大数据时代的管理决策

Lecture 1: Causal Inference in Social Science

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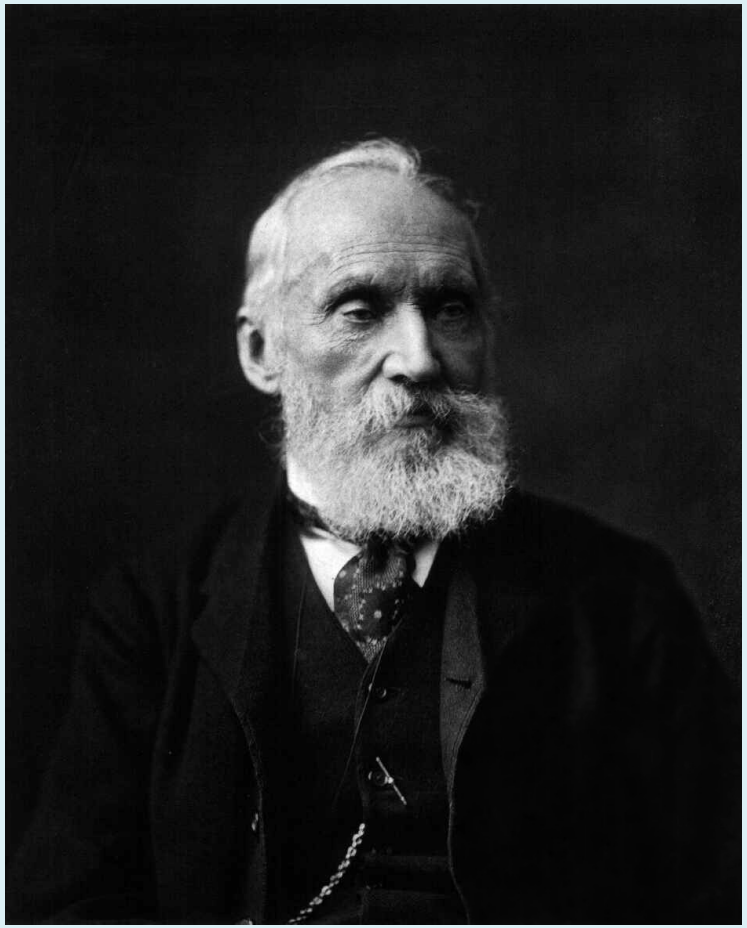
Review the Last Lecture

The Previous Lecture

- A Scientific Framework of Rational Cognition
  - Econometrical Analysis plays a key role
- **What is Econometrics?**
  - Using economic theories and statistical methods to analyze data
  - Two missions: **Causal Inference** and **Scientific Prediction**
- **Logistics**
- Course website
- Evaluation(you care about most)
  - Class Participation(20%)
  - Team Project: A research proposal(80%)
  - A team consists of **no more than 5** students.
  - **Oral Presentations(40%)**: 10 minutes for 10 pages slides.
  - **Written Proposals (40%)**: 5 pages in A4, approximately 2500-3000 words.

Causal Inference in Social Science

The Purposes of Empirical Studies



- **Lord Kelvin(1824-1907)**

- British mathematical physicist and engineer

> **"The objective of science is the discovery of the relations"**.

- In most cases,we often want to explore the relationship between two variables in one study.
  - education and wage
- Then, in simplicity, there are two relationships between two variables.
  - Correlation(相关)V.S. Causality (因果)

A Classical Example: Hemline Index(裙边指数)

- **George Taylor**, an economist in the United States, made up the phrase it in the 1920s. The phrase is derived from the idea that hemlines on skirts are shorter or longer depending on the economy.

- **Therefore what is about now?** Short shirt is resorting?

Causality and Big Data

- Some Big Data researchers think causality is not important any more in our times.

> **"Look at correlations. Look at the 'what' rather than the 'why', because that is often good enough." by Viktor Mayer-Schonberger(2013)**

Causality and Econometrics

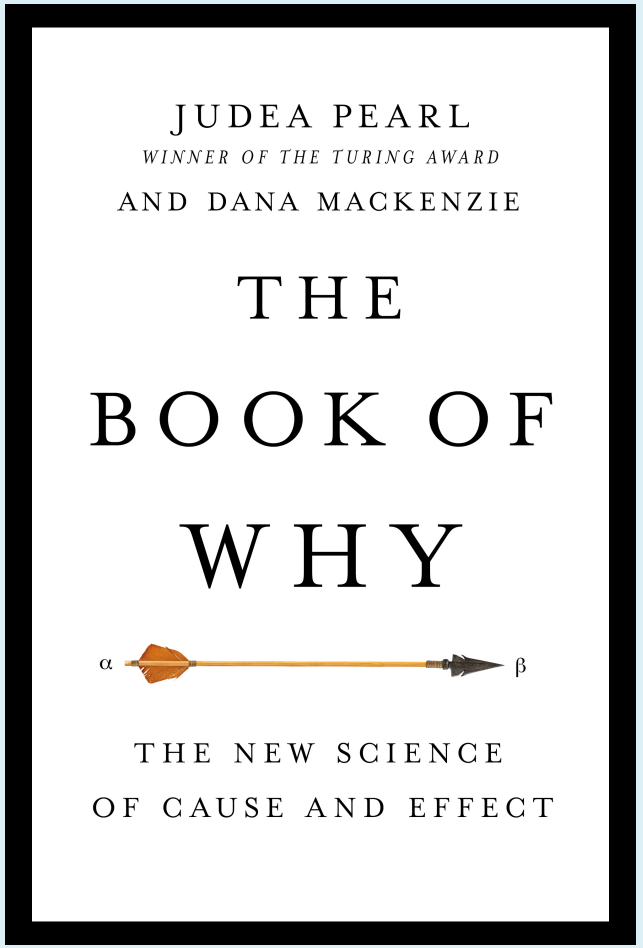
- Most empirical economists think that correlation only tell us the **superficial**, even **false** relationship while causal inference can provide solid evidence of the real relationship.

Joshhua Angrist(MIT,Noble Prize winner)

Jörn-Steffen Pischke(LSE)

> **"the most interesting and challenging research in social science is about cause and effect" by Angrist and Pischke(2009)**

Causality and Machine Learning



The Book of Why

Judea Pearl(UCLA),Turing Award winner

> **"Mind Over Data" and "Causal Revolution" by Judea Pearl(2018)**

Causality and Machine Learning

- Machine learning is a set of data-driven algorithms that use data to predict or classify some variable Y as a function of other variables X.
- Machine learning is mostly about prediction.
  - Having a good prediction does work sometimes but does NOT mean understanding causality.
- The biggest difference between machine learning and econometrics(or causal inference).
- Although two fields have developed in parallel for a while, a view to incorporating advantages of both methodologies is emerging.
  - eg. Causal Machine Learning

The Central Question of Causality

The Central Question of Causality(I)

- A simple example: **Do hospitals make people healthier?**
  - (Q: Dependent variable and Independent variable?)
- Two key questions are documented by the questionnaires from The National Health Interview Survey(NHIS)

1. > "During the past 12 months, was the respondent a patient in a hospital overnight?"
2. > "Would you say your health in general is excellent, very good, good ,fair and poor" and scale it from the number "1" to "5" respectively.

