Experiments 1: Simple randomization

LQRPS

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Recap from Tuesday:

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- omitted variable bias
- Gilens & Page + Bashir
- panel data (FE) & clustered se's
- multilevel models (RE)
- (interactions & limited DV's)

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- is it credible?
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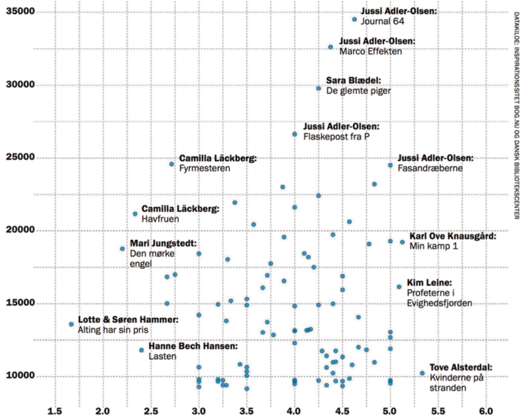

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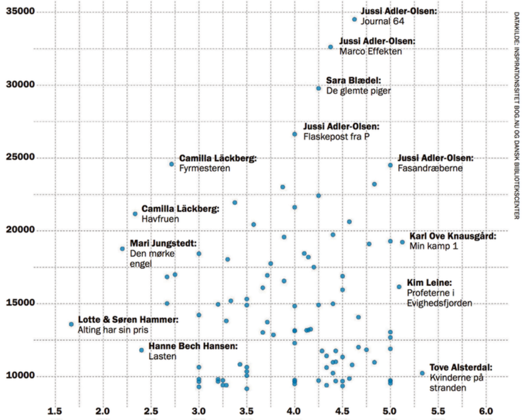

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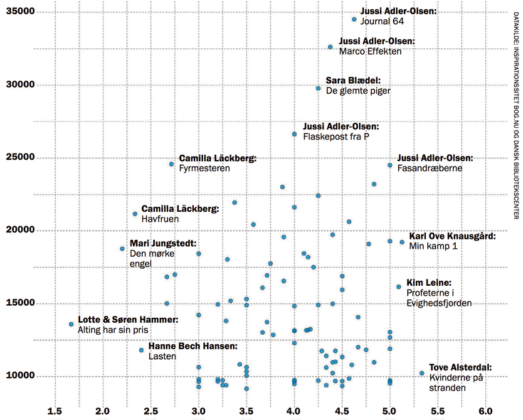

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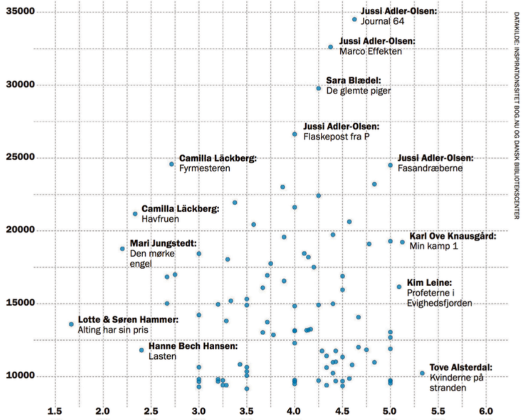

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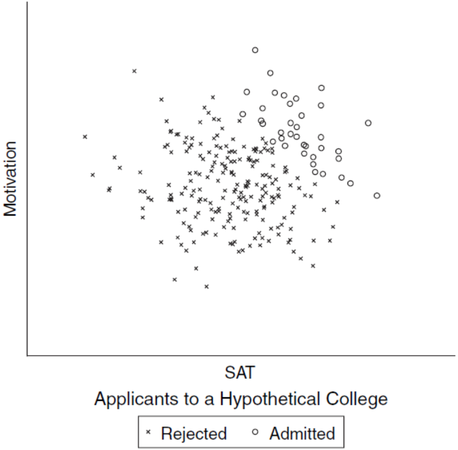

