ECON 251 Office Hours

Review + Extensions

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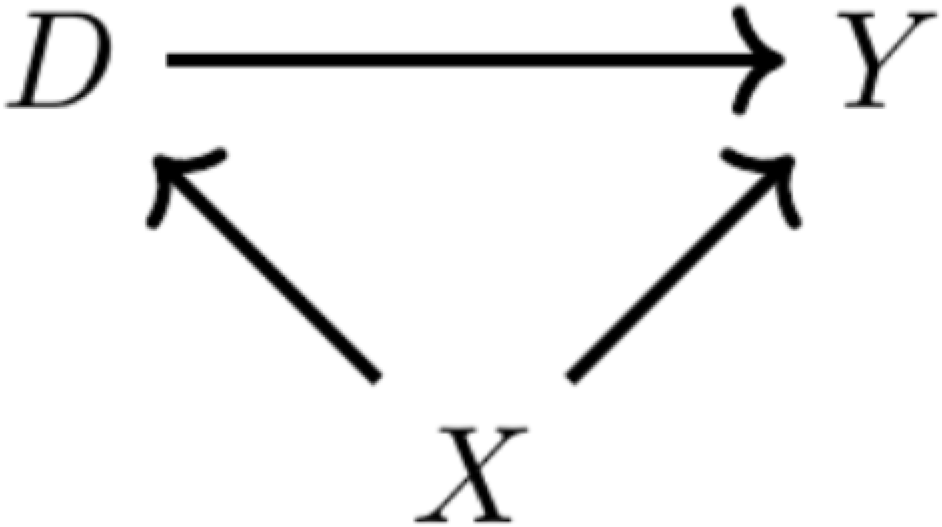
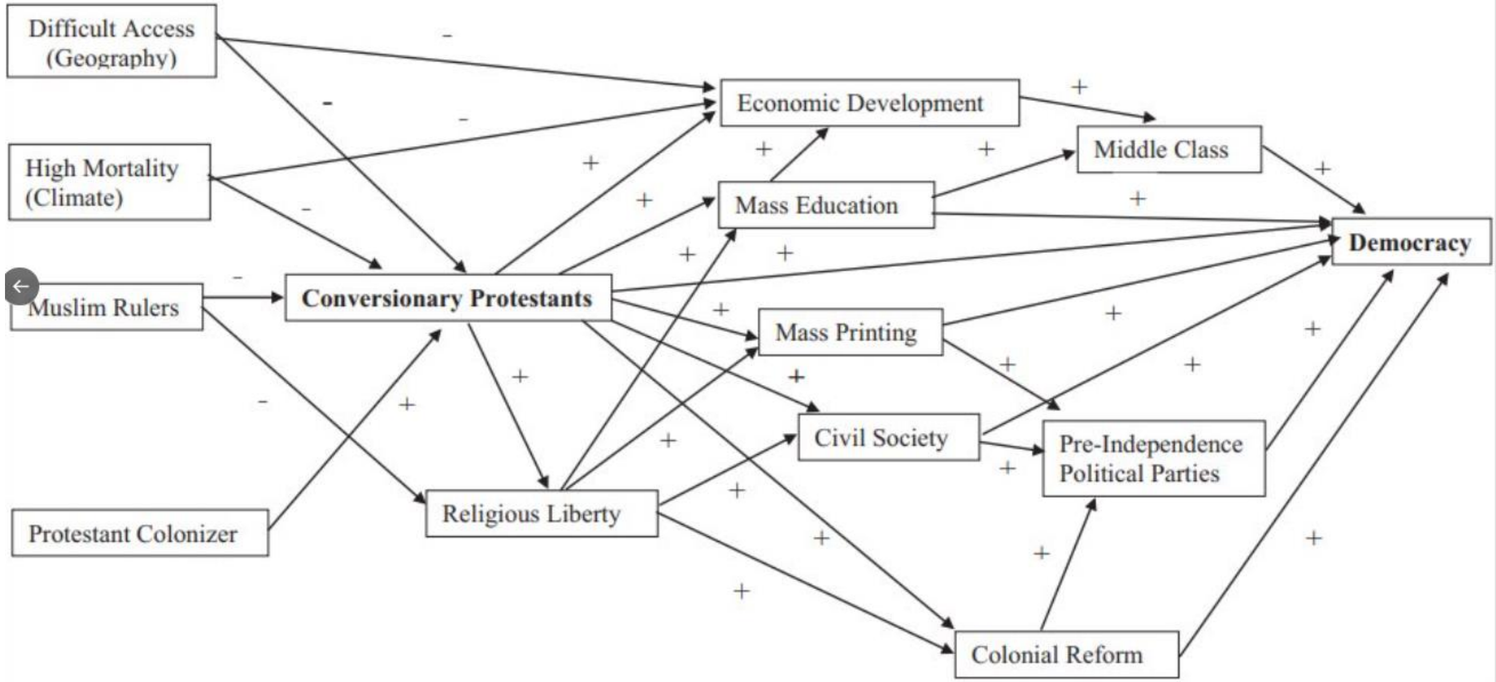
Fall 2022