- A naive solution:
  - Comparing the health status of those *who have been to the hospital* to the health of those *who have not*.

The Central Question of Causality(II)

Group	Sample Size	Mean Health Status	S.D
Hospital	7774	**2.79**	0.014
No Hospital	90049	**2.07**	0.003

- In favor of the non-hospitalized, WHY?
- Hospitals not only cure but also hurt people.
    1. hospitals are full of other sick people who might infect us.
    2. dangerous machines and chemicals that might hurt us.
- **More important**: **People with poorer health tend to visit hospitals.**
- The simple case exhibits that it is not easy to answer a causal question in reality, so let us **formalize a model** to show where the problem is.

The Central Question of Causality(III)

- A right way to answer the question is by constructing **a counterfactual world**

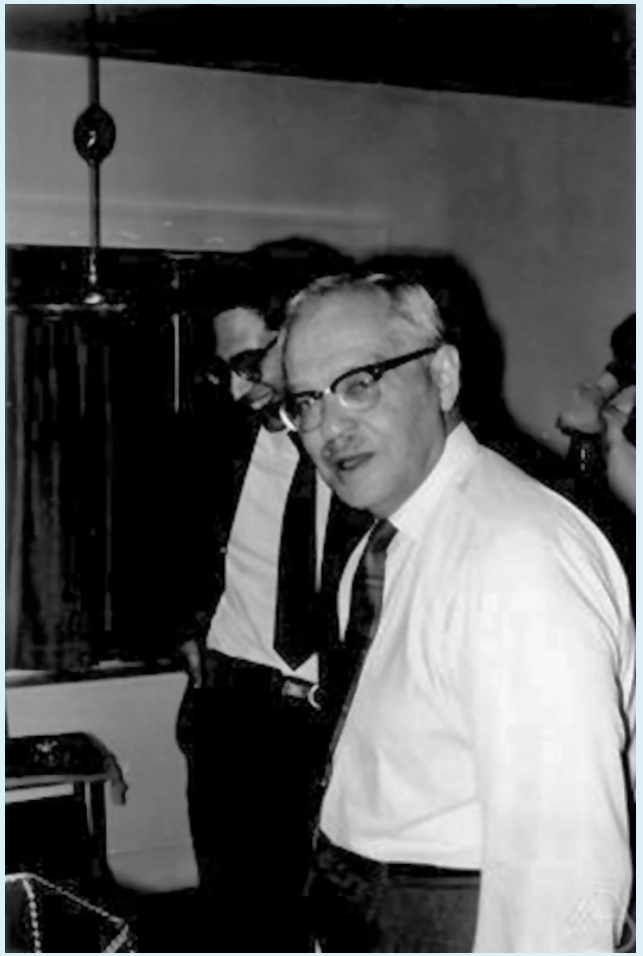
> What if ..., then

- For any respondent, we want to compare health outcomes between two states
  - Health status if he/she see the doctor.
  - Health status if he/she **had not** see the doctor.
- **Treatment** D_i is a dummy that indicate whether individual i receive treatment or not

$$D_i = \begin{cases} 1 & \text{if individual i received the treatment} \\ 0 & \text{otherwise} \end{cases}$$

- Examples
  - Go to college or not
  - Have health insurance or not
  - Join a training program or not

Formalization: Neyman–Rubin Causal Model



Jerzy Neyman(1894–1981)

Donald Rubin(1943-present)

Formalization: Potential Outcomes

- A **potential outcome** is the outcome that would be realized if the individual received a specific value of the **treatment**(intervention,action,interference).
- For each individual, two potential outcomes, Y_{1i} and Y_{0i}, one for each value of the treatment
  - Y_{1i}: Potential outcome for an individual i **with treatment**.
  - Y_{0i}: Potential outcome for an individual i **without treatment**.

$$\text{Potential Outcomes} = \begin{cases} Y_{1i} & \text{if } D_i = 1 \\ Y_{0i} & \text{if } D_i = 0 \end{cases}$$

- Then, the observed outcomes are realized as

$$Y_i = Y_{1i}D_i + Y_{0i}(1 - D_i)$$

Stable Unit Treatment Value Assumption (SUTVA)

- Implies that potential outcomes for an individual i are unaffected by the treatment status of other individual j
  - Individual i's potential outcomes are only affected by his/her own treatment.
- Rules out possible treatment effect from other individuals (spillover effect/externality)
  - Contagion
  - Displacement

Formalization: Causal Effects

- To know the difference between Y_{1i} and Y_{0i},two potential health outcomes,which can be said to be the causal effect of seeing a doctor on health for individual i.
  - Do you agree with it?
- Definition: **Causal effect** is **a comparison of counterfactuals under different treatment conditions on the same set of units**. It also call *Individual Treatment Effect(ICE)*,thus

$$\delta_i = Y_{1i} - Y_{0i}$$

- **Notes**:
  - the definition depends on the potential outcomes, **not which outcome is actually observed**.
  - the comparison is made for **the same unit at the same moment** in time post treatment.

Formalization: Causal Effects

- Further, knowing individual effect is not our final goal. As a social scientist, we would like more to know the average effect as a social pattern.
- Therefore it makes us focus on the average health status for a group of people.
  - How can we get the **average health benefits** from seeing a doctor?
- **Expectation**: We usually use $E[Y_i]$ (the expectation of a variable Y_i) to denote population average of Y_i
- **Conditional Expectation**: the expected value of a random variable given certain conditions or information.
  - The **average health status** for **those who see a doctor**:

$$E[Y_i|D_i = 1]$$

  - The **average health status** for **those who did not see a doctor**:

$$E[Y_i|D_i = 0]$$

Average Causal Effects

- **Average Treatment Effect(ATE)** is the average of ICEs **over the population**.

$$\alpha_{ATE} = E[\delta_i] = E[Y_{1i} - Y_{0i}]$$

- **Average Treatment Effect on the Treated(ATT)** is the average of ICEs **over the treated population**.

$$\alpha_{ATT} = E[\delta_i | D_i = 1] = E[Y_{1i} - Y_{0i} | D_i = 1]$$

- **Difficulty**: we can never directly observe causal effects (ICE, ATE or ATT)
  - Because we can never observe both potential outcomes Y_{0i}, Y_{1i} for any individual.
- Our aims is to compare **potential outcomes**, but we only have **observed outcomes**.
- By this view, **causal inference** refers to a series of methods that are used to **restore or construct counterfactuals** in order to address the missing data problem.

