KAIST Summer Session 2018

Module 1. Research Design for Data Analytics

Identification Strategy (1) Experiment

KAIST College of Business

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2 July, 2018

What is Causal Inference?

Potential Outcomes Framework

- Rubin Causal Model (Holland 1986)
  - Potential outcomes (Y_{iD})
    - Potential outcome if individual *i* is treated = Y_{i1}
    - Potential outcome if individual *i* is untreated = Y_{i0}
  - Average Treatment Effect (ATE)

    $$ATE = E[Y_{i1} - Y_{i0}]$$

  - ATE on the treated (ATT)

    $$ATT = E[Y_{i1} - Y_{i0} | D_i = 1]$$

  - An experiment identifies the treatment effect within the sample used in the study (i.e., ATT). For ATE, random sampling from the entire population is required.

Holland, P.W., 1986. Statistics and Causal Inference. *Journal of the American Statistical Association*, 81(396), pp.945-960.

Fundamental Problem of Causal Inference

- We cannot observe the potential outcomes (counterfactuals).
  - For ATE on the treated (ATT), we want to estimate:

    = (Outcome for treated if treated) – (Outcome for treated if not treated)

    Unobservable potential outcome

  - But, in reality, we can only observe:

    = (Outcome for treated if treated) – (Outcome for untreated if not treated)

  - (Example) Effect of PhD degree

    ATT

    = (Outcome when I entered a graduate school) – (Outcome when I did not enter)

    Observational estimate

    = (My outcome after entering a graduate school) – (Friends' outcome who did not enter)

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Orthogonality or Ignobility

- Selection bias
  - There are systematic differences between treated and untreated sample.
  - Observational estimate

    = (Outcome for treated if treated) – (Outcome for untreated if not treated)

    = (Outcome for treated if treated) – (Outcome for treated if not treated)

    + <u>(Outcome for treated if not treated) – (Outcome for untreated if not treated)</u>

    = ATT + <u>(Selection Bias)</u>

- If treatment assignment is independent of potential outcomes, observational estimate is same as the ATT (i.e., selection bias is eliminated).
  - Orthogonality or ignobility: $Y_{i1}, Y_{i0} \perp D_i$
  - (Outcome for treated if not treated) = (Outcome for untreated if not treated)

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Identification Strategy

- Identification strategy is a **research design** intended to solve the endogeneity problem, resting on **identification assumptions**.

- Let's impose the orthogonality

  => Randomized experiment

- Let's find as-if orthogonality

  => Quasi-experiment

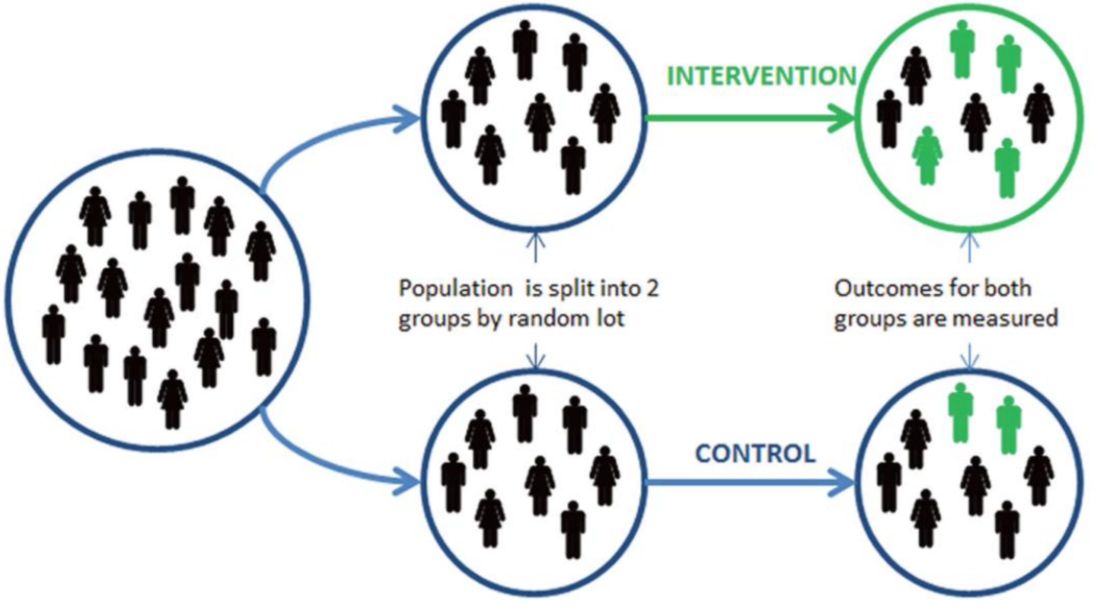
- Let's assume the orthogonality, conditional on observables

  => Selection on observables

Gold Standard of Causal Inference
: Randomized Experiment

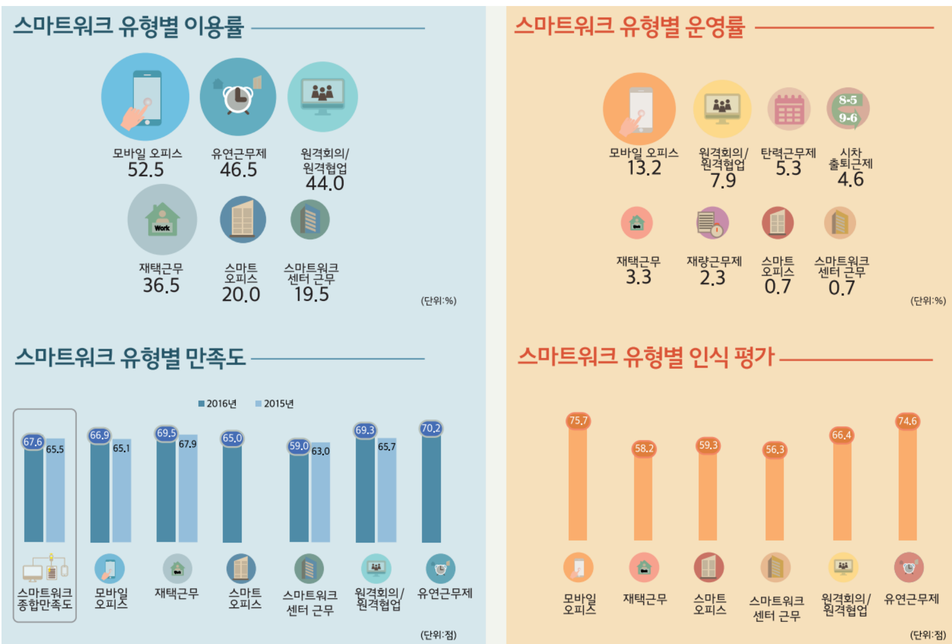
The Key is Random Assignment

- Random assignment guarantees orthogonality *asymptotically*.
  - ➢ Randomly assignment → potential outcomes are similar regardless of treatment
  - ➢ Orthogonality can be met ($Y_{i1}, Y_{i0} \perp D_i$)
  - ➢ (Outcome for treated if not treated) = (Outcome for untreated if not treated)



Case Study: Does Working from Home Work?

