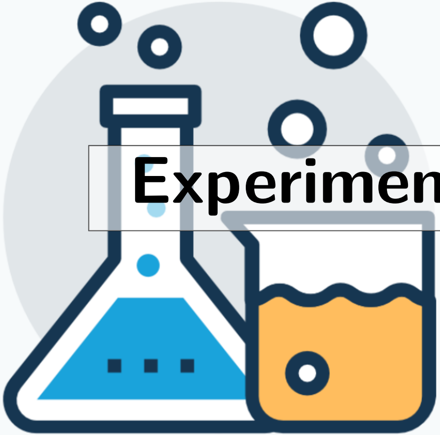
Experiments vs Observations



Today:

- Identify the key difference between experimental and observational data;
- Discuss considerations for experimental data;
- Introduce observational data.

Example 1: the effect of a sentence ‘toughness’ on recidivism

- **Question**: does tougher punishment diminish the likelihood that a convict will commit future crimes?

- **Data**: a sample of defendants from public records of the DC Superior Court restricted to felony drug offenses/no other offenses;
  - Demographics (name, DOB, race, gender, address);
  - Charge;
  - Judge at time of sentencing;
  - Sentence;
  - Subsequent recidivism;

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- **Random judge assignment**.

Table 2. Defendant Characteristics, by Calendar Assignment

	Calendar									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	***p* Value**
Age	31.9	35.1	33.2	32.8	33.8	32.2	33.3	34.2	32.3	.62
	(11.5)	(11.8)	(11.6)	(10.8)	(11.1)	(11.1)	(11.3)	(11.5)	(10.6)	
Female	13.1	7.1	7.6	10.5	9.5	8.6	10.1	9.1	11.8	.93
Non-Black	4.1	4.5	1.7	3.2	.9	2.2	1.8	1.0	2.7	.84
Prior arrest	81.1	86.6	85.6	83.1	87.1	81.7	78.9	90.9	93.6	.07
Prior drug arrest	68.0	74.1	74.6	71.8	80.2	64.5	66.1	73.7	75.5	.34
Prior felony arrest	63.1	73.2	70.3	74.2	75.9	67.7	70.6	72.7	79.1	.41
Prior felony drug arrest	54.1	58.9	59.3	57.3	59.5	48.4	45.9	56.6	56.4	.52
Prior conviction	59.8	69.6	64.6	71.0	72.4	67.7	62.4	66.7	70.9	.54
Prior drug conviction	50.0	53.6	52.5	58.1	66.4	54.8	47.7	53.5	57.3	.30
Prior felony conviction	43.4	58.9	55.1	54.0	59.5	50.5	50.5	54.6	59.1	.34
Prior felony drug conviction	35.3	44.6	47.5	44.4	50.0	39.8	34.9	44.4	43.6	.36
PWID charge	49.2	40.2	49.2	41.1	56.0	50.5	52.3	43.4	39.1	.25
Distribution charge	59.8	68.8	61.9	68.6	52.6	59.1	54.1	61.6	67.3	.20
Marijuana charge	22.1	17.0	17.0	17.0	23.3	18.3	17.4	18.2	20.9	.95
Cocaine charge	39.3	38.4	45.8	40.3	33.6	40.9	44.0	33.3	43.6	.75
Crack cocaine charge	14.8	15.2	18.6	19.4	20.7	23.7	24.8	22.2	19.1	.75
Heroin charge	23.8	31.3	29.7	25.8	30.2	29.0	15.6	29.3	22.7	.34
PCP charge	6.6	7.1	4.2	2.4	6.0	1.1	6.4	4.0	3.6	.52
Other drug charge	4.9	.0	3.4	4.0	3.5	2.2	4.6	3.0	3.6	.55
Nondrug charge	11.5	8.9	17.0	12.9	12.9	10.8	15.6	12.1	14.6	.81
n	122	112	118	124	116	93	109	99	110	

NOTES: Total N = 1,003. Entries are means (age) and percentages. For continuous variables, standard deviations are in parentheses. The p values in the final column refer to the significance of a multinomial regression in which judge calendar assignment was regressed on each variable individually. These p values were obtained from Monte Carlo simulations as explained in the text.