Observed Association and Selection Bias

- By using **observed data**, we can only establish **association(correlation)**, which is the observed difference in average outcome between those getting treatment and those not getting treatment.

$$\begin{aligned}\alpha_{corr} &= E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 0] \\ &= E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 1] + E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0]\end{aligned}$$

- The first term on the right side is actually **ATT**

$$E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 1]$$

- The second term on the right side is called as **Selection Bias(SB)**

$$E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0]$$

  - which implies the potential outcomes of treatment and control groups are different even if both groups did not receive the same treatment from the beginning.

- **Conclusion**: **Observed association** is neither necessary nor sufficient for causality for **SB**

$$\alpha_{corr} \neq ATT$$

Wrap Up

- Causal inference is the process of **estimating a comparison of counterfactuals** under different treatment conditions on the **same** set of units.
- The main goal of identification strategy is to **eliminate the selection bias** and **construct a more proper counterfactual** using the **observable data**.
- **The Next Question**:
  - **How to eliminate the selection bias?**

Experimental Design as a Benchmark

How to Eliminate the Selection Bias?

- **Answer**: Random assignment of treatment D_i can eliminates selection bias.
- Mathematically ,it makes D_i **independent** of potential outcomes, thus

$$D_i \perp (Y_{0i}, Y_{1i})$$

- **Math Review**: Two random variables are said to be **independent** if knowing the outcome of one provides **no** useful information about the outcome of the other. Thus,

$$P(X = x, Y = y) = P(X = x)P(Y = y)$$

- And

$$P(Y = y|X = x) = \frac{P(X = x, Y = y)}{P(X = x)} = P(Y = y)$$

  - Knowing outcome of $D_i(0, 1)$ does not help us understand what potential outcomes Y_{0i}, Y_{1i} will be.
  - In other words, the potential outcomes Y_{0i}, Y_{1i} are not correlated with $D_i(0, 1)$.

Random Assignment Solves the Selection Problem

- **Math Review**: **Expectation for Independent Random Variables**

$$E[Y \mid X = x] = \sum_{y \in R_y} y P_{Y|X}(y \mid x) = \sum_{y \in R_y} y P_Y(y) = E[Y]$$

- Then for D is independent to Y, we have

$$E[Y_{0i} | D_i = 1] = E(Y_{0i}) = E[Y_{0i} | D_i = 0]$$

- Then **the difference in means** between two groups with random assignment of D_i is

$$\begin{aligned}
&E[Y_i \mid D_i = 1] - E[Y_i \mid D_i = 0] \\
&= E[Y_{1i} \mid D_i = 1] - E[Y_{0i} \mid D_i = 0] \\
&= E[Y_{1i} \mid D_i = 1] - E[Y_{0i} \mid D_i = 1] \qquad \text{from random assignment of } D_i \\
&= E[Y_{1i} - Y_{0i} \mid D_i = 1] \\
&= E[\delta_i \mid D_i = 1] = ATT \\
&= E[\delta_i] = ATE
\end{aligned}$$

- Thus the **Selection Bias** equals to **ZERO**.The **Observed Association** equals to **ATT** and **ATE**.

$$\alpha_{corr} = \alpha_{ATT} = \alpha_{ATE}$$

Warp up

- Think of causal effects is about **comparing counterfactuals or potential outcomes**. However, we can never observe both counterfactuals
  - the fundamental problem of causal inference.
- To construct the counterfactuals, we could use two broad categories of empirical strategies

1.Random Controlled Trials/Experiments:

  - The data collected by RCTs is called experimental data, which is selection-bias free.
  - It can eliminates selection bias which is the most important bias arises in empirical research.
  - If we could observe the counterfactual directly, then just simply difference.

2.Nonexperimental Methods:

  - The data collected is **ex-post** data or **naturally-occuring** data which can not be selection-bias free.

Randomized Controlled Trials(RCTs)

RCTs: Introduction

- A randomized controlled trial (RCT) is a form of investigation in which units of observation (e.g. individuals, households, schools, states) are **randomly assigned** to **treatment** and **control** groups.
- RCT has two features that can help us hold other things equal and then eliminates selection bias

1.Random assign treatment:

- Randomly assign treatment (such as a coin flip) ensures that every observation has the same probability of being assigned to the treatment group.
- Therefore, the probability of receiving treatment is unrelated to any other confounding factors.

2.Sufficient large sample:

- Large sample size can ensure that the group differences in individual characteristics wash out.
- RCTs are considered the **gold standard** for establishing a causal link between an intervention and change.

RCTs in History: The first one in record

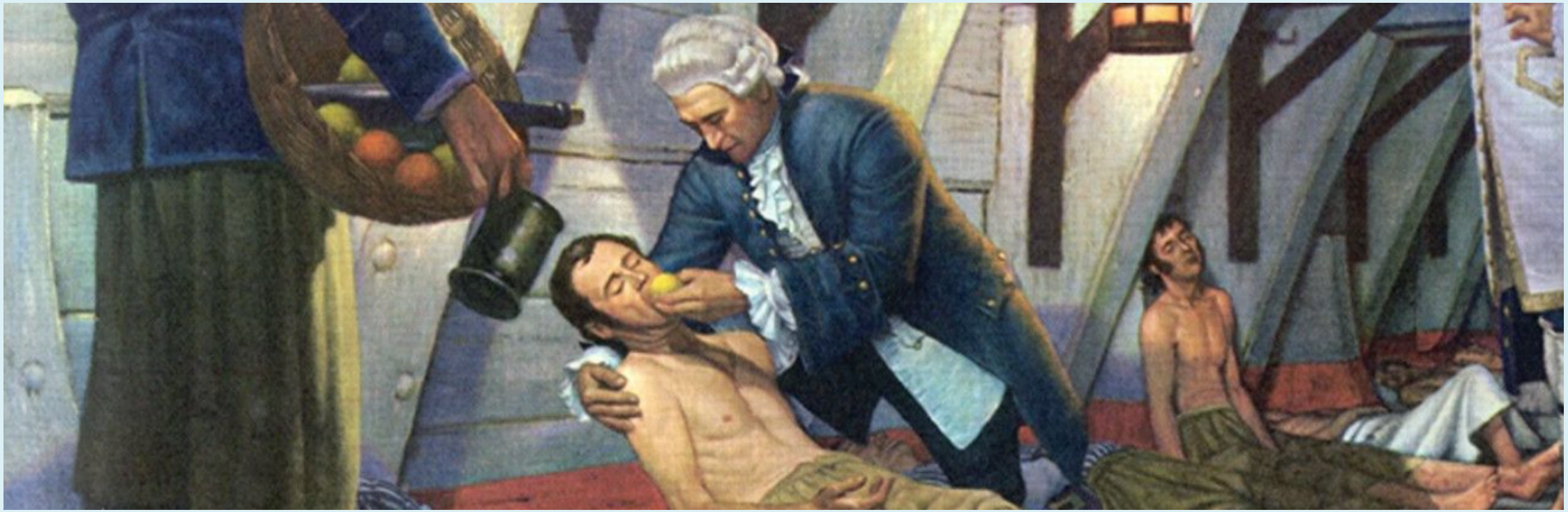
James Lind(1716-1794)

- a Scottish physician in the Royal Navy.