- Work from home (telework)
  - ➢ Lack of systematic evidence of telework effectiveness may lead to low adoption in practice



기업의 스마트워크 인식 평가는 모바일오피스(75.7점)와 유연근무제(74.6점)가 가장 높게 평가되었으나, 실제 운영 현황을 보면 모바일오피스(13.2%), 탄력근무제(5.3%), 재량근무제(2.3%) 등으로 기업체 단위에서의 스마트워크 운영률은 낮은 것으로 조사되었다.

– 이는 스마트워크를 운영하므로서 얻게 되는 수익 향상과 업무 효율성에 대한 영향력이 확인되지 않아 도입에 부담감을 느끼고 있는 것으로 분석되고 있다.

민간분야 2016년 스마트워크 실태조사 결과 http://www.kdi.re.kr/policy/ep_view.jsp?idx=162605&&pp=10&pg=3

Case Study: Does Working from Home Work?

- Bloom et al. (2014) conduct a randomized field experiment on the working from home (WFH) at Ctrip, Chinese travel agency.
  - ➢ Call center employees who volunteered to WFH were randomly assigned either to work from home or in the office.

Treatment groups were determined by a lottery

Working at home

Working at home

Working at home

- This study is an "exemplar" for randomized experiments.
  - ➢ "This was because one of the coauthors, James Liang (the co-founder and current chairman and CEO of Ctrip) was a doctoral student at Stanford University Graduate School of Business while we were working on the project." (p. 171)

Bloom, N., Liang, J., Roberts, J. and Ying, Z.J., 2014. Does Working from Home Work? Evidence from a Chinese Experiment. *Quarterly Journal of Economics*, 130(1), pp.165-218.

(1) Importance of Control Group

- "Without running a formal experiment, their view was that they could have interpreted the drop in treatment performance shown in Figure VI as a negative treatment effect." (p. 208)
- "The period of the experiment coincided with a business slow-down for Ctrip due to a combination of the (predicted) end of Shanghai Expo 2010 and an (unpredicted) increase in competition from other travel agencies." (p. 209)
- "The importance of having a well matched (ideally randomized) control group to strip out these kinds of seasonal and demand effects." (p. 209)

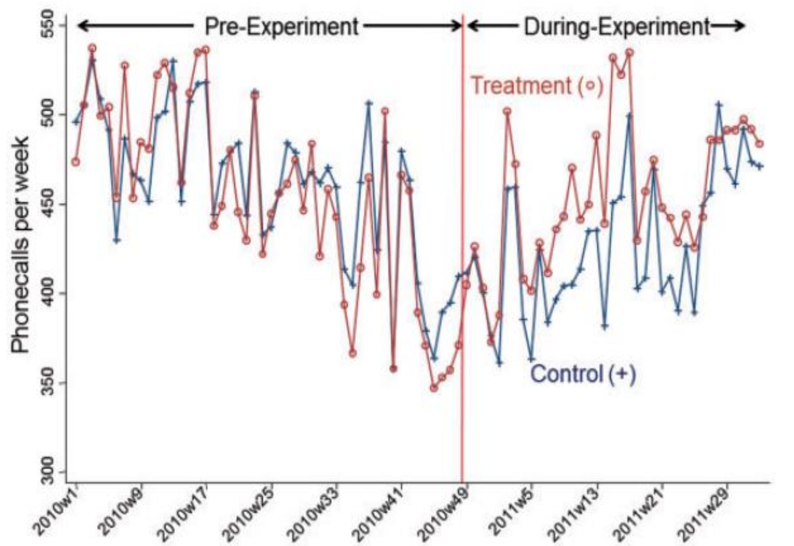


FIGURE VI
Performance of Treatment and Control Employees: Phone Calls

Bloom, N., Liang, J., Roberts, J. and Ying, Z.J., 2014. Does Working from Home Work? Evidence from a Chinese Experiment. *Quarterly Journal of Economics*, 130(1), pp.165-218.

(2) Power of Large Sample (Big Data)

- Large samples with universal coverage can allow us to "zoom in" to subgroups.

"Having the large sample of treatment and control employees allowed the firm to evaluate the impact on different types of employees. Somewhat surprisingly, they found no significant difference across types of employees." (p. 209)

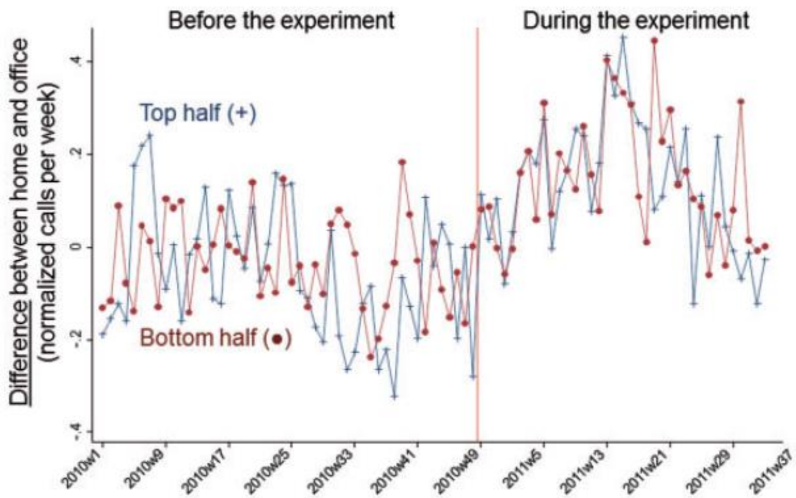


FIGURE X

The Top and Bottom Half of Employees by Pre-Experiment Performance Both Improved from Working at Home

Bloom, N., Liang, J., Roberts, J. and Ying, Z.J., 2014. Does Working from Home Work? Evidence from a Chinese Experiment. *Quarterly Journal of Economics*, 130(1), pp.165-218.

