Applying Statistics to Laws and Lawmaking

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How do statistics and law intersect?

- Statistics concerns data;
- More precisely, statistics concerns uncertainty (variation) in the data.
- Some data exist related to (effects of) laws.
- Question: Are the data sufficient?

Example 1: death penalty

National Research Council (2012) report "*Deterrence and the Death Penalty*" by Nagin and Pepper, discovered that[1]

- Statistics are no guide ....
- Because deficiencies in data must first be corrected, before research on the topic can possibly be informative (two out of three recommendations of the report);
    - data are currently unavailable on the non-capital component of state sanction regimes in the post-Gregg era;
    - reliable state-level data on the sanctions and the frequency of their use for all types of crime is unavailable.
- Judgement about capital punishments (currently) cannot be claimed to rest on evidence (i.e. data).

[1] In *Significance*, April 2014, a joint publication of the American Statistical Association and the Royal Statistical Society.

Example 2: gun law and crime

- Federal assault weapons ban –
  - It is doubtful that its revival would have any effect on the typical gun-related crime;
  - given that most gun-related crimes are committed using handguns.

- Concealed carry weapons (CCW) laws –
  - Many studies have looked at their effects;
  - Typically states with permissive (less restrictive) CCW laws have lower crime rates;
  - This seems to support the deterrent effect hypothesis of many gun rights proponents, though there may be other explanations.

Reference: *Significance*, April 2014, a joint publication of the American Statistical Association and the Royal Statistical Society.

Example 3: medical marijuana laws

Consumer Reports Sept. 2014 cover story: Deadly pain pills - everyday 46 American's die from legal pain pills.

Hypothesis: medical marijuana laws may lead to decrease in opioid painkiller overdoses (OD) and deaths.

Bachhuber *et al.* (2014, *JAMA Internal Medicine*; Aug. 31 *The NY Times*) examined opioid OD deaths in the US from 1999 to 2010.

- "Pinpointing the effects of laws ... is notoriously difficult."
- States that have passed these laws are different in important ways (e.g. social attitudes about drug use, overall health trends, etc.) from states that have not passed such laws.
- During 1999∼2010 states implemented various measure in response to the threat of opioid OD.

The authors did discover that despite overall increasing rate of OD deaths, implementation of a medical marijuana law was associated with a 25% lower yearly rate of OD deaths, in 2010 this was about 1,700 fewer OD deaths.

Causal inference

When studying the effects of a law, the question we are trying to answer is a causal one.

- Gold standard: randomized (controlled) experiments - randomization guarantees that on average there should be no systematic differences in *observed or unobserved* covariates, so that the difference in the outcomes should be due to the difference in treatments.
- Data we have seen so far: observational -
  - the treated and untreated groups may have large differences;
  - these differences can lead to **biased** estimates of treatment effect (i.e. causal effect of a law).

Statistical design of an experiment

Considerations:

- What are the outcomes we want to measure (eg. Wilderness Act: happiness, solitude; texting and driving)?
- Is it feasible to randomize?
  - If yes, what are the units of randomization? (cluster randomized?)
  - If no, what can we do to study the causal effect of a law?
- How do we sample the experimental unit? how many to sample?

Important: the sample should be representative of the population.

Statistical design details

Statistician's input:

- Objectives (hypotheses)
- Data collection
- Sample size justification, analysis plan

Observational studies

In observational studies, it helps (partially at least) if information on observed covariates is incorporated into the study design or into estimation of the exposure effect, via matching, stratification, and covariate adjustment.

A **confounder**

- Is a predictor for the outcome (typically identified before data collection);
- Controlling for it will reduce or eliminate bias in estimating the true treatment effect.

Operationally, one can compare a *crude* effect with an *adjusted* treatment effect; eg. $\geq 10\%$ change in estimates.

Other statistical issues

- Compliance problems;
- Missing data;
- ....

Interdisciplinary team building

- Recruit a statistician from the start;
  - Poorly designed experiment CAN NOT provide useful data to answer the question of interest!
- Subject field experts;
- Data management / informatics.