- The first recorded RCT was done in 1747.
- Scurvy(败血症) is a terrible disease caused by Vitamin C deficiency.
- Lind took 12 sailors with scurvy and split them into six groups of two.
- Groups were assigned:

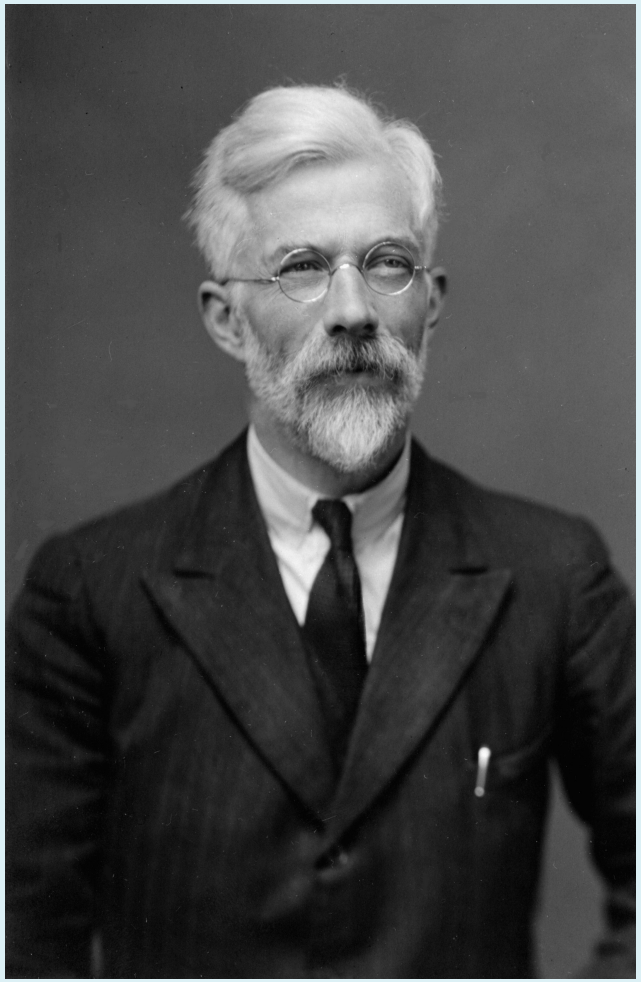
1. 1 qt cider(苹果酒)
2. 25 drops of vitriol(硫酸）
3. 6 spoonfuls of vinegar,
4. 1/2 pt of sea water,
5. garlic,mustard and barley water(大麦汤)
6. 2 oranges and 1 lemon

RCTs in History: The first one in record



- Only Group 6 (citrus fruit) showed substantial improvement.

RCTs in History: Modern era



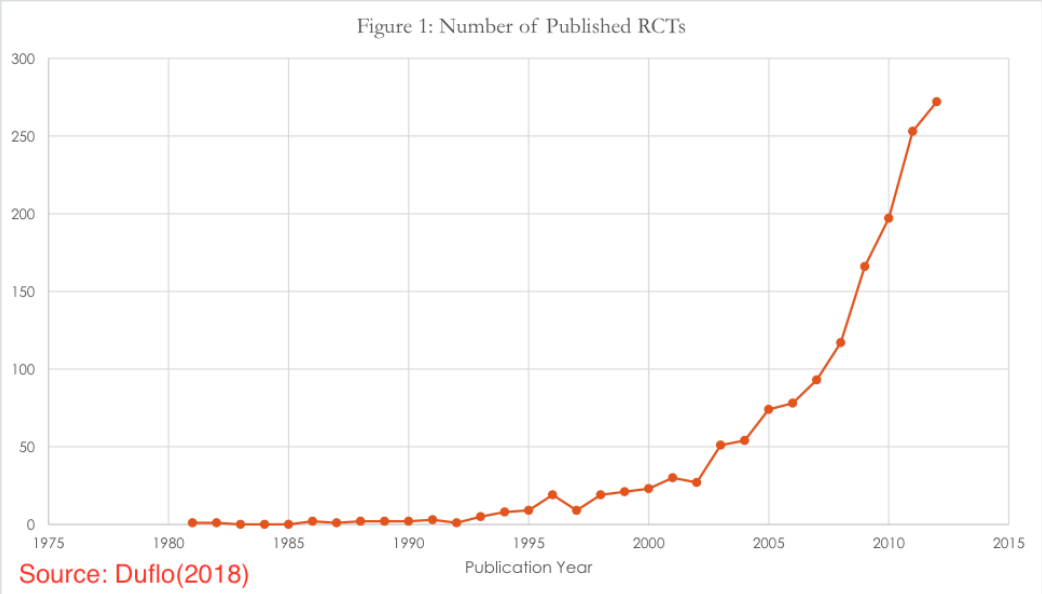
Ronald A. Fisher(1890-1962)

- British statistician and geneticist who pioneered the application of statistical procedures to the design of scientific experiments.

> "a genius who almost single-handedly created the foundations for modern statistical science."

- Rothamsted Experimental Station is one of the oldest agricultural research institutions in the world, having been founded in 1843.
- Fisher changed the way that agricultural experiments were designed and analyzed over 100 years ago.

RCTs in Economics



Published Papers in Economics Journals

Noble Prize 2019

†Duflo(2018),Randomized Controlled Trials,Development Economics and Policy Making in Developing Countries

RCTs in Public Policies

- According to Boruch et al(1978), 245 randomized field experiments had been conducted in U.S for social policies evaluations up to 1978.†
- The huge effort has been prompted by the 1% part of every social budget devoted to evaluation.
- Some of them were ambitious and very costly, and affected different kind of policies.
  - the Perry Preschool Program in 1961
  - The Rand Health Insurance Experiment from 1974-1982.