(3) Random Assignment and Asymptotic Orthogonality

- Random assignment guarantees orthogonality *asymptotically*.
  - That is, if sample size is not enough large, sample selection might not dissipate.

COMPARISON BETWEEN TREATMENT AND CONTROL GROUPS

	Treatment	Control	Std. dev.	p-value
Number	131	118		
Prior performance z-score	-0.028	-0.040	0.581	.88
Age	24.44	24.35	3.55	.85
Male	0.47	0.47	0.50	.99
Secondary technical school	0.46	0.47	0.50	.80
High school	0.18	0.14	0.36	.39
Tertiary	0.35	0.36	0.48	.94
University	0.02	0.03	0.15	.34
Prior experience (months)	18.96	16.76	25.88	.50
Tenure (months)	26.14	28.25	21.92	.45
Married	0.22	0.32	0.44	*.07*
Children	0.11	0.24	0.38	*.01*
Age of the child	0.53	0.71	1.92	.45
Rent apartment	0.25	0.20	0.42	.44
Cost of commute (yuan)	7.89	8.34	6.96	.61
Internet	0.99	1.00	0.06	.34
Own bedroom	0.97	0.99	0.14	.22
Base wage (yuan, monthly)	1,540	1,563	16	.26
Bonus (yuan, monthly)	1,031	1,093	625	.44
Gross wage (yuan, monthly)	2,950	3,003	790	.59
Number of order takers	68	66		.86
Number of order placers	36	32		.63
Number of order correctors	19	17		.74
Number of night shift workers	8	3		.14

$$Employee\ Performance_{i,t} = \alpha Treat_i \times Experiment_t + \beta_t + \gamma_i + \epsilon_{i,t}$$

"Since employees have large preexisting cross-sectional variations in performance, we appear to obtain more accurate (lower mean-squared error) estimations from using the difference in differences specification, estimated using the panel with employee fixed effects." (p. 188)

Bloom, N., Liang, J., Roberts, J. and Ying, Z.J., 2014. Does Working from Home Work? Evidence from a Chinese Experiment. *Quarterly Journal of Economics*, 130(1), pp.165-218.

(4) Noncompliance Issues

- Intention-to-Treat (ITT) effect
  - ITT results are based on the initial treatment assignment and not on the treatment eventually received. It ignores noncompliance.

"During the experiment, the percentage of treatment group working at home hovered between 80% and 90%. Since compliance was imperfect, our estimators take even birthdate status as the treatment status, yielding an intention-to-treat result on the eligible volunteers." (p. 183)

- Remedy for noncompliance → 2SLS
  - Variation from the treatment eventually received (in the first stage) is included in the second stage.

Dependent Variable	Overall Performance
Period	Pre and during experiment
Dependent Normalization	z-score
Second Stage	
Experiment_t*WFH_i	0.271***
	(0.073)
WFH_i	

First Stage	
Experiment_t*Treatment_i	0.856***
	(0.005)
Number of Employees	249
Number of Weeks	85
Individual Fixed Effects	Yes
Observations	17806

Bloom, N., Liang, J., Roberts, J. and Ying, Z.J., 2014. Does Working from Home Work? Evidence from a Chinese Experiment. *Quarterly Journal of Economics*, 130(1), pp.165-218.

(5) Stable Unit Treatment Value Assumption (SUTVA)

- SUTVA requires that the potential outcome observation on one unit should be unaffected by the particular assignment of treatments to the other units.
  - ➢ The treatment on the treatment group should not affect the control group.

"Perhaps the gap between treatment and control was caused not by the treatment group performing better but by the control group performing worse after they "lost" the randomization lottery." (p. 192)

	Comparable control groups
Treatment Group (Shanghai)	Other Sites (Nan Tong)
Control Group (Shanghai)	Non-volunteers (Shanghai)

Variables	(1) Overall performance (z-score)	(2) Phone calls (z-score)	(3) Overall performance (z-score)	(4) Phone calls (z-score)
Comparison group	Nan Tong	Nan Tong	Nonexperiment	Nonexperiment
$Experiment_t$*$treatment_i$	0.194***	0.281***	0.302***	0.312***
	(0.047)	(0.048)	(0.060)	(0.064)
$Experiment_t$*$control_i$	−0.035	−0.011	0.066	0.019
	(0.048)	(0.043)	(0.061)	(0.061)
Observations	99,753	86,589	27,823	15,261

Bloom, N., Liang, J., Roberts, J. and Ying, Z.J., 2014. Does Working from Home Work? Evidence from a Chinese Experiment. *Quarterly Journal of Economics*, 130(1), pp.165-218.

(6) Teasing Out Underlying Mechanisms

- Why is WFH effective?

  "About three quarters of the difference in the time on the phone was accounted for by the treatment group's spending more time on the phone per day worked." (p. 191)

Variables	Minutes on the phone	Minutes on the phone/days worked	Days worked	Minutes on the phone	Minutes on the phone/days worked	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

- Ruling out alternative explanations

  "An alternative story might be a gift-exchange type response (e.g., Falk and Kosfeld 2006) in that employees felt more positively toward Ctrip for allowing them to work at home and reciprocated by working harder. This is possible, of course, but some evidence appears to suggest this is not the primary driver. First…" (p. 194)

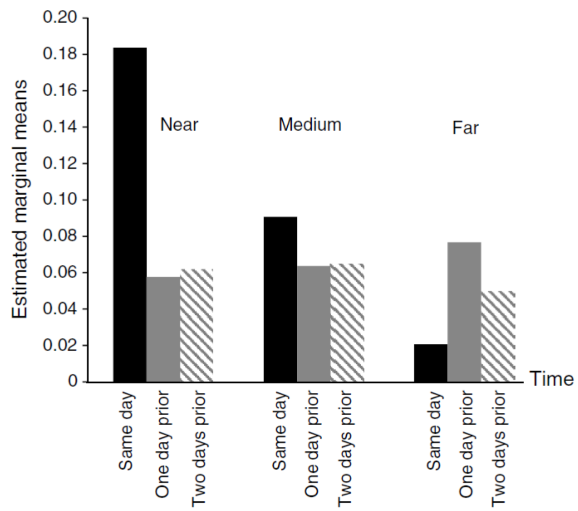
Bloom, N., Liang, J., Roberts, J. and Ying, Z.J., 2014. Does Working from Home Work? Evidence from a Chinese Experiment. *Quarterly Journal of Economics*, 130(1), pp.165-218.