Example 2: explaining civil wars

- **Question**: does the end of the cold war, ethnic nationalism, or something else cause civil wars?
- **Data**: a list of civil wars in which:
  - Organized groups fought agents of the state;
  - At least 1k deaths;
  - At least 100 dead on govt side;
- **Numerous other variables measuring**:
  - political economy (war, GDP, democracy);
  - territorial characteristics (contiguity, mountainous terrain);
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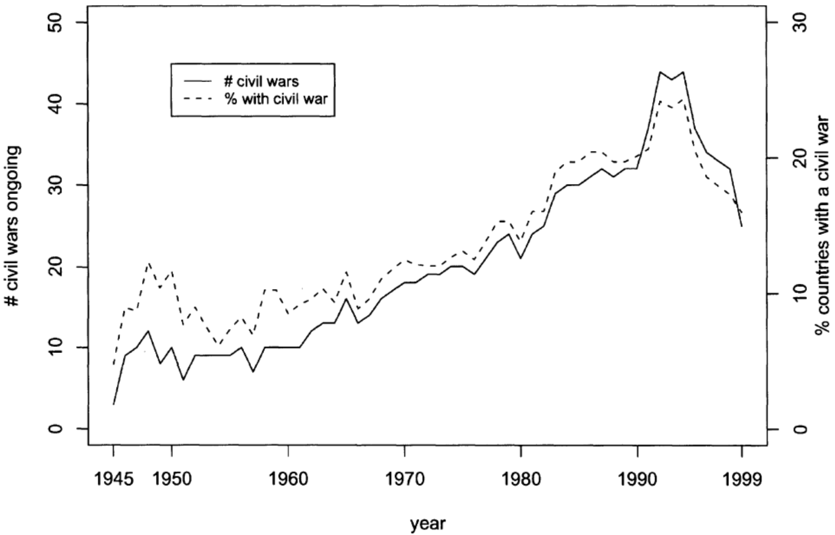

civil wars
% with civil war
# civil wars ongoing
% countries with a civil war
year
0
10
20
30
40
50
0
10
20
30
1945
1950
1960
1970
1980
1990
1999

Data Generating Process

- A useful (and ubiquitous) construct: **the data generating process** (DGP) – the set of all operations that lead to:
    1. the particular observations that appear in the dataset...
    2. ...and their structure;

- Occurs both IRL and at the researcher's desk – usually we know at most only part of the DGP;

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- Selected examples:
  1. Creation of events that could become data – e.g. only certain countries fight wars;
  2. Selection of selection of population units into the data sample – e.g. def of civil war;
  3. Categorization/Binarization – e.g. a Likert scale representation of preference;
  4. Analyst decisions to aggregate, group, or drop data;
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  5. **Assignment of independent variables to observations (e.g. selection of treatment and control groups)**;
- **If the researcher controls (5) the data is experimental.**

“Quiz”

- Is example 1 on tough sentencing experimental or observational?
- Is example 2 on causes of civil wars experimental or observational?
- Is the example from last time on political fundraising experimental or observational?
- Is the example on the gender wage gap experimental or observational?

Considerations with experiments

- A procedure used to **create** data capable of adjudicating between hypotheses, models, and theories;
- Independent variables vs dependent variables – generally known ahead of time;
- **Between unit design**: two+ groups exposed to one treatment each simultaneously;
  - Requires large numbers of units or sophisticated statistical procedures;
- **Within unit design**: units receive a sequence of treatments over time (crossover or longitudinal study);
  - Treatment sequences are randomly assigned – units 'cross over' between treatments;
  - Each unit serves as their own control;
  - May need to model attrition effects;
  - Order and carryover effects.

Considerations with experiments: a perfect visit advocate

Unit	Y_i(visit)	Y_i(none)	
1	\$675	**\$150**	
2	**\$3600**	\$2500	
3	**\$1900**	\$3300	Average CE is:
4	\$2300	**\$1000**	\$2129
5	**\$2600**	\$2000	
6	\$3000	**\$0**	
7	**\$1950**	\$2500	

Considerations with experiments: assignment effects

- What is the major issue in the 'perfect visit advocate' example?
- How could this happen?

