

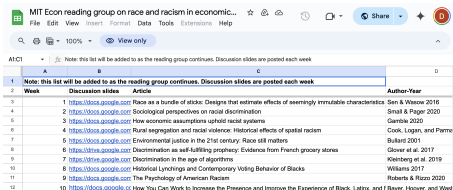
The Prejudices of Economic Ideology

The Exacerbation of Racial and Gender Inequalities by Economics
Training for Judges

The Prejudices of Economic Ideology

- Is economics racist?

- ▶ MIT Econ Race & Racism Reading Group - Do economic assumptions uphold racist systems?



MIT Econ reading group on race and racism in economic... ☆ ☆ ☆ Share

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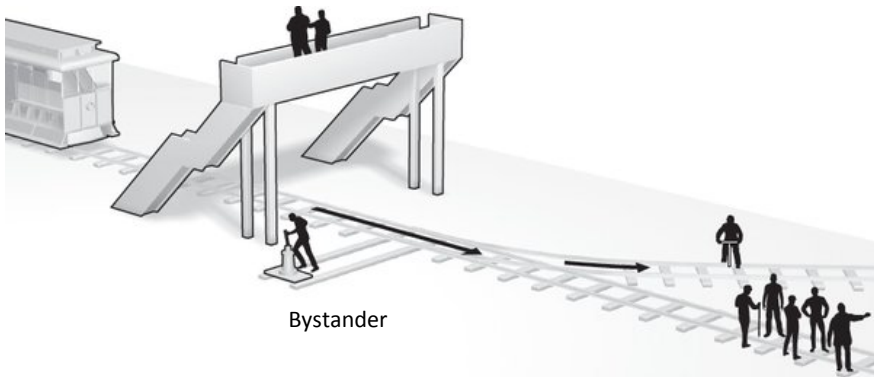
A1C1 Note: this list will be added to as the reading group continues. Discussion slides are posted each week

| | A | B | C | D |
|----|---|-------------------|--|-------------------------|
| 1 | Note: this list will be added to as the reading group continues. Discussion slides are posted each week | | | |
| 2 | Week | Discussion slides | Article | Author-Year |
| 3 | | 1 | https://docs.google.com Race as a bundle of sticks: Designs that estimate effects of seemingly immutable characteristics | Sen & Whence 2016 |
| 4 | | 2 | https://docs.google.com Sociological perspectives on racial discrimination | Small & Pager 2020 |
| 5 | | 3 | https://docs.google.com How economic assumptions uphold racist systems | Garnble 2020 |
| 6 | | 4 | https://docs.google.com Rural segregation and racial violence: Historical effects of spatial racism | Cook, Logan, and Parre |
| 7 | | 5 | https://docs.google.com Environmental justice in the 21st century: Race still matters | Bullard 2001 |
| 8 | | 6 | https://docs.google.com Discrimination as self-fulfilling prophecy: Evidence from French grocery stores | Glover et al. 2017 |
| 9 | | 7 | https://docs.google.com Discrimination in the age of algorithms | Kleinberg et al. 2019 |
| 10 | | 8 | https://docs.google.com Historical Lynchings and Contemporary Voting Behavior of Blacks | Williams 2017 |
| 11 | | 9 | https://docs.google.com The Psychology of American Racism | Roberts & Rizzo 2020 |
| 12 | | 10 | https://docs.google.com How You Can Work to Increase the Presence and Improve the Experience of Black, Latinx, and F | Bayer, Hoover, and West |

- ▶ “Many economists’ explanations for status of POC are blaming the victims. These explanations ignore work in other fields and often ignore institutional discrimination and promote white supremacy via ‘dysfunctionality’ arguments
- ▶ “Giving the same weight to an ‘unknown alternative’ (OVb) and a model that accounts for everything we currently think we know about how the world works”
- ▶ “Systemic racism and racist policies remain in place because certain people benefit; includes production of ideas”
- ▶ “What Economics Misses About American Racial Inequality: An Interdisciplinary Perspective”

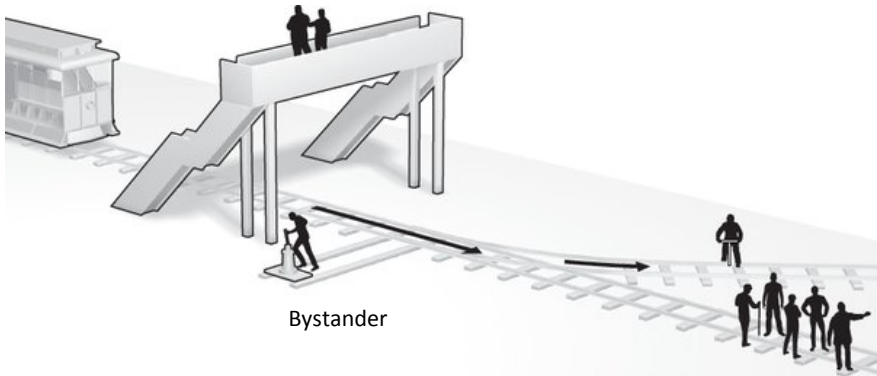
Ideas Have Consequences:
The Impact of Law and Economics on American Justice