(6) Teasing Out Underlying Mechanisms

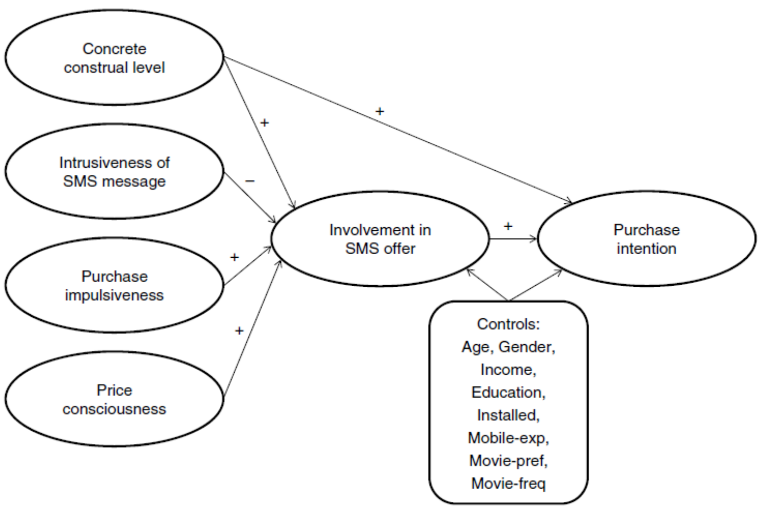
- Merely causal estimates are not enough.
  - ➢ Delving into underlying mechanisms or mediation effects would lend support to the theoretical argument why a factor causally influences another factor.

Randomized experiment

Figure 3 **Effect of Mobile Promotions via Combining Temporal and Geographical Targeting**



Follow-up survey



Luo, X., Andrews, M., Fang, Z., & Phang, C. W. 2013. Mobile Targeting. *Management Science*, *60*(7), 1738-1756.

(6) Teasing Out Underlying Mechanisms

- Firstly, substantiate the causal relationship.

Table 3. Moderating Effects of Updates

Dependent variable:	ln(Funding_amount)			
	Projects w/o Updates		Projects w/ Updates	
	(1)	(2)	(3)	(4)
Has_video	0.580***	0.662***	0.573***	0.674***
	(0.144)	(0.141)	(0.175)	(0.170)
Has_video × Has_pitch	0.599***		0.811***	0.063
	(0.147)		(0.121)	(0.206)
Has_video × Pitch_analytical		0.905**		0.063
		(0.356)		(0.206)
Has_video × Pitch_conscientiousness		1.083***		0.355*
		(0.343)		(0.190)
Has_video × Pitch_openness		-0.499		0.521**
		(0.366)		(0.219)
Has_video × Pitch_extroversion		-0.082		0.149
		(0.353)		(0.196)
Has_video × Pitch_agreeableness		-0.870***		-0.097
		(0.260)		(0.149)

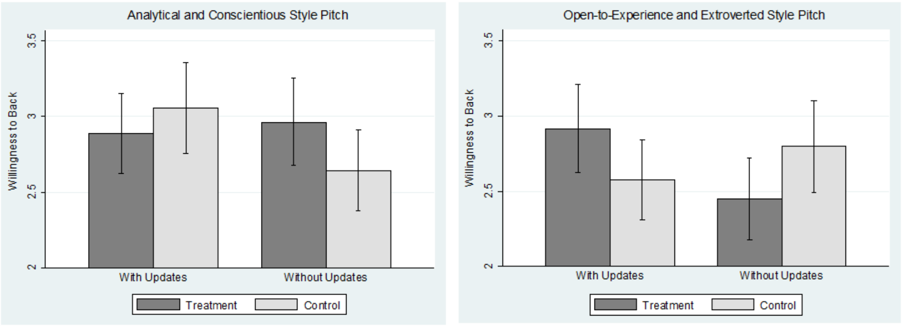
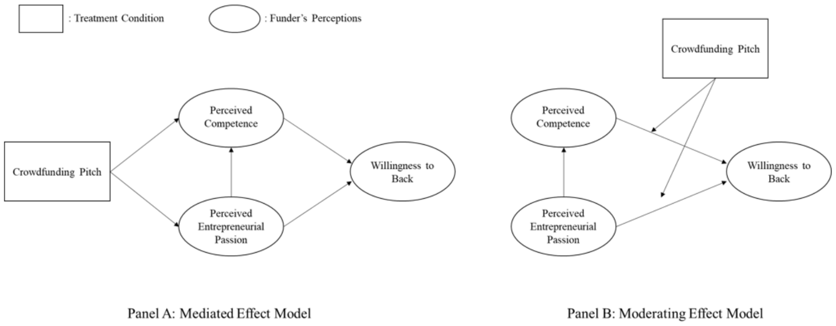


Figure 2. Effect of Pitch Treatment on Willingness-to-Back, by Pitch Style

Notes: Plots indicate 95% confidence intervals.

- Then, tease out the underlying mechanisms.

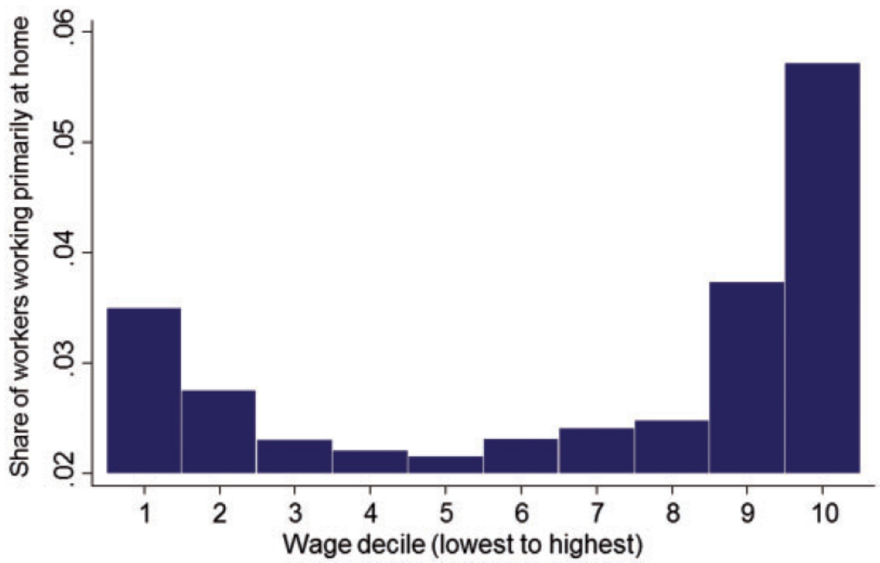


Park, J., Kim, J., Cho, D. and Lee, B., 2018. Pitching with Style: The Role of the Entrepreneur's Video Pitch on Online Crowdfunding. *KAIST Working Paper*.

