{1i}$ ), but we only observe one of them
- A *causal effect* is the difference between these (e.g.,  $Y_{X=1} - Y_{X=0}$ ), all else constant

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- Is this what we want to know?
  - Yes, if  $X$  randomized
  - Yes, if all confounds controlled

MT

Causality

Counterfactuals

Randomized Experiments



# Preview of next week

- What is a “scientific literature”?
- How do we accumulate scientific evidence?



# Mill's Methods

# Agreement

If two or more instances of the phenomenon under investigation have only one circumstance in common, the circumstance in which alone all the instances agree, is the cause (or effect) of the given phenomenon.

# Difference

If an instance in which the phenomenon under investigation occurs, and an instance in which it does not occur, have every circumstance save one in common, that one occurring only in the former; the circumstance in which alone the two instances differ, is the effect, or cause, or an necessary part of the cause, of the phenomenon.

# Agreement and Difference

If two or more instances in which the phenomenon occurs have only one circumstance in common, while two or more instances in which it does not occur have nothing in common save the absence of that circumstance; the circumstance in which alone the two sets of instances differ, is the effect, or cause, or a necessary part of the cause, of the phenomenon.

# Residue

Subduct from any phenomenon such part as is known by previous inductions to be the effect of certain antecedents, and the residue of the phenomenon is the effect of the remaining antecedents.

# Concomitant variations

Whatever phenomenon varies in any manner whenever another phenomenon varies in some particular manner, is either a cause or an effect of that phenomenon, or is connected with it through some fact of causation.