Moral Trolley Problem



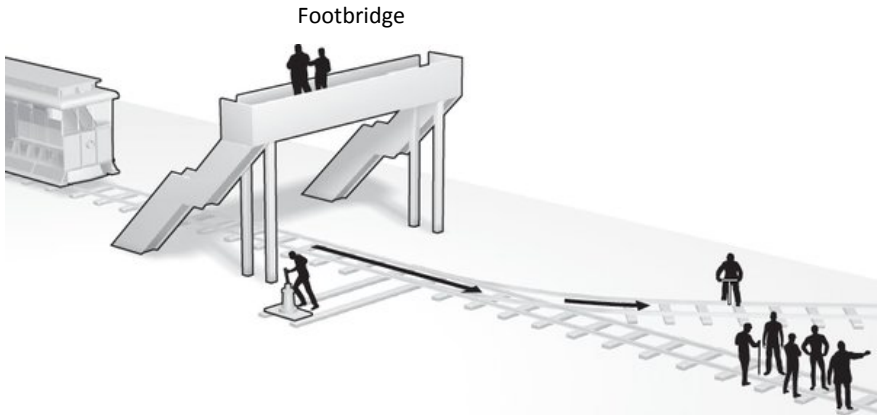
Consequentialism: Maximize the lives saved minus those killed

Moral Trolley Problem



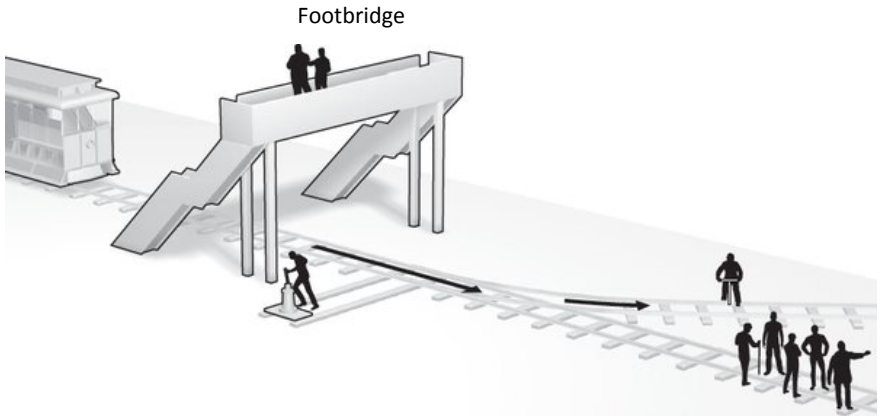
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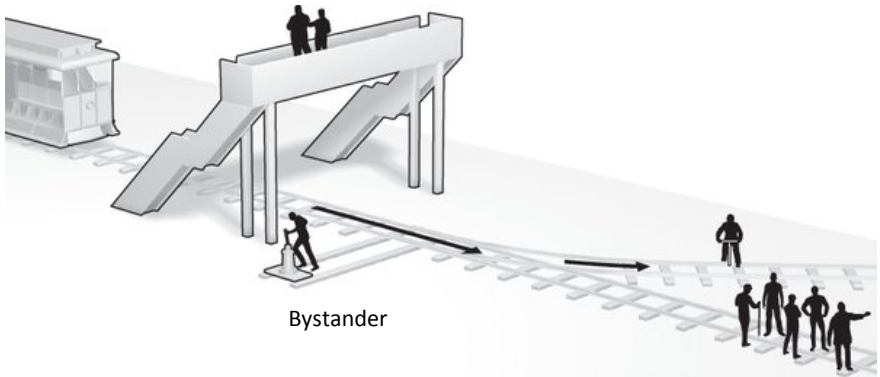
Deontological: Duty not to do the act of pushing someone to their death