(7) Limitation of Randomized Experiment

- Lack of external validity
  - ➢ This randomized experiment only tells about the WFH effectiveness for low-income type employees.

Largest occupations:
Telesales, IT Support and Childcare



Largest occupations:
Managers, Sales and IT

FIGURE I

In the United States Working Primarily from Home is Relatively More Common for the Highest and Lowest Wage Deciles

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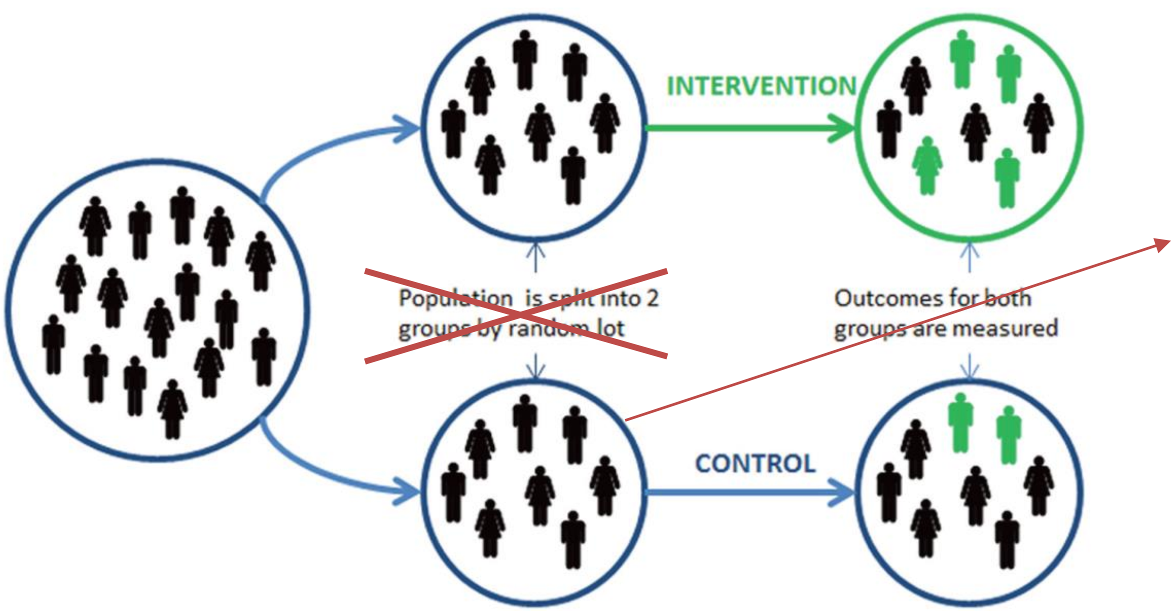
Bloom, N., Liang, J., Roberts, J. and Ying, Z.J., 2014. Does Working from Home Work? Evidence from a Chinese Experiment. *Quarterly Journal of Economics*, 130(1), pp.165-218.

Experiment without Random Assignment
: Quasi-Experiment

Finding Comparable Controls

- Quasi-experiments share similarities with the randomized experiment, but they specifically lack random assignment to treatment or control.
- The goal of quasi-experiments is to find comparable controls.
    - ➢ It’s not algebra. It’s all about research design and empirical context.



Comparable controls

= As-if orthogonality

= There is almost no selection bias

= Identification assumption satisfied

Finding Comparable Controls

- Example: Returns to education
  - Twins study (Ashenfelter and Krueger 1994)
    - Twin siblings are (nearly perfect) comparable controls.

$$\ln w_{1,j} = \alpha + \rho S_{1,j} + \beta \boldsymbol{A_j} + \gamma \boldsymbol{F_j} + e_{1,j}$$

$$\ln w_{2,j} = \alpha + \rho S_{2,j} + \beta \boldsymbol{A_j} + \gamma \boldsymbol{F_j} + e_{2,j}$$

where j stands for family, and A_j and F_j are a set of abilities and family factors (e.g., parents' job) shared by the twins.

  - First-differencing

$$\ln w_{1,j} - \ln w_{2,j} = \rho\left(S_{1,j} - S_{2,j}\right) + (e_{1,j} - e_{2,j})$$

Variable	OLS (i)	First difference (v)
Own education	0.084 (0.014)	0.092 (0.024)
Sibling's education	—	—
Age	0.088 (0.019)	—
Age squared (÷100)	−0.087 (0.023)	—
Male	0.204 (0.063)	—
White	−0.410 (0.127)	—

Ashenfelter, O. and Krueger, A., 1994. Estimates of the Economic Return to Schooling from a New Sample of Twins. *American Economic Review*, 84(5), pp.1157-1173.

Quasi-Experiments Depend on Empirical Contexts

- Example: Neighborhood and children's outcomes (Chetty and Hendren 2018)

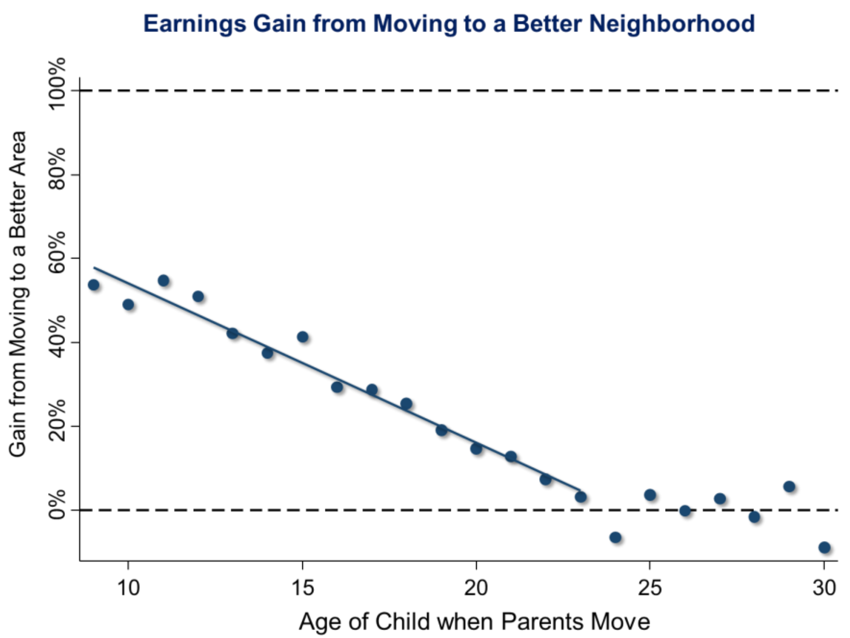
- Two very different explanations for variation in children's outcomes across areas:
  - Sorting: different people live in different places
  - Causal effects: places have a causal effect on upward mobility for a given person