Just kidding of course! :)





Outline

1. Review: HW4 solutions
2. Review: Final exam questions
3. Review: OLS, IV, DID, LPM

4. Recommendations for further reading
    - Directed Acyclic Graphs (DAGs) for intuition and identification
    - Bayesian methods in econometrics
    - James-Stein Paradox and shrinkage estimators

Review HW4 solutions

Review for Final Exam

- HW3 solutions
- Midterm solutions
- HW2 solutions
- HW1 solutions

- Discussion notes solutions
- Lecture notes solutions

Review

1. OLS assumptions and theorems
2. IV assumptions and results
3. DID assumptions and results
4. LPM intuition and results

OLS $\min_{\{\beta_0,\beta_1,\ldots,\beta_k\}} \frac{1}{N}\sum_{i=1}^{N}(Y_i - \beta_0 - \beta_1 X_{i1} - \cdots - \beta_k X_{ik})^2 \quad \Rightarrow \quad \hat{\beta}_j^{OLS}$

- MLR1 (linear outcome model) $Y_i = \beta_0 + \beta_1 X_{i1} + \cdots + \beta_k X_{ik} + U_i$
- MLR2 (random sampling) $\{Y_i, X_{i1}, \ldots, X_{ik}\}_{i=1}^{N}$ is random draw
- MLR3 (no collinearity) no X_{ij} linear function of any other X_{il}
- MLR4 (independence) $E[U_i | X_{i1}, \ldots, X_{ik}] = 0$
- MLR5 (homoskedasticity) $\text{Var}(U_i | X_{i1}, \ldots, X_{ik}) = \sigma^2$
- MLR6 (normality) $U_i \sim N(0, \sigma^2)$

- T1 (unbiased) MLR1+2+3+4 $\Rightarrow$ $E\left[\widehat{\beta}_j^{\,OLS}\right] = \beta_j \quad \forall j = \{0,1,\ldots,k\}$
- T2 (efficient-GM) MLR1+2+3+4+5 $\Rightarrow$ $E\left[\widehat{\beta}_j^{\,OLS}\right] = \beta_j \quad \forall j$

$$\text{Var}\left[\widehat{\beta}_j^{\,OLS}\right] \leq \text{Var}\left[\widehat{\beta}_j^{\,\text{other linear}}\right]$$

- T3 (efficient-CL) MLR1+2+3+4+5+6 $\Rightarrow$ $\widehat{\beta}_j^{\,OLS} \sim N\left(\beta_j, \text{Var}\left[\beta_j\right]\right) \quad \forall j$

Linear Probability Model (LPM) $Y = \beta_0 + \beta_1 X + U$
Binary Outcome $Y \in \{0,1\}$

- Independence + binary Y gives "change in prob(Y=1)" interpretation (pp!)

$$E[Y|X] = P[Y = 1|X] \cdot 1 + P[Y = 1|X] \cdot 0 = P[Y = 1|X]$$
$$\Rightarrow \beta_1 = \frac{\partial}{\partial X} P[Y = 1|X]$$

- LPM is nice because…
  1. Easy to estimate
  2. Easy to interpret
- LPM is problematic because…
  1. Predicted values of outcome can be outside of $[0,1]$ interval
  2. Does not make sense for X to change $P[Y = 1|X]$ linearly
  3. Homoskedasticity is always violated: $\mathrm{Var}(Y|X) = P(Y = 1|X)[1 - P(Y = 1|X)]$

Omitted variable bias (OVB)

"True" model	$\log Y_i = \alpha + \beta \cdot S_i + \delta^{X \to Y} \cdot X_i + U_i$	$\mathrm{Cov}(S_i, U_i) = 0$
Our model	$\log Y_i = a + b \cdot S_i + E_i$	
Auxiliary model	$X_i = c + \gamma^{S \to X} \cdot S_i + \eta_i$	