† Boruch RF, Mcsweeny AJ, Soderstrom EJ. Randomized field experiments for program planning, development, and evaluation: an illustrative bibliography. Eval Q. 1978 Nov;2(4):655-95.

RCTs in Public Policies

Education: the Perry Preschool Program

- 123 children born between 1958 and 1962 in Michigan
- Half of them (drawn at random) entered the Perry school program at 3 or 4 years old.
- Education by skilled professionals in nurseries and kindergarten.
- Program duration circle 30 weeks
- follow-up survey (age : 14, 15, 19, 27 and 40 years old)

Health Care: The Rand Health Insurance Experiment

- 5809 people randomly assigned in 1974 to different insurance programs with 0%, 25%, 50% and 75% sharing.
- They were followed until 1982.
- Main results : paying a portion of health cost make people give up some “superfluous” cares, with little harm on their health.
- But some heterogeneity : not true for poor people.

RCTs in Public Policies

Scott Rozelle(Standford)

- "One egg a day" program in rural China by REAP at Stanford.
  - One egg a day
- "Free-lunch" program in primary schools at Western China.
  - Free Lunch
- Talk: 中国农村儿童发展怎样影响未来中国

RCT in Business

- An interesting question: **What is the optimal color for taxis?**

Taxi in NYC

Taxi in NJ

- Ho, Chong and Xia(2017), Yellow taxis have fewer accidents than blue taxis because yellow is more visible than blue,PNAS

RCT in Business

- Another Critical Question for Business: **Is Working at Home is better than Working at Office**?

James Liang(梁建章)

- Bloom, Liang, Roberts and Ying,(2015), “Does Working from Home Work? Evidence from a Chinese Experiment”, The Quarterly Journal of Economics
- Bloom, Han and Liang(2022),"How Hybrid Working From Home Works Out",NBER working papers w30292

Types of RCTs

- **Lab Experiments**
  - eg: students evolves a experiment in a classroom.
  - eg: computer game for gamble in Lab
- **Field Experiments**
  - eg: the role of women in household's decision or fake resumes in job application
- **Quasi or Natural Experiments**: some unexpected institutional change or natural shock
  - eg: Germany Reunion, Great Famine in China and U.S Bombing in Vietnam.

RCTs and Statistical Inference

RCTs and Comparing Means

- In an RCT, we want to know the average causal effects over **the population**

$$\mathrm{ATE} = \mathrm{ATT} = \mathrm{E}\{\mathrm{Y_i}(1) - \mathrm{Y_i}(0)\}$$

- However, we only have **random samples** from the population. And then what we can **estimate** instead

$$\Delta = \text{difference in mean} = \overline{\mathrm{Y}}_{\text{treated}} - \overline{\mathrm{Y}}_{\text{control}}$$

- This the difference between two samples and not the population. Therefore we have to **inference** the difference in population from the results.

- Hypothesis Tests for the Difference Between Two Means

$$\mathrm{H}_0 : \mu_{\text{treated}} - \mu_{\text{control}} = 0$$

$$\mathrm{H}_1 : \mu_{\text{treated}} - \mu_{\text{control}} \neq 0$$

- And Confidence Intervals for the Difference Between Two Means

Class Size and Student Performance in CA

- Draw schools (n = 420) randomly from all school in California
- Randomly assign them to small class(< 20 students) and large class (≥ 20 students)
- Variables:
  - Outcomes: grade test scores (Stanford-9 achievement test, combined math and reading), district average
  - Covariates: family income,parents education,migration status,....

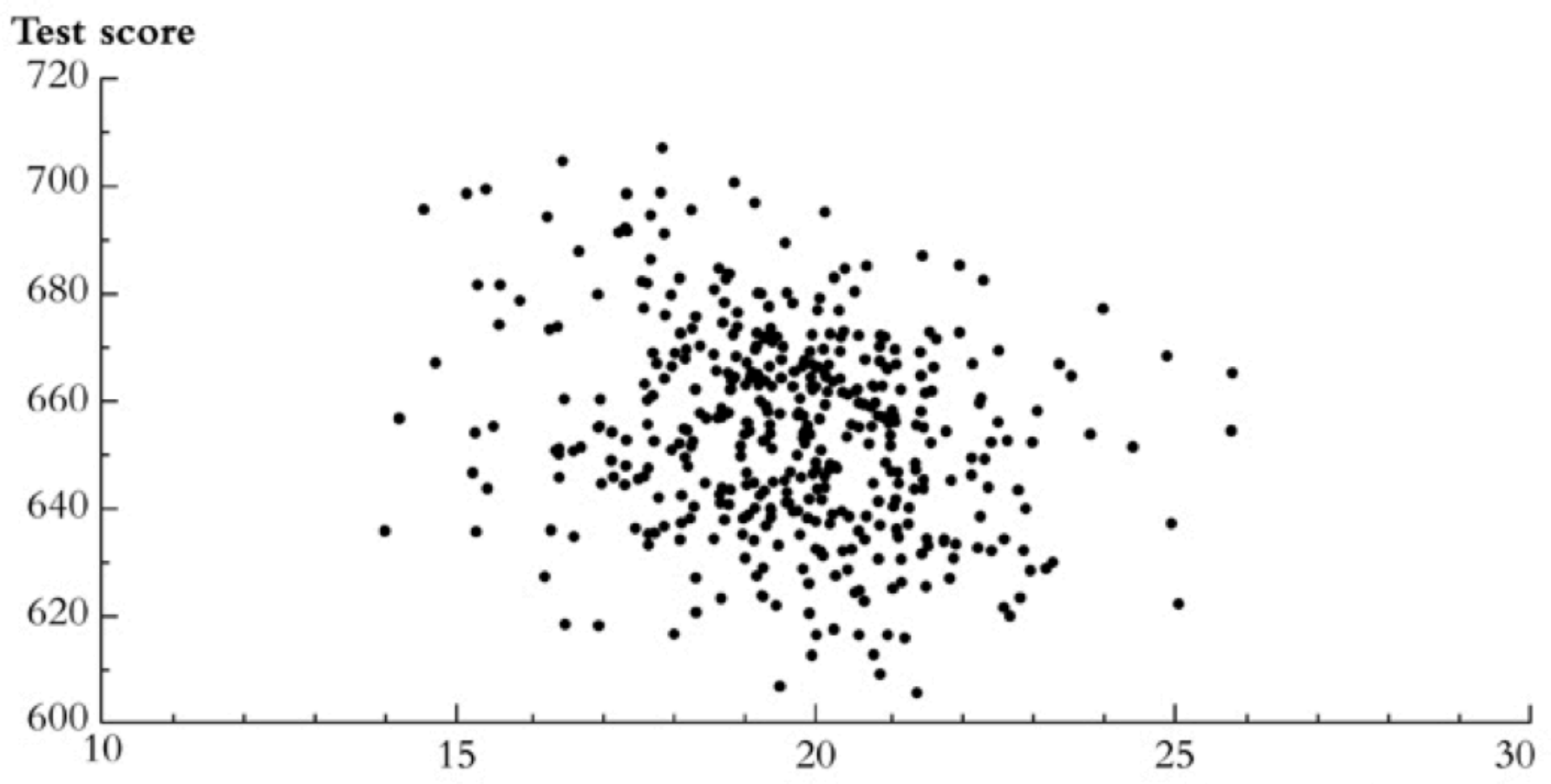
Class Size and Student Performance in CA