- Ideal experiment: randomly assign children to neighborhoods and compare outcomes in adulthood

Chetty, R. and Hendren, N., 2018. The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects. *Quarterly Journal of Economics*, forthcoming

Quasi-Experiments Depend on Empirical Contexts

- Chetty and Hendren (2018) approximate this experiment using a quasi-experimental design.
  - Key idea: exploit variation in age of child when family moves to identify causal effects of environment
  - Key assumption: timing of moves to a better/worse area unrelated to other determinants of child's outcomes



Chetty, R. and Hendren, N., 2018. The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects. *Quarterly Journal of Economics*, forthcoming

Quasi-Experiments Depend on Empirical Contexts

- This assumption might not hold for two reasons:
  - Parents who move to good areas when their children are young might be different from those who move later.
  - Moving may be related to other factors (e.g., change in parents' job) that affect children directly.

- Chetty and Hendren (2018) use a quasi-experiment design of family moves.

family move →

13 years old

11 years old

Comparing the future income between siblings to identify an effect of "2 years exposure" to new town

Chetty, R. and Hendren, N., 2018. The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects. *Quarterly Journal of Economics*, forthcoming

Difference-in-Differences

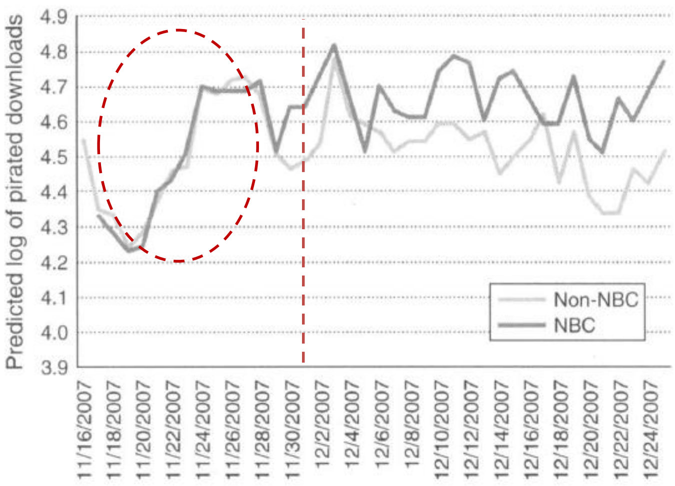
Natural Experiments

- In a natural experiment, individuals expose to the experimental and control conditions which are determined by nature or by other factors outside the control of the investigators.
  - ➢ (Identification assumption) the process governing the exposures arguably resembles random assignment.

    = Treatment and control groups have parallel trends without treatment.

- (Example) NBC's decision to remove its own content from iTunes (Danaher et al. 2010)

Figure 1 NBC vs. Non-NBC Piracy Surrounding December 1, 2007



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Danaher, B., Dhanasobhon, S., Smith, M.D. and Telang, R., 2010. Converting Pirates without Cannibalizing Purchasers: The Impact of Digital Distribution on Physical Sales and Internet Piracy. *Marketing Science*, 29(6), pp.1138-1151.

Difference-in-Differences

- Natural experiments are well-equipped into difference-in-differences specifications with fixed effects.
  - ➢ DID is an extension of fixed effects model.

    = (individual- and time-specific) fixed effects + time-varying unobservables

	Before Treatment	**After Treatment**
Treatment Group	T_B	T_A
Control Group	C_B	C_A

With fixed effects, it could capture the within-variation caused by treatment

$$\text{DID estimator} = (T_A - T_B) - (C_A - C_B)$$

With fixed effects, it could capture time-varying unobservables

Difference-in-Differences

- DID specification as a regression

	Before Treatment	After Treatment
Treatment Group	T_B $= \boldsymbol{\beta_0} + \boldsymbol{\beta_2}$	T_A $= \boldsymbol{\beta_0} + \boldsymbol{\beta_1} + \boldsymbol{\beta_2} + \boldsymbol{\beta_3}$
Control Group	C_B $= \boldsymbol{\beta_0}$	C_A $= \boldsymbol{\beta_0} + \boldsymbol{\beta_1}$

$$y_{it} = \beta_0 + \beta_1 After_{it} + \beta_2 Treat_{it} + \beta_3 After_{it} \times Treat_{it} + \tau_i + \gamma_t + \varepsilon_{it}$$

DID estimator = $(T_A - T_B) - (C_A - C_B) = \boldsymbol{\beta_3}$

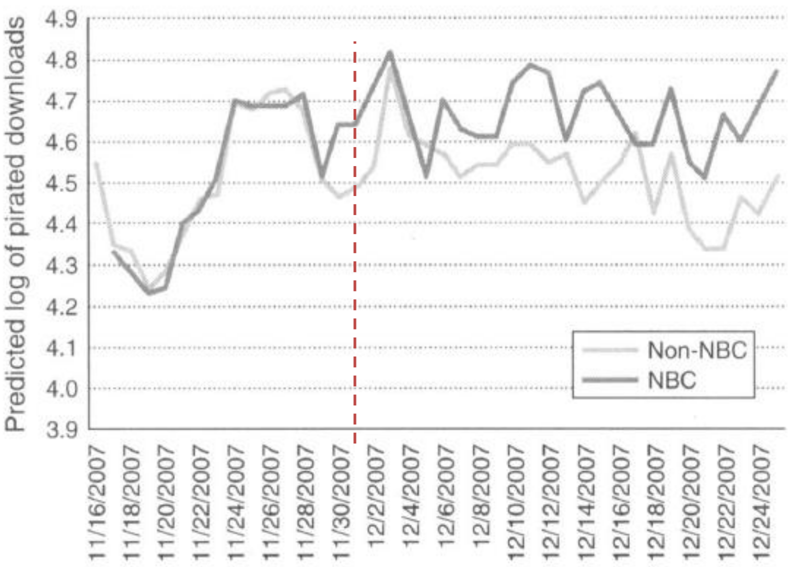
Difference-in-Differences

- Example: NBC's decision to remove its own content from iTunes (Danaher et al. 2010)

$$\log(\text{downloads}_{it}) = \alpha_i + \beta D_t + \gamma \text{NBC}_i \times D_t + \varepsilon_{it}$$