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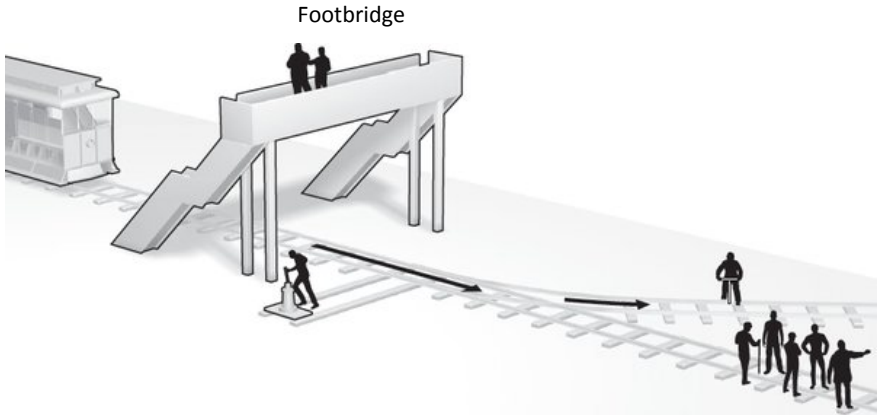
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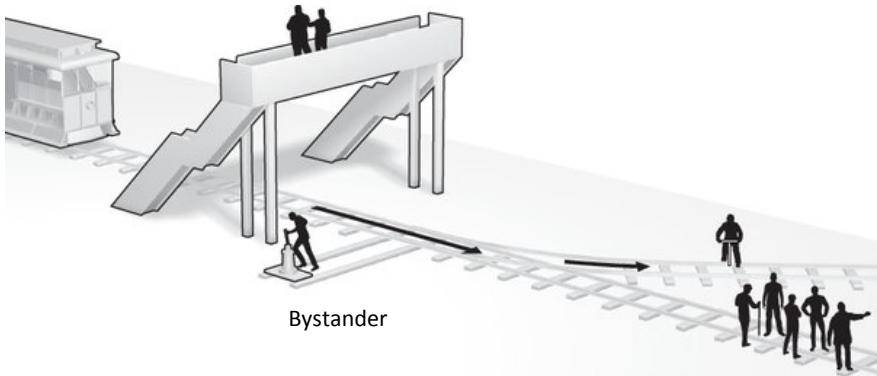
Consequentialism: Calculations of Costs and Benefits

Moral Trolley Problem



Deontological: Following Duties and Obligations

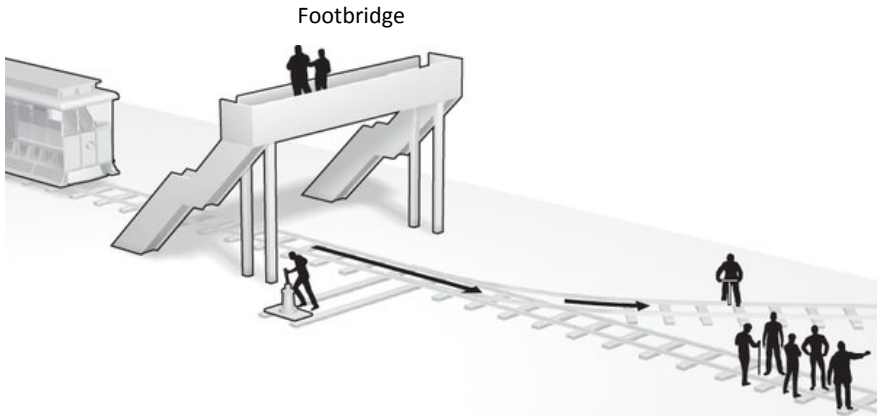
Moral Trolley Problem



Bystander

Evaluating Trade-Offs

Moral Trolley Problem



Consequentialist Reinterpretation of Duty

Efficient Breach Theory in Contracts

- **Duty posits a general obligation to keep promises** vs.
- a party should be allowed to breach a contract and pay damages, if doing so would be more **economically efficient** than performing under the contract.
- Posner in *Lake River Corp. v. Carborundum Co.*, 769 F.2d 1284 (7th Cir. 1985)

Least Cost Avoider in Torts

- **Duty of care** is breached when $PL > B$
- P is the probability of loss (L) * L is the gravity of loss
- B is the cost (burden) of taking precautions

Expected Deterrence in Criminal Law

- $\text{Pr}(\text{detection}) * \text{sanction} = \mathbb{E}[\text{sanction}]$
- Costs of detection \gg cost of sanction
- Approach as social planner

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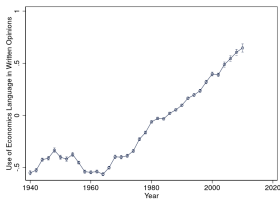
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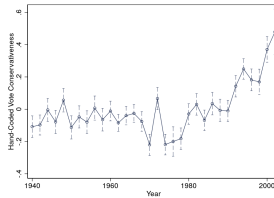
- Social Planner (“An Exit Interview With Richard Posner”, New York Times, 9/11/2017)
 - ① “I pay very little attention to legal rules, statutes, constitutional provisions ... The first thing you do is ask yourself — **forget about the law** — **what is a sensible resolution of this dispute?**”
 - ② “See if a recent Supreme Court precedent or some other legal obstacle stood in the way of ruling in favor of that sensible resolution.”
 - ③ “When you have a Supreme Court case or something similar, **they’re often extremely easy to get around.**”
 - ◀ Natural Laboratory
 - ◀ Judges Most Textually Similar to Posner
- Influential in criminal law, antitrust, labor regulation, and more
 - Becker’s analysis of crime & punishment (Posner 2004; Harcourt 2011)
 - “Rational criminals” **went against prevailing wisdom** re mental illness
 - ~~retribution, rehabilitation,~~ deterrence, legitimacy, fairness
 - Antitrust laws
 - Economic analysis **has attained near complete consensus.** (Judge Ginsburg)
 - Should promote economic efficiency and consumer welfare, rather than shield individuals from competitive market forces or redistribute income.
 - Law-and-economics judges’ decisions are appealed less. (Baye et al. 2011)
 - Against New Deal labor law and union protections (Posner 1984, Epstein 1983)
 - Against EPA regulation \approx govt expropriation (Epstein 1993, Blumm 1995)
- Conservatism: Law-and-economics focuses on efficiency. **Its key criticism of regulatory policies is that they have perverse, unintended economic consequences.**