TABLE 4.1 Summary of the Distribution of Student–Teacher Ratios and Fifth-Grade Test Scores for 420 K–8 Districts in California in 1998

			Percentile						
	Average	Standard Deviation	10%	25%	40%	50% (median)	60%	75%	90%
Student–teacher ratio	19.6	1.9	17.3	18.6	19.3	19.7	20.1	20.9	21.9
Test score	665.2	19.1	630.4	640.0	649.1	654.5	659.4	666.7	679.1

- Does this table tell us anything about the relationship between test scores and the STR?

Class Size and Student Performance in CA



- What does this figure show? and it may suggest...?

Class Size and Student Performance in CA

- We need to get some numerical evidence on whether districts with low STRs have higher test scores.
- But how?
    1. Compare average test scores in districts with low STRs to those with high STRs (“estimation”)
- Don't forget! our sample is just a random sample from the population of all California schools.
    1. Test the “null” hypothesis that the mean test scores in the two types of districts are the same, against the “alternative” hypothesis that they differ (“hypothesis testing”)
    2. Estimate an interval for the difference in the mean test scores, high v. low STR districts (“confidence interval”)

Class Size and Student Performance in CA

- Compare districts with **small** and **large** class sizes:

Class size	Average score	Standard deviation	N
Small	657.4	19.4	238
Large	650	17.9	182

1. Estimation of Δ is difference between group means $657.4 - 650 = 7.4$

2. Test the hypothesis that $\Delta = 0$

3. Construct a confidence interval for Δ

Class Size and Student Performance in CA

- Let us discuss the distribution of $\Delta = \overline{Y}_s - \overline{Y}_l$
- Recall $\overline{Y}_s$ is approximately distributed $N(\mu_s, \frac{\sigma_s^2}{n_s})$ and $\overline{Y}_l$ is approximately distributed $N(\mu_l, \frac{\sigma_l^2}{n_l})$ according to the C.L.T.(the Center Limited Theorem))
- Then $\overline{Y}_s - \overline{Y}_l$ is distributed as

$$\sim N(\mu_s - \mu_l, \frac{\sigma_s^2}{n_s} + \frac{\sigma_l^2}{n_l})$$

- If σ_s^2 and σ_l^2 are known, then the this approximate normal distribution can be used to compute p-values for the test of the null hypothesis.
- In practice, however, these population variances are typically unknown so they must be estimated
- Thus the **standard error** of $\overline{Y}_s - \overline{Y}_l$ is

$$SE(\overline{Y}_s - \overline{Y}_l) = \sqrt{\frac{s_s^2}{n_s} + \frac{s_l^2}{n_l}}$$

Class Size and Student Performance in CA

- The t-statistic for testing the null hypothesis is constructed analogously to the t-statistic for testing a hypothesis about a single population mean, thus a simplest t-statistic for comparing two means is

$$t_{act} = \frac{\overline{Y}_s - \overline{Y}_l - d_0}{SE(\overline{Y}_s - \overline{Y}_l)}$$

- If both $n_s$and n_l are large, then this t-statistic has a standard normal distribution when the null hypothesis is true,thus

$$\overline{Y}_s - \overline{Y}_l = 0$$

- Reject the null hypothesis if

$$|t^{act}| = \left| \frac{\overline{Y}_m - \overline{Y}_w - d_0}{SE(\overline{Y}_m - \overline{Y}_w)} \right| > \text{critical value}$$

- or if

$$p - value < \text{significance level}$$

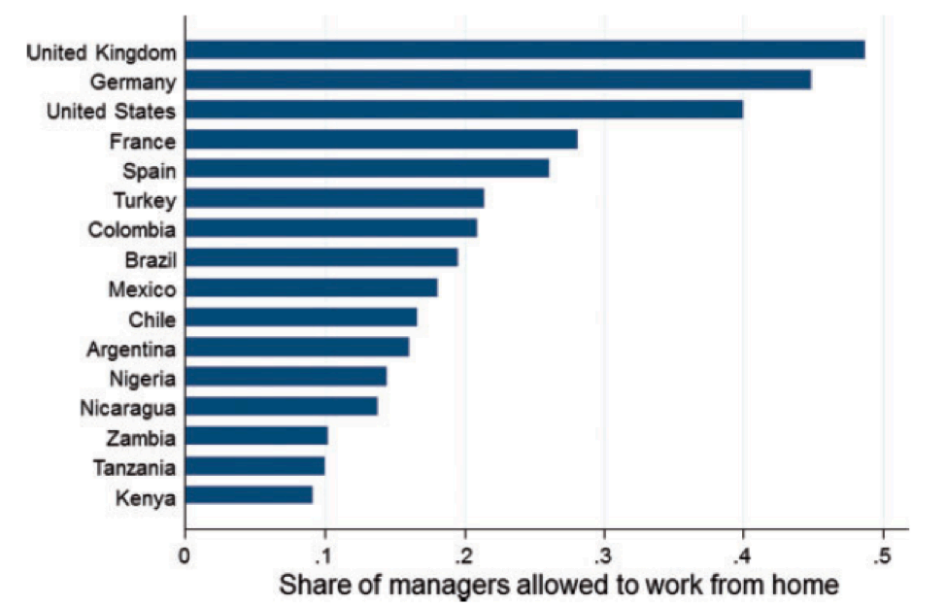
Randomized Controlled Trials(RCTs) in Business

WFH v.s WFO

- “Does Working from Home Work? Evidence from a Chinese Experiment”,by Nicholas A. Bloom, James Liang, John Roberts, Zhichun Jenny Ying The Quarterly Journal of Economics,February 2015, Vol. 130, Issue 1, Pages 165-218.
- Basic Question: WFH=SFH?
  - SFH(Shirking from Home)?