D_t is a single indicator variable equal to one if the observation occurs in the two weeks after December 1, 2007 and equal to zero if it is in the two weeks before that date

Figure 1 NBC vs. Non-NBC Piracy Surrounding December 1, 2007



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Difference-in-Differences

- Example: Clean air act amendments (Chay and Greenstone 2005)
  - Key identification assumption: Parallel trends before treatment

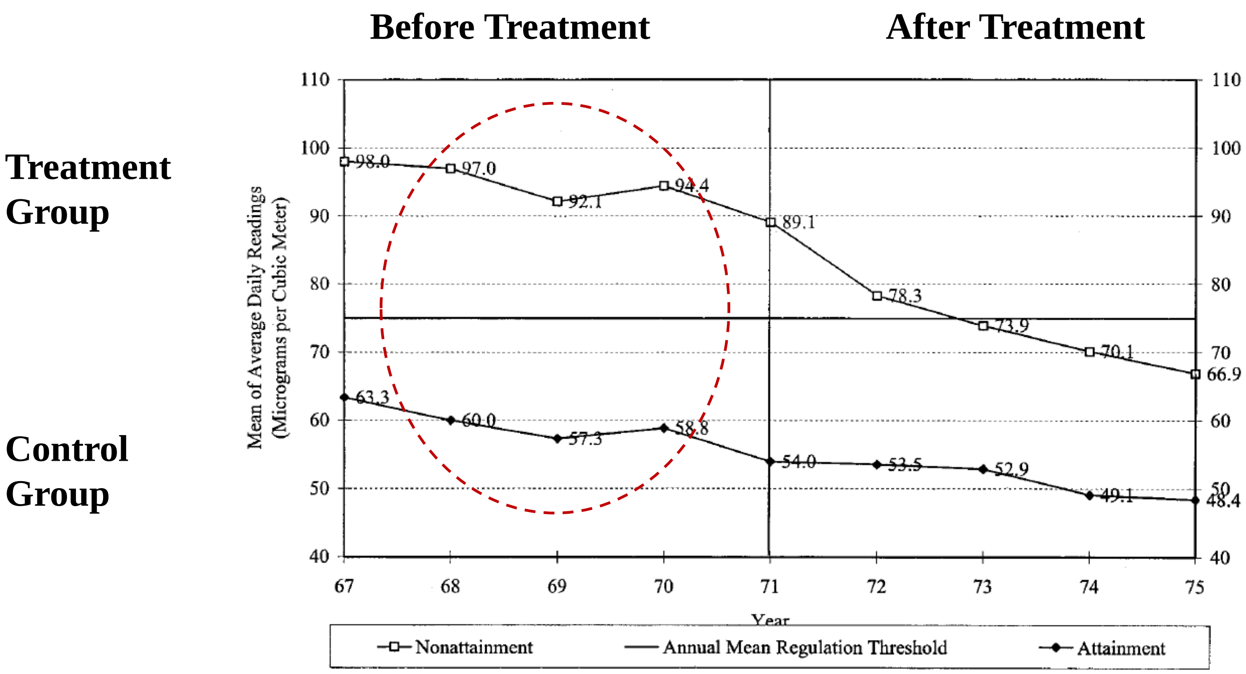


Fig. 2.—1967–75 trends in TSPs concentrations, by 1972 attainment status. The data points are derived from the 228 counties that were continuously monitored in this period. The 116 attainment counties had a 1970 population of approximately 25.8 million people, whereas about 63.4 million people lived in the 112 nonattainment counties in the same year. Each data point is the unweighted mean across all counties in the relevant regulatory category.

Chay, K.Y. and Greenstone, M., 2005. Does Air Quality Matter? Evidence from the Housing Market. *Journal of Political Economy*, 113(2), pp.376-424.

DID Relative Time Model

- Relative time model includes a series of chronological time dummies before and after treatment.

- Example: Uber's entry as a natural shock (Greenwood and Wattal 2017)

  "Econometrically, the primary benefit of this model is that it can determine if a pretreatment trend exists (i.e., a significant difference between treated and untreated counties before treatment) in order to determine if the untreated counties are an acceptable control group." (p. 170)

Table 4. Relative Time Model of Uber Entry on Alcohol Related Moto

Dependent Variable	(1) ln(Num Deaths)
Model	**Uber X**
Rel Time $_{(t-4)}$	0.0435
	(0.0280)
Rel Time $_{(t-3)}$	-0.00199
	(0.0270)
Rel Time $_{(t-2)}$	-0.0314
	(0.0274)
Rel Time $_{(t-1)}$	-0.0159
	(0.0272)
Rel Time $_{(t0)}$	Omitt
Rel Time $_{(t+1)}$	-0.0494*
	(0.0292)
Rel Time $_{(t+2)}$	-0.0301
	(0.0312)
Rel Time $_{(t+3)}$	-0.0539*
	(0.0314)
Rel Time $_{(t+4)}$	-0.214***
	(0.0705)
Rel Time $_{(t+5)}$	-1.124***
	(0.300)
Constant	0.216***
	(0.0185)
Time Fixed Effects	Yes
City Fixed Effects	Yes
N	12,420
R-squared	0.041

Greenwood, B.N. and Wattal, S., 2017. Show Me the Way to Go Home: An Empirical Investigation of Ride-Sharing and Alcohol Related Motor Vehicle Fatalities. *MIS Quarterly*, 41(1), pp.163-187.

DID with Matching

- One of the most challenging problems is to compose the control group who is very similar to the treatment group in all respects but for the treatment.
  - Unlike natural experiments, research context with self-selection might violate "random assignment."

- Matching technique:
  - Its goal is to construct the control group that is as possible to the treatment group on the observed characteristics.
  - Propensity score matching (Rosenbaum and Rubin 1983): reducing various variables into one dimension (i.e., propensity to be treated)
  - Coarsened exact matching (Blackwell et al. 2009): matching for all variables

Rosenbaum, P.R. and Rubin, D.B., 1983. The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, 70(1), pp.41-55.