Increasing pro-market orientation in U.S. judiciary

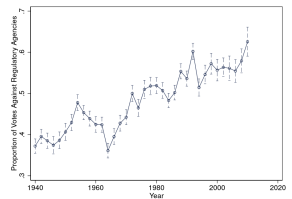
Economics style



◀ Conservative vote share



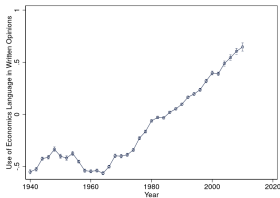
Voting against government regulation



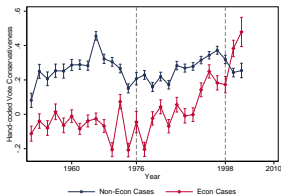
◀ Natural Laboratory

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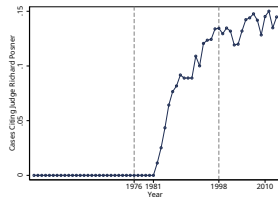
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Citation to Richard Posner



◀ Natural Laboratory

US Federal Courts as “Natural Laboratory”

- Do schools of thought matter for policymaking? ◀ Examples of Cases
- We have recently seen the importance of US federal courts ruling against DT.

Federal appeals court rules against Trump, refuses to reinstate travel ban



Mark Abell · 12
@Hb.R. 2017, 4:25 PM A 36,432



• The Best Tom Hanks Movies Ever
(Fresh Fandom — It's Original)

• End Your Nightly Shoring Nightmar...
(501 Charming Images)

• Best Flashlight Ever in Selling Like...
(Shutterstock Flashlights)

• This amazing new technology also...
(Tech Radar)

Sponsored Links

A federal appeals court unanimously ruled against President Donald Trump on Thursday, refusing to reinstate his travel ban.

The ruling, issued by a three-judge panel on the San Francisco-based 9th Circuit Court of Appeals, means refugees and citizens of the seven majority-Muslim countries affected by the ban can continue entering the US as the ban makes its way through the court system.



President Donald Trump. Credit: WireImage/Getty Images



- Judges interpret the law and make precedent under uncertainty
 - Subjective decision-making creates scope for **schools of thinking**
 - Ideas and **normative commitments** forming basis for policy (Rodrik 2014)
 - Principles of thinking agents use to organize **values** (Benabou et al. 2018)
 - **Heuristics** to focus on salient attributes when deciding (Koszegi et al. 2013)
 - **Salience** in judicial decision making (Bordalo et al. 2015)
 - e.g. **Originalism**, Critical Legal Theory, or **Law and Economics** (this paper).

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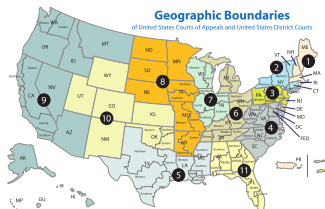


President Donald Trump. (Chris Wedel/Getty Images)



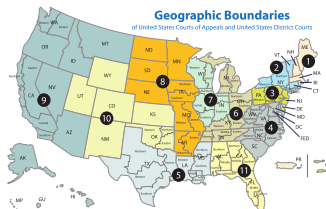
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US Federal Courts as “Natural Laboratory”



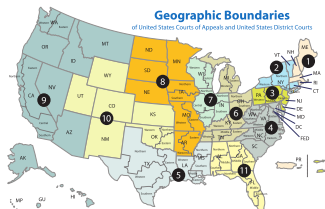
- Incremental common-law space; new rules, distinctions (Gennaioli et al. 2007)
 - Random assignment to cases & panels of 3 (in Circuit courts, no juries)
 - Appointed for life (179 Circuit judges in 12 C; 678 District judges in 94 D)
 - 327K cases/yr in D \Rightarrow 67K cases/yr in C \Rightarrow 100 cases/yr in Supreme Ct
- Influential and controversial economics training program for judges
 - “Big Corporations Bankroll Seminars For US Judges” (*Washington Post*, 1/20/1980)
 - By 1990, 40% of federal judges had attended economics training (Butler 1999)
 - Despite “swamped with criminal cases .. not seeing relevance of economics”
- Sentencing has undergone several moral revolutions (~~retribution~~, ~~rehabilitation~~,
 - **Deterrence**: severity substitutes for low detection probability (Becker 1968)
 - One justification for massive build-up of prisons in 1980s and 1990s
 - Mass incarceration as “new Jim Crow” (Davis 1998, Gilmore 2007)

US Federal Courts as “Natural Laboratory”