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  - ...so that contributions are related to assignments;
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  - Control group (no visit) entirely composed of lowest 20% of income distribution;
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- How could this happen? Not hard to imagine – correlate assignment with income:
  - Control group (no visit) entirely composed of lowest 20% of income distribution;
  - Treatment group (visit) entirely composed of highest 20% of income distribution;
- How to deal with this? First steps: **large sample**, **randomized assignment**;
  - As sample size increases the probability of an imbalance in some unobserved characteristic between treatment and control gets arbitrarily low;
  - Treatment assignment is independent of the potential outcomes.

Stable Unit Treatment Value Assumption

- We estimated the causal effect in a really simple way in the Rubin Causal Model:

$$\frac{1}{n_T}\sum_i Y_i(\mathrm{T}) - \frac{1}{n_C}\sum_i Y_i(\mathrm{C})$$

- **Fair warning**: should acknowledge that potential outcomes could depend on other stuff, e.g.:

$$Y_1(\underbrace{\mathrm{C}}_{\text{assignment for unit 1}}, \overbrace{\mathrm{T}, \mathrm{T}, \mathrm{C}, \mathrm{T}, \mathrm{C}, \mathrm{T}}^{\text{assignments for rest}})$$

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- It is a **modeling assumption** that we can write:

$$Y_1(\mathrm{C}, \mathrm{T}, \mathrm{T}, \mathrm{C}, \mathrm{T}, \mathrm{C}, \mathrm{T}) = Y_1(C);$$

  This is called the **Stable Unit Treatment Value Assumption** (SUTVA)!

Stable Unit Treatment Value Assumption

- What does SUTVA mean?

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  - Potential outcomes for each unit (party member) are not related to treatment assignment for any other unit;
- How could this fail to hold?

Stable Unit Treatment Value Assumption

- What does SUTVA mean? It means:
  - Potential outcomes for each unit (party member) are not related to treatment assignment for any other unit;
- How could this fail to hold? Imagine that party members 1 and 2 live in the same household! Then:
  - SUTVA is pretty dubious and...
  - ...there are four, totally reasonable potential outcomes to think about:

Unit	Y_i(visit,visit)	Y_i(visit, none)	Y_i(none, visit)	Y_i(none, none)
1	\$675	?	?	?
2	$\vdots$	$\vdots$	$\vdots$	$\vdots$

Stable Unit Treatment Value Assumption

- How many causal effects are there?

$$
\begin{array}{ll}
Y_i(\text{visit}, \text{none}) - Y_i(\text{none}, \text{none}) & \text{CE of treatment on 1 given 2 untreated} \\
Y_i(\text{none}, \text{visit}) - Y_i(\text{none}, \text{none}) & \text{Spillover for a not treated 1 given 2 treated} \\
Y_i(\text{visit}, \text{visit}) - Y_i(\text{none}, \text{visit}) & \text{CE of treatment on 1 given 2 treated} \\
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Y_i(\text{visit}, \text{visit}) - Y_i(\text{visit}, \text{none}) \quad & \text{Spillover for a treated 1 given 2 treated}
\end{aligned}$$

- Spillover examples when SUTVA does not hold:
  - **Contagion** – the effect of vaccination on probability of sickness depends on vaccination of others;
  - **Displacement** – intervention intended to suppress something in one location moves it to other locations;
  - **Communication** – informational interventions may spread across people;
  - **Comparison** – an intervention that assists the treatment group may change how the control groups views their conditions;
  - **Persistence/memory** – in a within subject study, outcomes for a unit are tracked over time, meaning that treatments could persist across time periods;

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Characteristics of observation

- A procedure used to **collect** data capable of adjudicating between hypotheses, models, and theories;
- Can be used for exploratory purposes.
- Why not just use experiments? In some fields, the independent variables under study are not subject to manipulation, and so not subject to experiments, e.g.:
  - Astronomy (lack of influence);
  - Epidemiology (ethics);
  - International relations (both!);

Why should we care?

We will work with both types of data this semester and the methods applied to analyze each will be somewhat different.