Naively assuming $\mathrm{Cov}(S_i, E_i) = 0$ in our model implies

$$b = \frac{\mathrm{Cov}(S_i, \log Y_i)}{\mathrm{Var}(S_i)}$$

$$= \beta + \gamma^{S \to X} \cdot \delta^{X \to Y}$$

= causal effect + (var in S related to X) $\cdot$ (var in X related to Y)

Mincer (1974) model of earnings $\log Y_i = \alpha + \beta \cdot S_i + U_i$

Instrumental variable (IV) Z_i decomposes S_i into S_i^{X} and S_i^{N}

- First stage generates predicted values for treatment $\hat{S}_i \coloneqq \hat{\pi}_0 + \hat{\pi}_1 Z_i$
- We estimate returns β from model $\log Y_i = \alpha + \beta \cdot \hat{S}_i + U_i$

- A valid instrument satisfies
  1. <u>Relevance</u> $\mathrm{Cov}(Z_i, S_i) \neq 0$
  2. <u>Exogeneity</u> $\mathrm{Cov}(Z_i, U_i) = 0$
  3. <u>Exclusion</u> no direct effect of Z_i on Y_i

Doing IV can be worse than OLS

- The OVB formula for OLS implies that it converges to

$$\operatorname*{plim}_{N\to\infty} \hat{\beta}^{OLS} = \beta + \frac{\mathrm{Cov}(S_i, U_i)}{\mathrm{Var}(S_i)}$$

- We have just shown that the MM estimator converges to

$$\operatorname*{plim}_{N\to\infty} \hat{\beta}^{MM} = \beta + \frac{\mathrm{Cov}(Z_i, U_i)}{\mathrm{Cov}(Z_i, S_i)}$$

- What if $\mathrm{Cov}(S_i, U_i) = 0$ or $\mathrm{Cov}(Z_i, U_i) = 0$ are not exactly $= 0$?
- Not clear which is more likely to hold without more context, but...
- $\mathrm{Cov}(Z_i, S_i) \approx 0$ (weak IV) ⇒ minor violations of IV exogeneity lead to large bias!

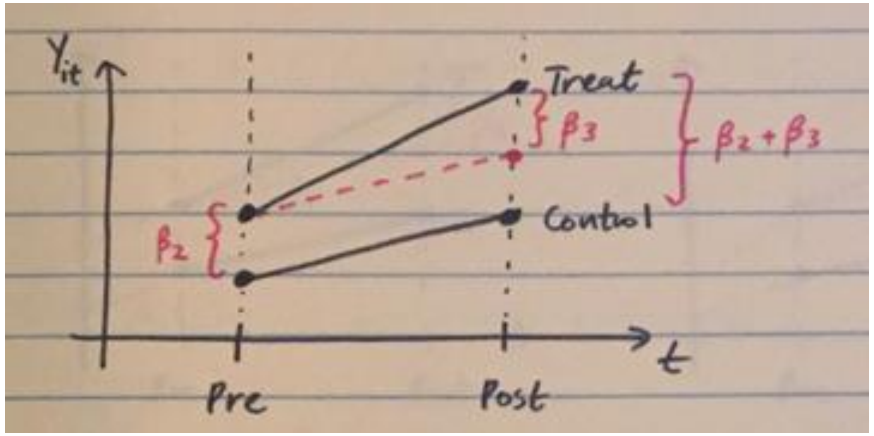
Difference-in-differences = compare Y change of units exposed to some policy T with Y change of unexposed

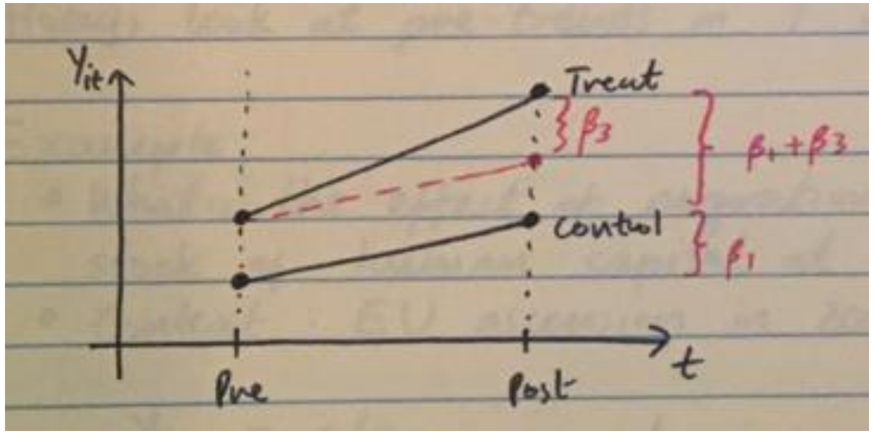
2 periods (before/after) and 2 groups (treated/control)