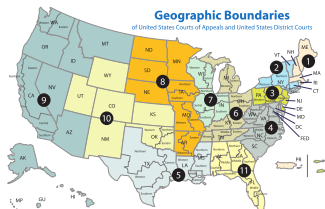
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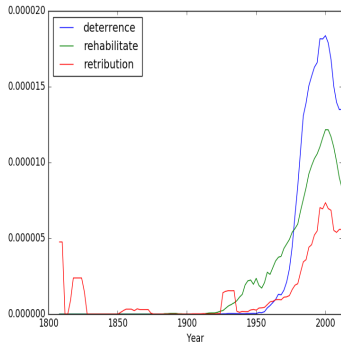


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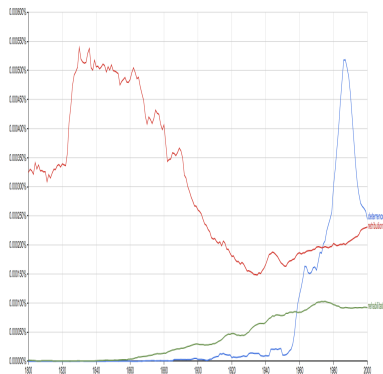
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Word Frequency in State Court Opinions



Word Frequency in Google Books

◀ Massive build-up of prisons

Impact of Law and Economics on American Justice

- Create textual measure of ways of moral reasoning.
 - All 380K cases, 1,150K judge votes, 94 topics, from 1891- in Circuit Courts
 - 2B N-grams of length 8, 5M citation edges across cases
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Validating the N-grams

Predicting Liberal vs. Conservative decisions ~ facts or reasonings salient to judge ~ not just words

| | | |
|--------------------|--|---|
| Campaign Finance | advertis influenc outcom vote, argument appel consid definit, challeng present, case controversi district, disclosur sourc | Expens, inform elector mean provis, compel court went histori, buckley court limit |
| Capital Punishment | duti make reason, Involuntari, materi reason probabl, mental health | consid mitig, Attack, Inelig, counti jail |
| EPA | act impos, board character, Chevron, Elimin, interst transport hazard wast | factor demonstr, id statut silent ambigu respect, requir provis |

(Buckley held that election spending limits are unconstitutional)

◀ WhatWeDo

◀ Manne Program

◀ ModelFit

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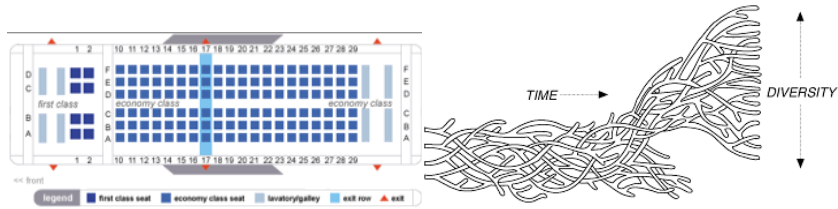
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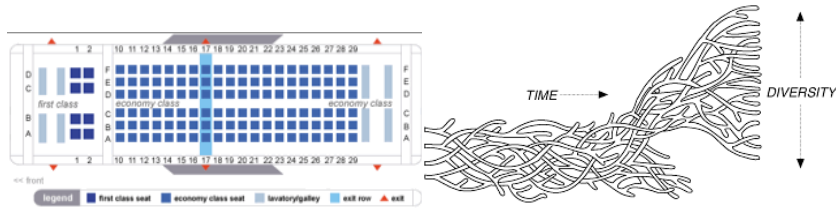
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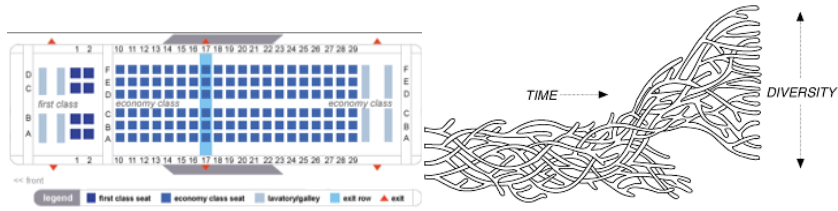
- 4. Exogenous topic ordering to identify *memes*
 - e.g., phrases portable across topics, and direction of transmission
- 5. Exogenous homophily to identify *active or passive persuasion*
 - e.g., does transmission occur more in like-minded groups? or during foment?
- 6. Word embeddings to identify *implicit (or explicit) associations*
 - e.g., does economics affect stereotypes vs. use of stereotypes?
- 7. Citation network to identify *geneology of ideas*
 - e.g., a meme index for phrases that propagate across the network
- 8. Exogenous minority exposure to identify *mitosis* of ideology
 - e.g., does exposure to sameness cause you to see distinctions?