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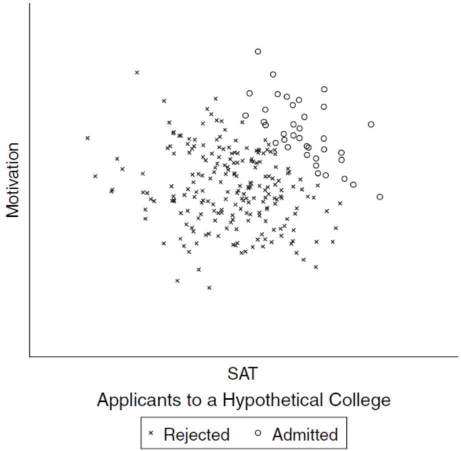

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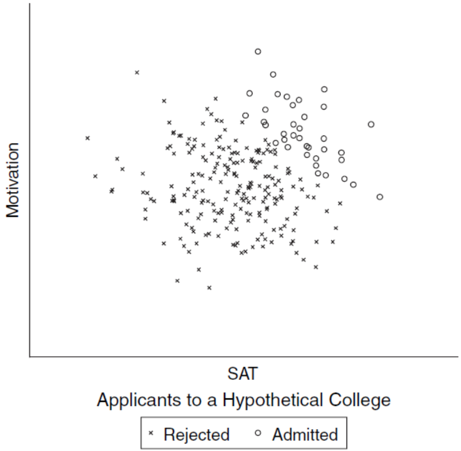

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Motivating example: NHIS ($N \approx 18.600$)

TABLE 1.1
Health and demographic characteristics of insured and uninsured couples in the NHIS

	Husbands			Wives		
	Some HI (1)	No HI (2)	Difference (3)	Some HI (4)	No HI (5)	Difference (6)
A. Health						
Health index	4.01	3.70	.31	4.02	3.62	.39
	[.93]	[1.01]	(.03)	[.92]	[1.01]	(.04)
B. Characteristics						
Nonwhite	.16	.17	−.01	.15	.17	−.02

Two MIT students, **K**huzdar & **M**aria

$$Y_{1K} - Y_{0K} = 4 - 3 = 1 \tag{1}$$

$$Y_{1M} - Y_{0M} = 5 - 5 = 0 \tag{2}$$

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Full potential outcomes schedule for Khuzdar & Maria:

	Khuzdar	Maria
Y_{0i}	3	5
Y_{1i}	4	5
D_i	1	0
Y_i	4	5
$Y_{1i} - Y_{0i}$	1	0

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Observed outcomes:

	Khuzdar	Maria
Y_{0i}	?	5
Y_{1i}	4	?

$$\rightarrow \bar{Y}_1 - \bar{Y}_0 = 4 - 5 = -1$$

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A simple comparison of outcomes reflects ATE among the treated + selection bias:

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\begin{aligned}
Y_K - Y_M &= Y_{1K} - Y_{0M} && (3)\\
&= Y_{1K} - Y_{0K} + Y_{0K} - Y_{0M} && (4)\\
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With more general notation, cf. GG:

$$E[Y_{1i}|D_i = 1] - E[Y_{0i}|D_i = 0] =$$
$$E[Y_{1i} - Y_{0i}|D_i = 1] + E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0] \quad (7)$$

when treatment is assigned randomly, $Y_0 i$ is independent of D_i:

$$E[Y_{0i}|D_i = 1] - E[Y_{0i}|D_i = 0] = 0 \quad (8)$$

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We can evaluate the effectiveness of randomization using *balance tests*

TABLE 1.3
Demographic characteristics and baseline health in the RAND HIE

	Means	Differences between plan groups			
	Catastrophic plan (1)	Deductible – catastrophic (2)	Coinsurance – catastrophic (3)	Free – catastrophic (4)	Any insurance – catastrophic (5)
A. Demographic characteristics					
Female	.560	−.023	−.025	−.038	−.030
		(.016)	(.015)	(.015)	(.013)
Nonwhite	.172	−.019	−.027	−.028	−.025
		(.027)	(.025)	(.025)	(.022)
Age	32.4	.56	.97	.43	.64
	[12.9]	(.68)	(.65)	(.61)	(.54)
Education	12.1	−.16	−.06	−.26	−.17
	[2.9]	(.19)	(.19)	(.18)	(.16)
Family income	31,603	−2,104	970	−976	−654
	[18,148]	(1,384)	(1,389)	(1,345)	(1,181)
Hospitalized last year	.115	.004	−.002	.001	.001
		(.016)	(.015)	(.015)	(.013)
B. Baseline health variables					
General health index	70.9	−1.44	.21	−1.31	−.93
	[14.9]	(.95)	(.92)	(.87)	(.77)