$Y_{it} \coloneqq$ outcome of interest

$P_t \coloneqq 1\{t \text{ is after treatment occurs}\}$

$T_i \coloneqq 1\{i \text{ is treated/exposed}\}$



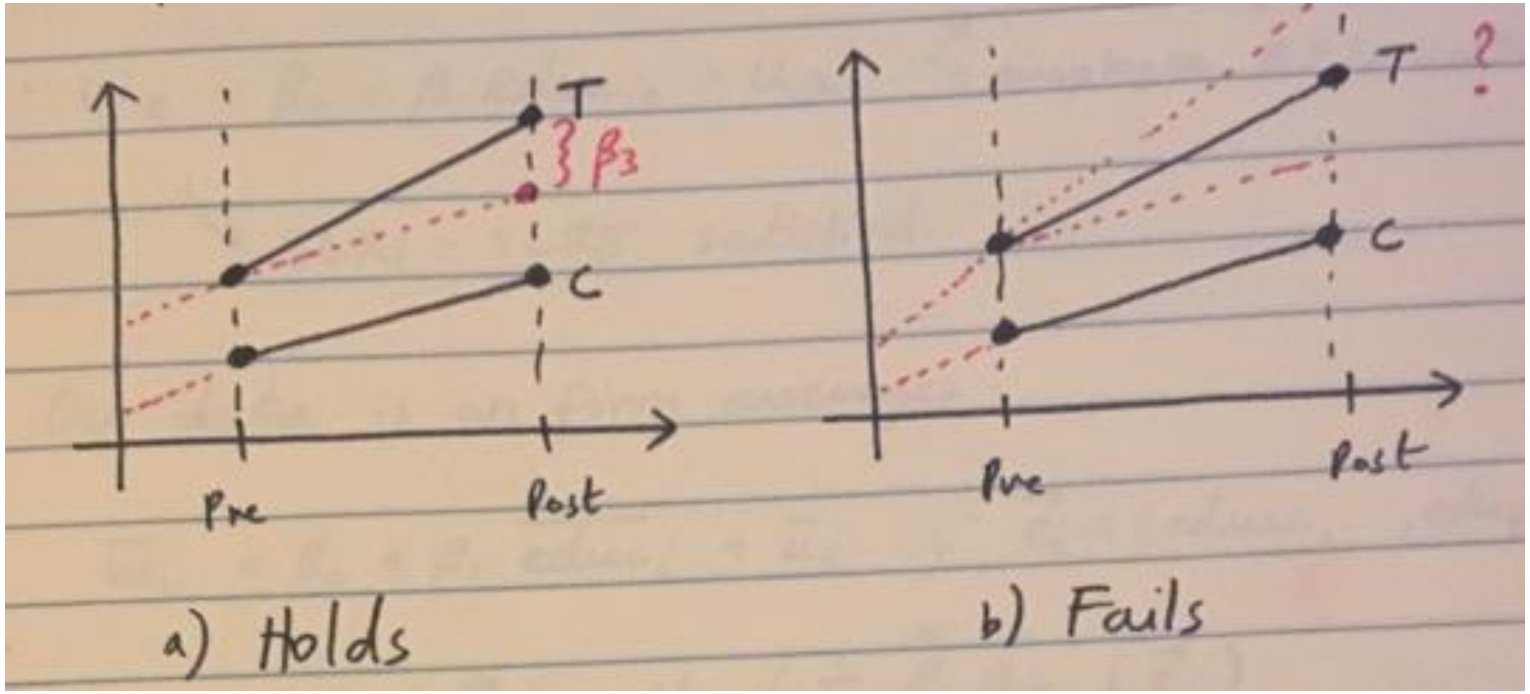


$$Y_{it} = \beta_0 + \beta_1 P_t + \beta_2 T_i + \beta_3 [P_t \cdot T_i] + U_i$$

	Before	After	After – Before
Control	β_0	$\beta_0 + \beta_1$	β_1
Treated	$\beta_0 + \beta_2$	$\beta_0 + \beta_1 + \beta_2 + \beta_3$	$\beta_1 + \beta_3$
Treat – Control	β_2	$\beta_2 + \beta_3$	β_3