Impact of Law and Economics on American Justice



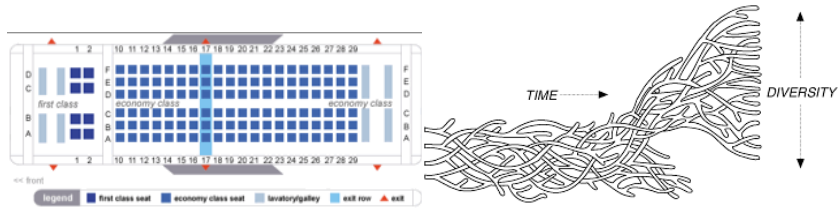
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Impact of Law and Economics on American Justice



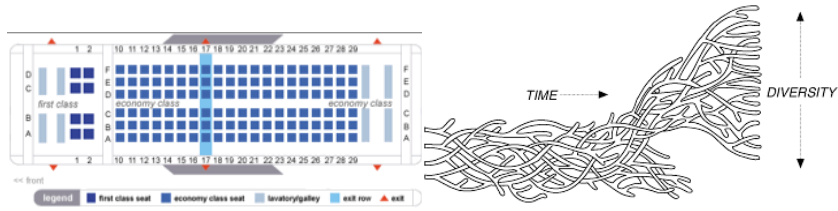
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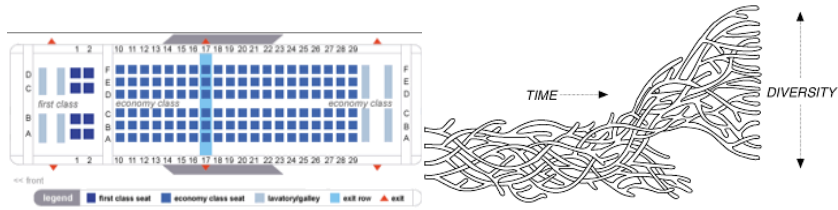
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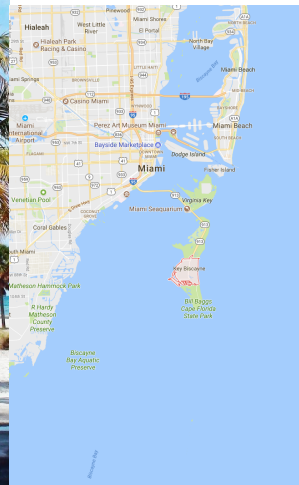
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- 1 Manne Program
- 2 Event Studies
- 3 Discretion
- 4 Peer Effects
- 5 Language
- 6 Long-Difference Impact of Economics Judges
- 7 Impact of Economics Training on Criminal Cases
- 8 General Equilibrium Impacts of Economics Training
- 9 Concluding Remarks and Bonus Slides

Public Perception



Large Corporate Donors

1982-83 Contributors

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Ms Amy S Mann
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Mr C M Ruprecht
Ms Marietta Julie Tausig
Mr and Mrs William W Weston

105 corporate contributors are almost always before a federal judge somewhere, often in antitrust, regulatory, or affirmative-action cases. Probably all federal judges face some possibility (*Washington Post*, 1/20/1980)

Photo Evidence (from annual reports - FOIA)

"FROM THE BEGINNING, THE JUDGES DEFERRED TO THEIR TEACHERS," wrote a *New York Times* reporter. Below, Nobel Laureate Milton Friedman elaborates a point at an IEC



Economics Institute for Federal Judges. Thirty-nine judges were graduated from this intensive two-week



program of study of market economics in the Center's fourth year, bringing to 58 the total number of



Photo Evidence (from annual reports - FOIA)



Class in session at First Economics Institute for Federal Judges. Students get reading assignment for the evening from LEC's director, Dr. Henry G. Manne.

19 U.S. Judges Study Economics To Help Them in Work on Bench

Special to The New York Times

KEY LARGO, Fla., Dec. 18—For three weeks, 19 Federal judges from around the country took a grueling, six-day-a-week course in economics that ended here yesterday.

With classes starting at 9 A.M. and sometimes ending at 10 P.M. or later, the judges received the equivalent of a full semester at the college level.

Their teachers were, among others, two Nobel laureates in economics, Paul Samuelson and Milton Friedman. The courses, sponsored by the Law and Economics Center of the University of Miami School of Law, made up what is believed to have been the first such institute for Federal judges.

"It was a very enriching experience," said Chief Judge John W. Reynolds of the Federal District Court in the Eastern District of Wisconsin. "We were here not to become economists, but to understand the language of economics. Courts are only as good as judges and the lawyers who appear before us. By and large, our training in economics is not really satisfactory, and yet we are being increasingly called upon to decide economic issues."

The program dealt basically with eco-

not to relate the theoretical studies cases now pending in Federal court. "One has to be very cautious in dealing with Federal judges," said Henry Mann, director of the center. "Our goal has been to give them the most recent thinking in economic theory and enable them to better understand the testimony of expert witnesses and lawyers."

Chief Judge David N. Edelstein of the Federal District Court in the Southern District of New York, who is the judge in the International Business Machines Corporation antitrust case—regarded as one of the most important antitrust litigations of the century—informally asked the attorneys in the case of his intention to attend the institute to clear any future questions about a possible conflict of interest.