Context: the heyday of behavioralist research

Motivation: the R. A. Fisher legacy

»Perhaps Fisher's most fundamental contribution has been the concept of achieving pre-experimental equation of groups through randomization. This concept, and with it the rejection of the concept of achieving equation through matching (as intuitively appealing and misleading as that is) has been difficult for educational researchers to accept.«

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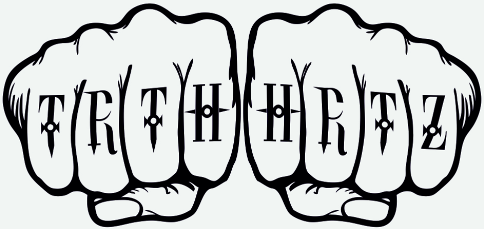
»For the usual highly motivated researcher the nonconfirmation of a cherished hypothesis is actively painful. As a biological and psychological animal, the experimenter is subject to laws of learning which lead him inevitably to associate this pain with the contiguous stimuli and events. These stimuli are apt to be the experimental process itself, more vividly and directly than the 'true' source of frustration, i.e., the inadequate theory. This can lead, perhaps unconsciously, to the avoidance or rejection of the experimental process.«



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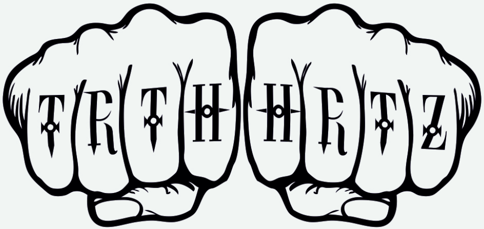

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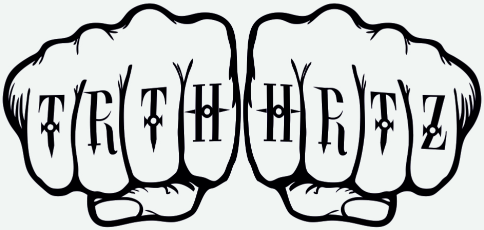

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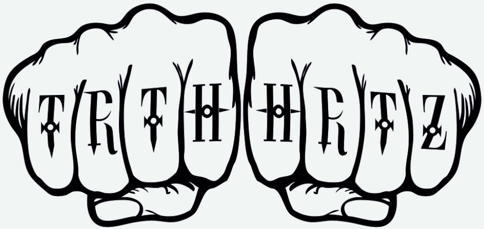

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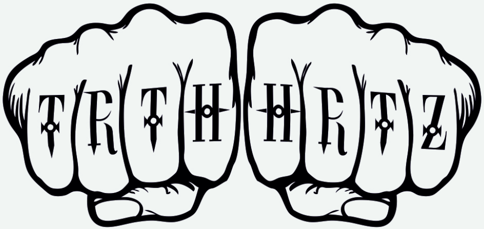

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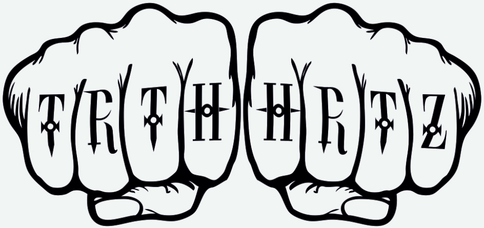

Canonical distinction: internal vs. external validity

Threats to internal validity:

1. history
2. maturation
3. testing
4. instrumentation
5. statistical regression
6. selection bias
7. experimental mortality
8. selection-maturation interaction

Threats to external validity:

1. interaction effect of testing
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2. one-group pretest-posttest design
3. static-group comparison
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5. Solomon four-group design
6. posttest-only control group design

The severity of each threat depends on choice of ‘pre-experimental’ (1-3) or ‘true experimental’ (4-6) design

1. one-shot case study
2. one-group pretest-posttest design
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Threats to validity across design types