Parallel Trends Assumption = exposed units Y without policy T would have changed like unexposed units Y

- PTA is an untestable assumption, just like OLS exogeneity or IV exogeneity
- However, if we have access to more data before policy, we can assess how likely it is to hold in practice… commonly known as "checking for pre-trends"
- One reason why people seem to like DD… visual check of identifying assumption!



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Causal Inference
The Mixtape

3 Directed Acyclic Graphs

The history of graphical causal modeling goes back to the early twentieth century and Sewall Wright, one of the fathers of modern genetics and son of the economist Philip Wright. Sewall developed path diagrams for genetics, and Philip, it is believed, adapted them for econometric identification (Matsueda 2012).[1]

But despite that promising start, the use of graphical modeling for causal inference has been largely ignored by the economics profession, with a few exceptions (J. Heckman and Pinto 2015; Imbens 2019). It was revitalized for the

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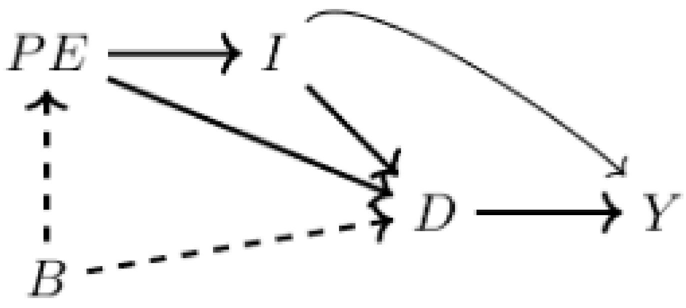
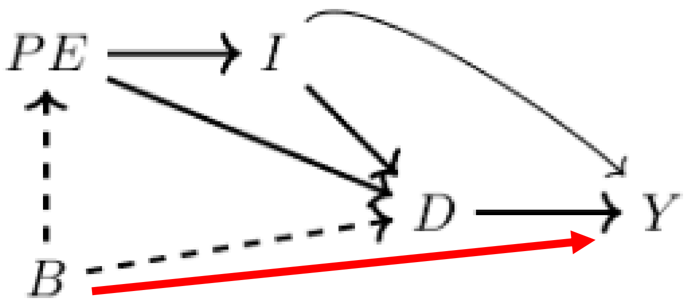
Example: Mincer (1974) model



Now that we have a DAG, what do we do? I like to list out all direct and indirect paths (i.e., backdoor paths) between D and Y. Once I have all those, I have a better sense of where my problems are. So:

1. $D \rightarrow Y$ (the causal effect of education on earnings)
2. $D \leftarrow I \rightarrow Y$ (backdoor path 1)
3. $D \leftarrow PE \rightarrow I \rightarrow Y$ (backdoor path 2)
4. $D \leftarrow B \rightarrow PE \rightarrow I \rightarrow Y$ (backdoor path 3)



Bayesian (vs frequentist) statistics

Psychon Bull Rev (2018) 25:155–177
DOI 10.3758/s13423-017-1272-1

BRIEF REPORT

Bayesian data analysis for newcomers

John K. Kruschke[1] · Torrin M. Liddell[1]

Published online: 12 April 2017

Abstract This article explains the foundational concepts of Bayesian data analysis using virtually no mathematical notation. Bayesian ideas already match your intuitions from everyday reasoning and from traditional data analysis. Simple examples of Bayesian data analysis are presented that illustrate how the information delivered by a Bayesian

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Psychon Bull Rev (2018) 25:178–206
DOI 10.3758/s13423-016-1221-4

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BRIEF REPORT

The Bayesian New Statistics: Hypothesis testing, estimation, meta-analysis, and power analysis from a Bayesian perspective

John K. Kruschke[1] · Torrin M. Liddell[1]