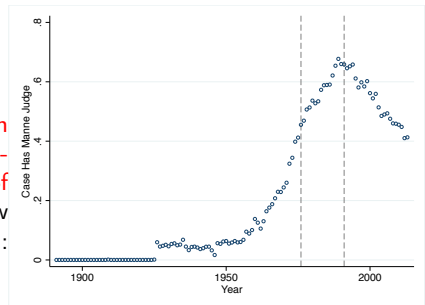
"All the lawyers were very cordial and replied that they saw no grounds for a conflict of interest in my coming here," Judge Edelstein said.

From the beginning, the judges, some of them 60 years old or over, behaved like students, deferring to their teachers and reminiscing about undergraduate

Manne Program in Law and Economics (now also funded by Koch Brothers)

- 2-3 week economics course for federal judges:
 - Ran continuously from 1976 to 1998 (1999 to present) [◀ Recent LEC](#)
 - Lectures by Friedman, Samuelson, Alchian, Demsetz, .. [◀ All Instructors](#)
 - [Coase Theorem](#), demand/supply theory, expected value/utility, bargaining, externalities, torts, contracts, monopoly theory, statistics, basic regression
 - *Law & Economics* (Cooter & Ulen), *Exchange & Production* (Alchian & Allen)
- By 1990, forty percent of sitting federal judges had attended

"[academic attention to the role of economics in law] could actually be the most lasting contribution of the judges' program to the development of law and economics." (Henry Manne, "How Law and Economics was Marketed in a Hostile World: A Very Personal History")



Syllabi 1989 (from annual reports - FOIA)

3/29/89

George Mason Univ. School of Law
Law and Economics Center (LEC)

LEC ECONOMICS INSTITUTE FOR FEDERAL JUDGES
Callaway Gardens Resort, Pine Mountain, GA
April 2 - 15, 1989

SCHEDULE

SUNDAY, APRIL 2

| | | |
|-----------|-----------|-----------------------|
| 7:00 p.m. | Reception | Conference Ctr lounge |
| 7:45 p.m. | Dinner | Conference Ctr 104 |

MONDAY, APRIL 3

8:30 - 12:00 noon CLASS #1 ALCHIAN
Topic: Competition, Demand, Exchange
Assignment: A&A, chapters 1, 2, 3
Samuelson cross-reference: chapters 1 & appen, 2, 3A, pp. 53-55, 4, 18A, 19
Recommended Reading: Alchian, "Uncertainty, Evolution, and Economic Theory"

TUESDAY, APRIL 4

8:30 - 12:00 noon CLASS #2 ALCHIAN
Topic: Prices and Markets, Information Costs
Assignment: A&A, chapters 4, 5
Samuelson cross-reference: chapters 3B, 18B, pp. 468-472

1:00 - 4:30 p.m. CLASS #3 ALCHIAN
Topic: Capital Values, Future Yields, Interest
Assignment: A&A, chapter 6
Samuelson cross-reference: chapter 30, pp. 51-53
Recommended Reading: Alchian, "Words: Musical or Meaningful?"

WEDNESDAY, APRIL 5

8:30 - 12:00 noon CLASS #4 ALCHIAN
Topic: Production
Assignment: A&A, chapters 7, 8
Samuelson cross-reference: chapters 21, 22

7:45 - 9:15 p.m. DISCUSSION: ALCHIAN

THURSDAY, APRIL 6

8:30 - 12:00 noon CLASS #5 GOETZ
Topic: Price Takers, Price Searchers
Assignment: A&A, chapters 10, 11
Samuelson cross-reference: chapters 22, 23

FRIDAY, APRIL 7

8:30 - 12:00 noon CLASS #6 GOETZ
Continuation of Topic: Competitive and Monopoly Markets
Assignment: A&A, chapters 11 (cont'd), 12, 13
Samuelson cross-reference: chapters 3B, 23C, 24, 32B, pp. 607-609
Recommended Reading: Goetz, pp. 441-447 (Second-Best Theory)

Friday's schedule continued on next page.

-3-

WEDNESDAY, APRIL 12

8:30 - 12:00 noon CLASS #12 SAMUELSON
Topic: Economics of Comparative Advantage
Assignment: Samuelson, "International Trade for a Rich Country"
Samuelson cross-reference: chapters 38, 39, 40, especially chapter 38
Recommended reading: Samuelson, "To Protect Manufacturing?"

1:00 - 4:30 p.m. CLASS #13 ASHENFELTER
Topic: Econometrics
Assignment: No advance reading; lecture only

THURSDAY, APRIL 13

8:00 - 10:00 a.m. Breakfast available

1:00 - 4:30 p.m. CLASS #14 GOETZ
Topic: Monopoly and Competition
Assignment: Brozen, "The Antitrust Task Force Deconcentration Recommendation"
Brozen, "Concentration and Profits: Does Concentration Matter?"
Brozen, "Bain's Concentration and Rates of Return Revisited and Rejoinders by Wenders; Brozen; MacAvoy, et al.; Brozen.
Demsetz, "Two Systems of Belief about Monopoly"
Demsetz, "Barriers to Entry"

FRIDAY, APRIL 14

8:30 - 12:00 noon CLASS #15 GOETZ
Topic: Property Rights
Assignment: Demsetz, "Toward a Theory of Property Rights"
Coase, "The Problem of Social Cost"
Demsetz, "When Does the Rule of Liability Matter?"
Demsetz, "Wealth Distribution and the Ownership of Rights"

SATURDAY, APRIL 15

8:30 - 12:00 noon CLASS #16 GOETZ
Topic: Law and Economics
Assignment: Goetz, pp. 49- 68 (Nuisance)
166-176 (Prejudgment Interest)
375-391 (Costs and Damages)

Please checkout before class and pay individual account directly to hotel.