WFH is becoming popular across the world

- Working from home is a modern management practice which appears to be spreading in the US and Europe.
    - 20 million people in US report working from home at least once per week



- Little evidence on the effect of workplace flexibility
    - productivity(shirking)
    - employee satisfaction

Ctrip Experiment

- Ctrip, China's largest travel-agent, with 16,000 employees, $6bn NASDAQ in 2015.
- **James Liang**,Co-founder of Ctrip,was an Econ PhD at Stanford and decided to run a experiment to test WFH at his own company.
- The experiment runs on **airfare & hotel departments** in Shanghai.
- **Main Work**: Employees take calls and make bookings.

Citrip SH Office

The Experimental Design

- **Treatment**: work 4 shifts (days) a week at home and to work the 5th shift in the office.
- **Control**: work in the office on all 5 days.
- **Timeline**:
  - early Nov.2010, all employees were informed of the WFH program(994 employees).
    - 503 (51%) volunteered for the experiment,249 (50%) of the employees are eligible.
    - The treatment and control groups were then determined from this group of 249 employees through a **public lottery**.

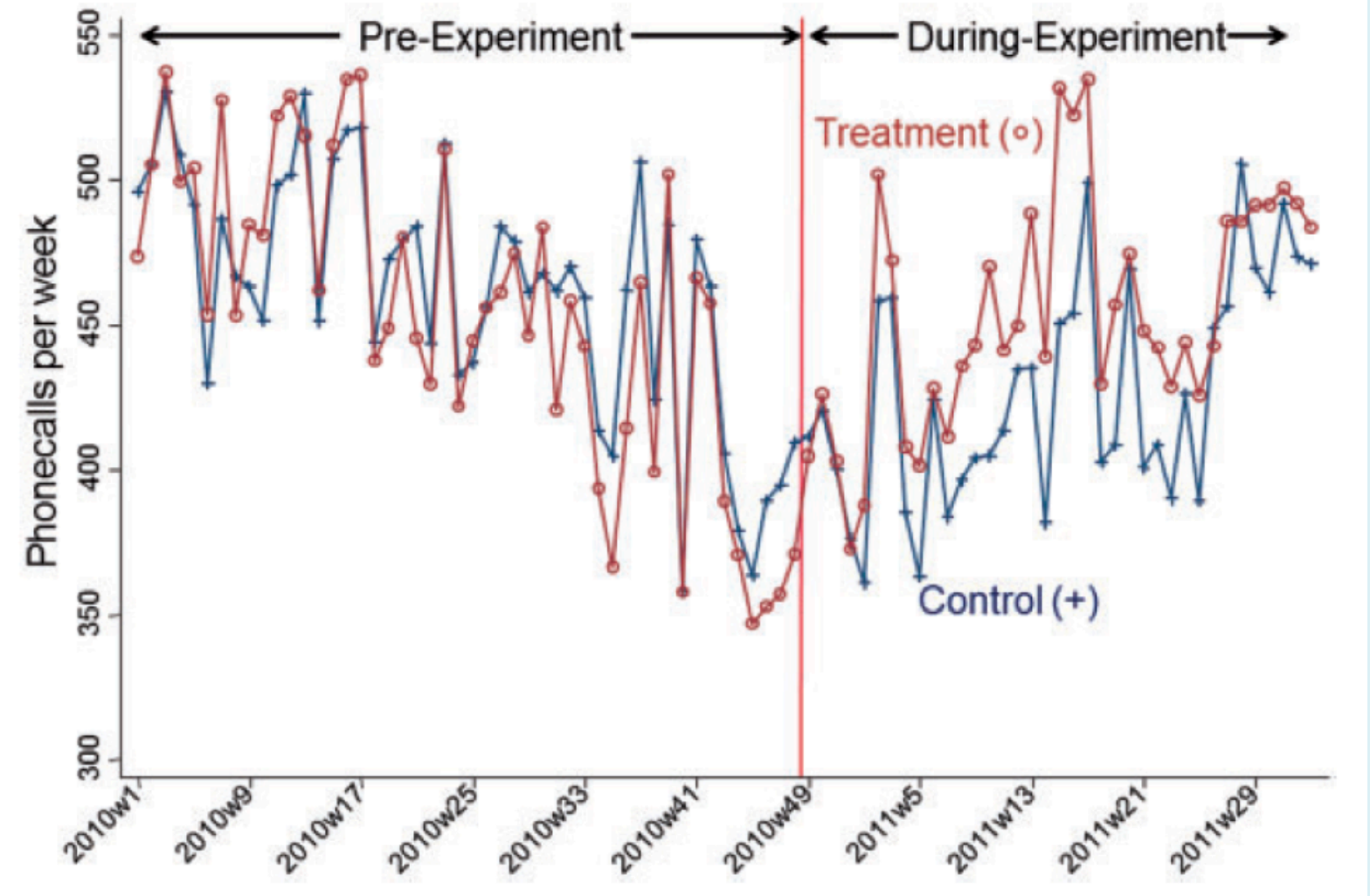
Citrip WFH

Balanced Checks

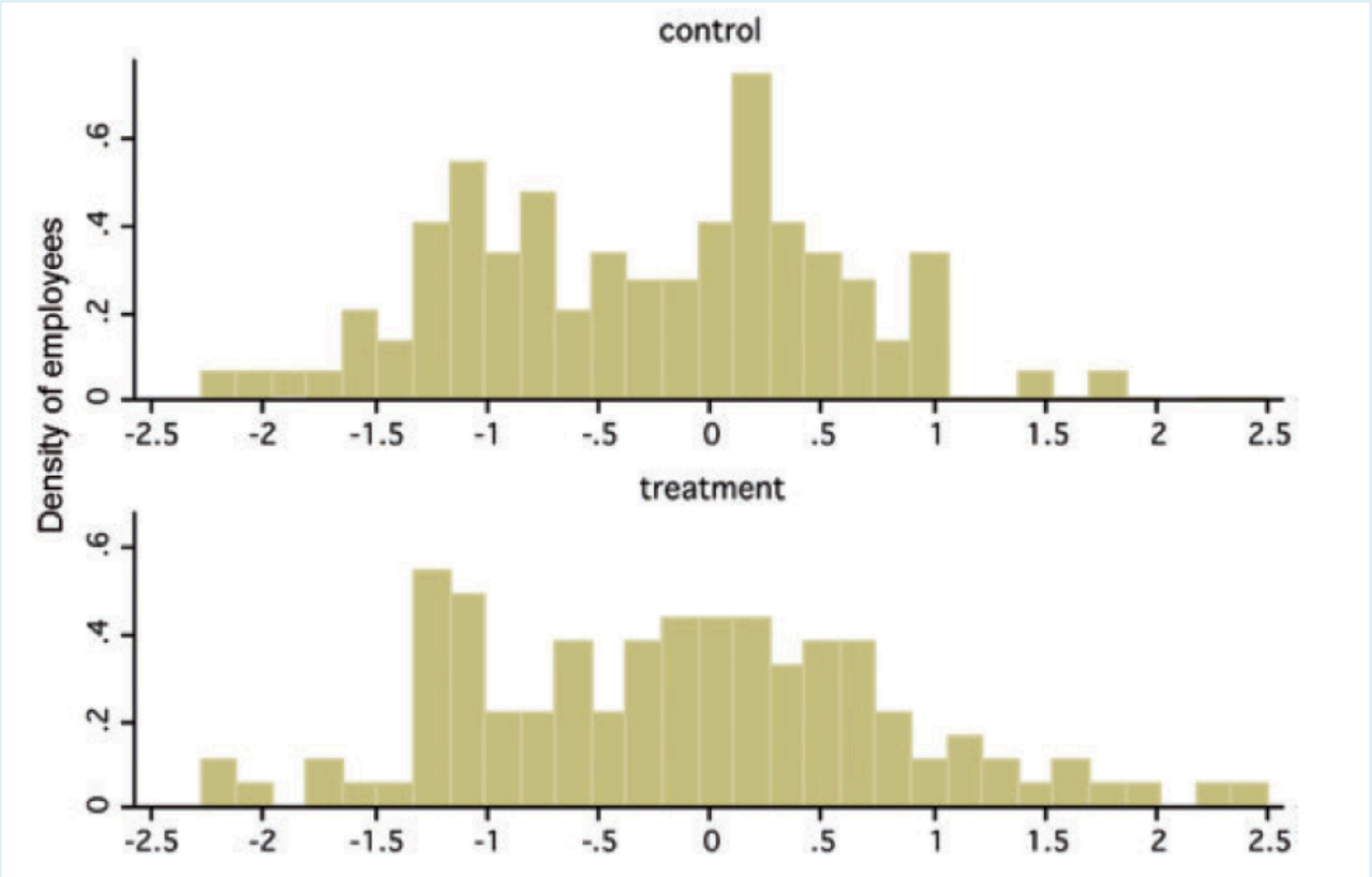
Table 20.1 Covariate balance

	Treatment mean	Control mean	Std.dev.	p-value of test of equal means
Number of observations	131	118	249	
Prior performance z-score	−0.03	−0.04	0.58	0.87
Age	24	24	4	0.85
Male	0.47	0.47	0.50	0.99
Secondary technical school	0.46	0.47	0.50	0.80
High school	0.18	0.14	0.36	0.38
Tertiary	0.35	0.36	0.48	0.94
University	0.02	0.03	0.15	0.91
Prior experience (months)	19	17	26	0.48
Tenure (months)	26	28	22	0.45
Married	0.22	0.32	0.44	0.07
Children	0.11	0.24	0.38	0.01
Age of youngest child	4.60	3.00	3.35	0.14
Rent apartment	0.24	0.20	0.42	0.44

Results:the number of receiving calls



Results: Working hours



Results: Productivity

Variables	(1) Minutes on the phone	(2) Minutes on the phone/days worked	(3) Days worked	(4) Minutes on the phone	(5) Minutes on the phone/days worked	(6) Days worked
$Experiment_t$*$Treatment_i$	0.088***	0.063***	0.025**	0.069**	0.049*	0.021
	(0.027)	(0.024)	(0.012)	(0.030)	(0.027)	(0.013)
$Experiment_t$*$Treatment_i$* [total commute > 120 min]$_i$				0.069*	0.055*	0.014
				(0.036)	(0.031)	(0.017)
Number of employees	134	134	134	134	134	134
Number of weeks	85	85	85	85	85	85
Observations	9,426	9,426	9,426	9,426	9,426	9,426

Notes. The regressions are run at the individual by week level, with a full set of individual and week fixed effects. *Experiment*treatment* is the interaction of the period of the experimentation (December 6, 2010, until August 14, 2011) by an individual having an even birthdate (2nd, 4th, 6th, etc. day of the month). The pre-experiment period refers to January 1, 2010, until November 28, 2010. During the experiment period refers to December 6, 2010, to August 14, 2011. In columns (4)–(6), *Experiment* × *Treatment* is further interacted with a dummy variable indicating whether an employee's total daily commute (to and from work) is longer than 120 minutes (21.3% of employees have a commute longer than 120 minutes). Standard errors are clustered at the individual level. Once employees quit they are dropped from the data. *** denotes 1% significance, ** 5% significance, and * 10% significance. Minutes on the phone are recorded from the call logs.