Blackwell, M., Iacus, S.M., King, G. and Porro, G., 2009. CEM: Coarsened Exact Matching in Stata. *The Stata Journal*, 9(4), pp.524-546.

DID with Matching

- Example: Social media participation (Rishika et al. 2013)
  - Customers tend to self-select into social media participation. That is, treatment and control groups may be systematically different, which influences the outcomes (e.g., customer visit).

	Before Treatment	After Treatment
Treatment (Social media participants)	T_B	T_A
Control (Social media non-participants)	C_B	C_A

Rishika, R., Kumar, A., Janakiraman, R. and Bezawada, R., 2013. The Effect of Customers' Social Media Participation on Customer Visit Frequency and Profitability: An Empirical Investigation. *Information Systems Research*, 24(1), pp.108-127.

Regression Discontinuity

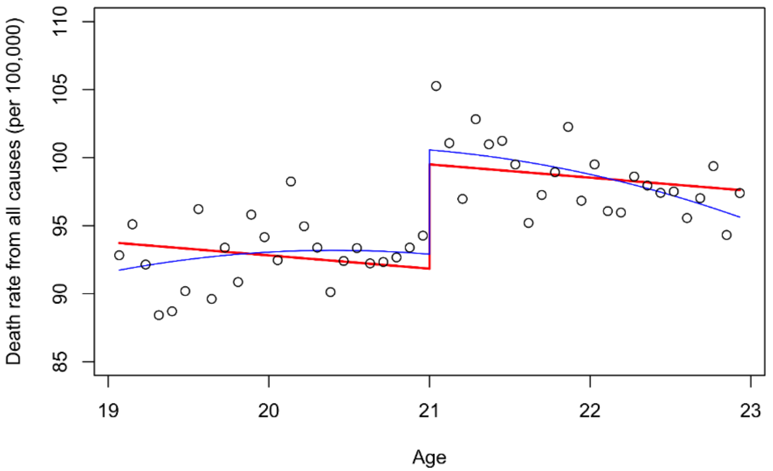
Regression Discontinuity

- Sharp regression discontinuity
  - This method can be useful especially when treatment status is a deterministic function of a running variable.
  - (Example) Alcohol and death (running variable: age)

$$D_a = \alpha + \rho A_a + \boxed{\gamma a} + e_a$$

$$A_a = 1 \text{ if } a \geq 21, 0 \text{ otherwise}$$

where D_a is death rate and a is age (alcohol is allowed since 21).



If this term can account for all trends between age and death rate, A_a should be free from endogeneity. (Note that A_a is just a function of age.)

Regression Discontinuity

- Fuzzy regression discontinuity
  - ➢ It uses sharp regression discontinuity as instruments in the first stage.
  - ➢ (Example) Long-term effects of class size (Fredriksson et al. 2012)

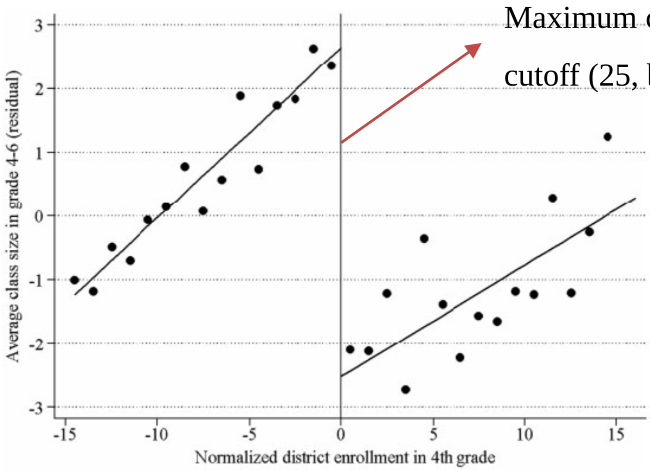
For an individual i, the outcome equation of interest is

$$y_{id\tau} = \beta CS_{d\tau} + \alpha_\tau + f_\tau^k(e_{d\tau}) + \epsilon_{id\tau} \ , \quad (2)$$

where we use $Above_{d\tau}$ as the instrument for class size ($CS_{d\tau}$):

$$CS_{d\tau} = \gamma Above_{d\tau} + \delta_\tau + g_\tau^k(e_{d\tau}) + \nu_{d\tau}, \quad (3)$$

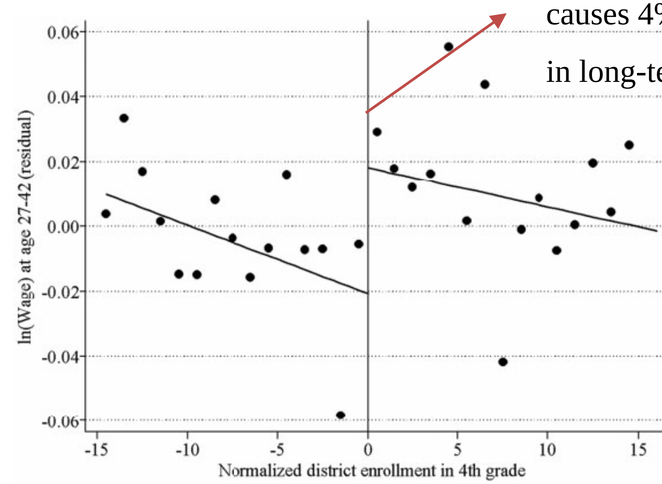
First stage



Maximum class size cutoff (25, by law)

(Second stage) Reduced-form

Class size reduction causes 4% increase in long-term earning



Fredriksson, P., Öckert, B. and Oosterbeek, H., 2012. Long-Term Effects of Class Size. *Quarterly Journal of Economics*, 128(1), pp.249-285.

Conclusion

It's All about Research Design and Empirical Context

- Researchers will be "successful at identifying the causal effect not because of the complex statistical methods that are applied to the data, but due to the effort in developing a design before data are collected." (Keele 2015, p. 331)

- The plausibility of an identification strategy depends on the empirical context.
  - ➢ For every identification strategy, researchers can find contexts where it is plausible and other contexts where that same strategy is indefensible.

Keele, L., 2015. The Statistics of Causal Inference: A View from Political Methodology. *Political Analysis*, 23(3), pp.313-335.

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