TABLE 1

SOURCES OF INVALIDITY FOR DESIGNS 1 THROUGH 6

	Sources of Invalidity											
	Internal								External			
	History	Maturation	Testing	Instrumentation	Regression	Selection	Mortality	Interaction of Selection and Maturation, etc.	Interaction of Testing and X	Interaction of Selection and X	Reactive Arrangements	Multiple-X Interference
Pre-Experimental Designs:												
1. One-Shot Case Study *X O*	–	–				–	–			–		
2. One-Group Pretest-Posttest Design *O X O*	–	–	–	–	?	+	+	–	–	–	?	
3. Static-Group Comparison *X O* *O*	+	?	+	+	+	–	–	–		–		
True Experimental Designs:												
4. Pretest-Posttest Control Group Design *R O X O* *R O O*	+	+	+	+	+	+	+	+	–	?	?	
5. Solomon Four-Group Design *R O X O* *R O O* *R X O* *R O*	+	+	+	+	+	+	+	+	+	?	?	
6. Posttest-Only Control Group Design *R X O* *R O*	+	+	+	+	+	+	+	+	+	?	?	

Exercise RQ: Effect of exposure to misinformation on social media on political trust

→ what would an effective research design look like? How would it guard against the threats identified by Campbell & Stanley?

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Questions or comments?

Gerber & Green's procedure:

»First, determine N, the number of subjects in your experiment, and m, the number of subjects who will be allocated to the treatment group. Second, set a random number 'seed' using a statistics package, so that your random numbers may be reproduced by anyone who cares to replicate your work. Third, generate a random number for each subject. Fourth, sort the subjects by the random numbers in ascending order. Finally, classify the first m observations as the treatment group.« (37)

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Questions or comments?

TABLE 2. Effects of Four Mail Treatments on Voter Turnout in the August 2006 Primary Election

	Experimental Group				
	Control	Civic Duty	Hawthorne	Self	Neighbors
Percentage Voting	29.7%	31.5%	32.2%	34.5%	37.8%
N of Individuals	191,243	38,218	38,204	38,218	38,201

Neighbors mailing

30423-3

For more information: (517) 351-1975
email: etov@grebner.com
Practical Political Consulting
P. O. Box 6249
East Lansing, MI 48826

PRSRT STD
U.S. Postage
PAID
Lansing, MI
Permit # 444

ECRLOT **C050
THE JACKSON FAMILY
9999 MAPLE DR
FLINT MI 48507

Dear Registered Voter:

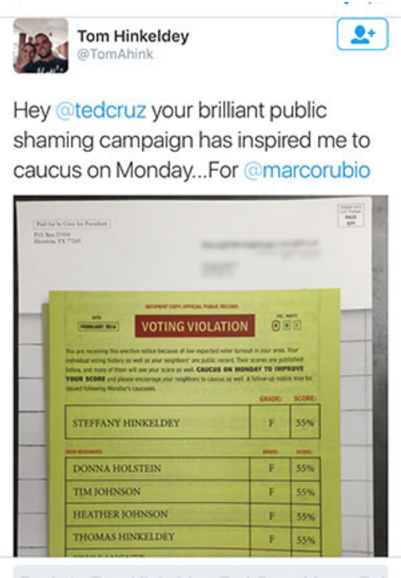
WHAT IF YOUR NEIGHBORS KNEW WHETHER YOU VOTED?

Why do so many people fail to vote? We've been talking about the problem for years, but it only seems to get worse. This year, we're taking a new approach. We're sending this mailing to you and your neighbors to publicize who does and does not vote.

The chart shows the names of some of your neighbors, showing which have voted in the past. After the August 8 election, we intend to mail an updated chart. You and your neighbors will all know who voted and who did not.

DO YOUR CIVIC DUTY — VOTE!

MAPLE DR	Aug 04	Nov 04	Aug 06
9995 JOSEPH JAMES SMITH	Voted	Voted	_____
9995 JENNIFER KAY SMITH		Voted	_____
9997 RICHARD B JACKSON		Voted	_____
9999 KATHY MARIE JACKSON		Voted	_____


Tom Hinkeldey
@TomAhink
Hey @tedcruz your brilliant public shaming campaign has inspired me to caucus on Monday...For @marcorubio
VOTING VIOLATION
GRADE: SCORE:
STEFFANY HINKELDEY F 55%
DONNA HOLSTEIN F 55%
TIM JOHNSON F 55%
HEATHER JOHNSON F 55%
THOMAS HINKELDEY F 55%

Break for lunch