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Conclusion: Very positive

- They found a highly significant 13% increase in employee performance from WFH,
  - of which about 9% was from employees working more minutes of their shift period (fewer breaks and sick days)
  - and about 4% from higher performance per minute.
- Home workers also reported substantially higher work satisfaction and psychological attitude scores, and their job attrition rates fell by over 50%.

Limitations of RCTs

RCTs are not easy in practice!

- High Costs, Long Duration
- Small sample: Student Effect
- Hawthorne effect(霍桑效应）： The subjects are in an experiment can change their behavior.
- Attrition（样本流失）： It refers to subjects dropping out of the study after being randomly assigned to the treatment or control group.
- Failure to randomize or failure to follow treatment protocol: People don't always do what they are told.
    - eg. Wearing glasses program in Western Rural China.

Limitations of RCTs

RCTs are far from perfect!

- Limited Generalizability
- RCTs allow us to gain knowledge about causal effects but without knowing the mechanism.
- Potential Ethical Problems:

> “Parachutes reduce the risk of injury after gravitational challenge, but their effectiveness has not been proved with randomized controlled trials."

- Some classical examples
  - Milgram Experiment
  - Stanford Prison Experiment
  - Monkey Experiment

Nonexperimental methods

- We can generate the data of our interest by controlling experiments just as **physical scientists or biologists** do. However, it is quite obvious that we face **more difficult and controversial situations** than those in any other sciences.
- The various approaches using naturally-occurring data provide alternative methods of constructing the proper counterfactuals
  - **Econometrics**
- Congratulation! We work and study in a field that is **tougher and more challenging than others**, which includes a vast amount of scientific knowledge.
- When conducting empirical research, regardless of the methods we use, we should consider **randomized experimental methods as our benchmark**.

Program Evaluation Econometrics

- Since non-experimental data suffer from selection bias inherently, or in terms of "endogeneity," building a reasonable counterfactual world using naturally occurring data to find proper control groups is the core of econometric methods.
- Here you Furious Seven Weapons in Applied Econometrics(七种盖世武器）

1. RCTs（随机对照试验）
2. Regression(回归)
3. Matching and Propensity Scores(匹配与倾向得分)
4. Instrumental Variable(工具变量)
5. Regression Discontinuity(断点回归)
6. Differences in Differences(双差分)
7. Synthetic Control(合成控制)


Let's Start Our Journey