Published online: 7 February 2017

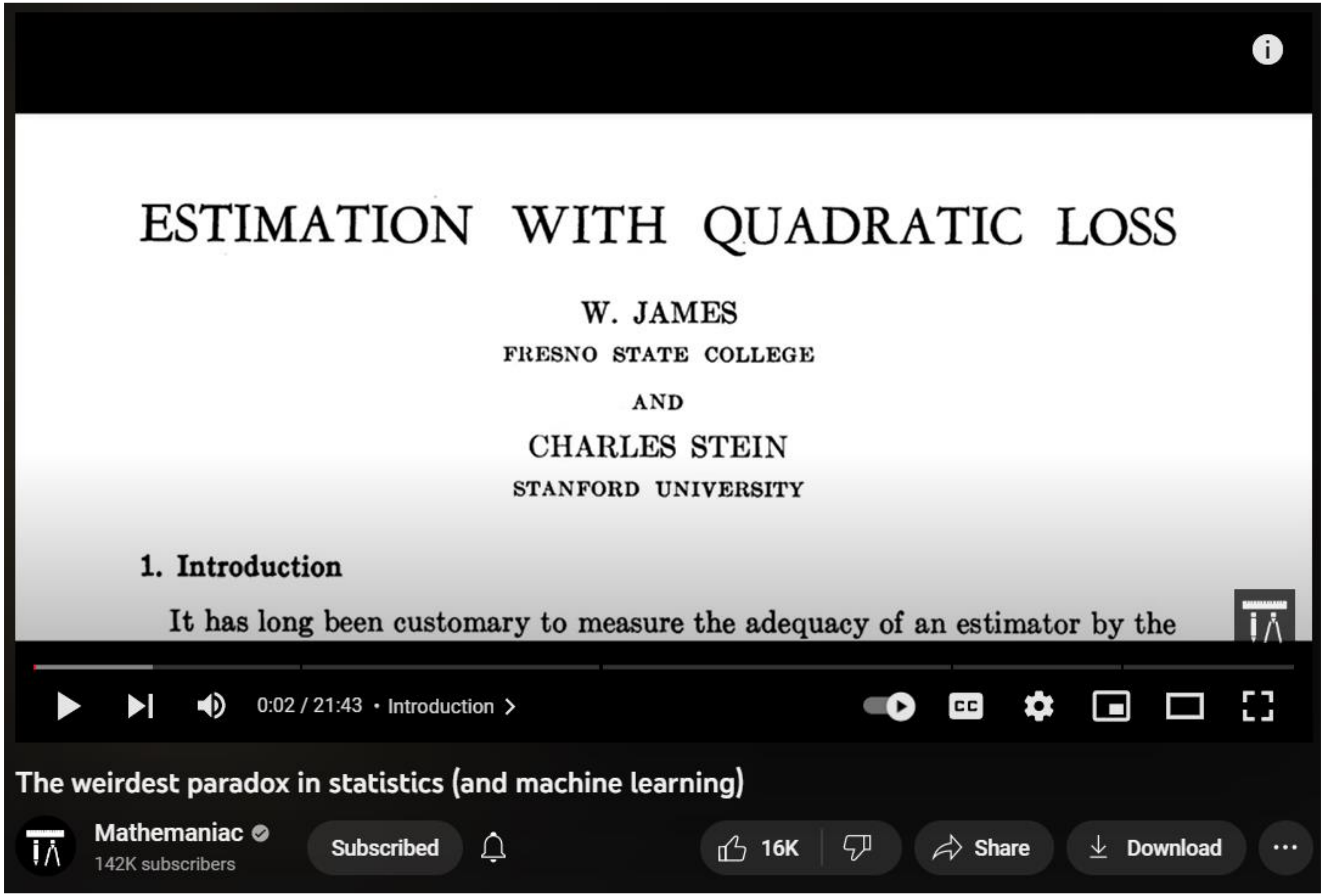
Abstract In the practice of data analysis, there is a conceptual distinction between hypothesis testing, on the one hand, and estimation with quantified uncertainty on the other. Among frequentists in psychology, a shift of emphasis from hypothesis testing to estimation has been dubbed "the New Statistics" (Cumming, 2014). A second conceptual to eschew NHST, with its seductive lapse to black-and-white thinking about the presence or absence of effects. There are also many reasons to promote instead a cumulative science that incrementally improves estimates of magnitudes and uncertainty. These reasons were recently highlighted in a prominent statement from the American Statistical Asso-

James-Stein (1961) estimator (and paradox)

Warm up = prove that sample mean is OLS when model has no covariates

James-Stein (1961) estimator (and paradox)

https://www.youtube.com/watch?v=cUqoHQDinCM



Thank you for a fun semester! I learned a lot :)