Syllabi 1998 (from Butler 1999)

THE BASIC ECONOMICS INSTITUTE FOR FEDERAL JUDGES

Omni Tucson National Golf Resort & Spa, Tucson, Arizona

Saturday, October 17 - Tuesday, October 27, 1998

AGENDA

SATURDAY, PM, OCTOBER 17

7:00 p.m. Reception
7:45 p.m. Dinner

SUNDAY, AM & PM, OCTOBER 18

8:30 a.m. - 9:30 a.m. Continental Breakfast
12:00 noon Lunch
1:00 p.m. - 5:00 p.m. **Class 1: Dr. Robert Cooter**
Topic: Bargaining and Demand

Assignments:

Bargaining:
Cooter and Ulen, Law and Economics (2nd ed., 1996):
"Bargaining Theory," pp. 72-74;
"Coase Theorem," pp. 79-84.

Scarcity, Demand, and Exchange:
Alchian & Allen, Exchange and Production (3rd ed., 1983):
Chapter 2 Consumer Demand, pp. 13-28. (Do not labor over the explanation of the elasticity of demand on pp. 25-28).

Recommended: Alchian & Allen, Exchange and Production (3rd ed., 1983):

SUNDAY, AM & PM, OCTOBER 25

8:30 a.m. - 9:30 a.m. Continental Breakfast
12:00 noon Lunch
1:00 p.m. - 4:30 p.m. **Class 7: Dr. Darrell Williams**
Topic: Economics Regulation

Assignment: Demsetz, Why Regulate Utilities?,
Journal of Law & Economics, 11 April
1968, pp. 55-65.

Demsetz, Barriers to Entry,
American Economic Review, March
1982, pp. 47-57.

6:30 p.m. - 6:50 p.m. Reception
7:00 p.m. - 8:00 p.m. Dinner

MONDAY, AM & PM, OCTOBER 26

7:30 a.m. - 8:25 a.m. Continental Breakfast
8:30 a.m. - 12:00 noon **Class 8: Dr. Orley Ashenfelter**
Topic: Econometrics

Assignment: Paulos, Innumeracy, Chapters 1 and 2.

12:00 p.m. - 12:45 p.m. Lunch
1:00 p.m. - 2:30 p.m. *Discussion Period with Available
Instructors*
Reception
7:20 p.m. - 8:30 p.m. Dinner

TUESDAY, AM, OCTOBER 27

7:20 a.m. - 8:10 a.m. Breakfast (Note earlier start)
8:15 a.m. - 11:30 a.m. **Class 9: Orley Ashenfelter**
Topic: Statistical Inference

Assignment: Paulos, Innumeracy, Chapter 5.

11:30 a.m. Lunch

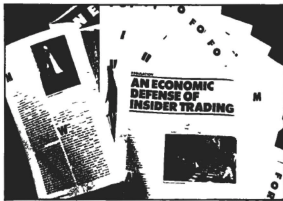
Instructors' Views (from annual reports - FOIA)

“FOR ALL THE RHETORIC ABOUT THE UNFAIRNESS OF INSIDER TRADING, ITS OPERATIONAL EFFECT IS TO MAKE THE STOCK MARKET A FAIRER GAME THAN IT OTHERWISE WOULD BE”

Daniel Seligman In the article Seligman writes. “When insiders trade on their information, they make the market more efficient

For all the rhetoric about the unfairness of insider trading, its operational effect is to make the stock market a fairer game than it otherwise would be.”

The *Fortune* essay also points out that Dr. Manne “has been laboring for years to make law professors and judges more cognizant of “economic principles” *Fortune* last covered Dr. Manne and the L+EC with a 1979 cover story on the Federal Judges’ program



A September 1983 issue of *Fortune* magazine found “time to say a few kind words about insider trading” and about L+EC director Henry Manne as well

“It is ironic that the word ‘profit’ has become a swear word, since profit is the only decent measure of the real public benefit provided by business.”

—Dr. Henry Manne in “Myths of Regulation”

Professor Goetz spoke on “‘Unequal’ Punishment for ‘Equal’ Crime,” arguing that discrimination in punishment can be analyzed in terms of economic efficiency.

Relevant criteria, he said, include at least three principal characteristics. First, the desire of potential victims to lower harm to themselves from any given crime. Second, citizen interest in lowering the total cost of punishment. Third, the wish of individuals to reduce their own costs of accidentally (or even intentionally) committing a crime.

Reducing the costs of these components **leads to the conclusion that society will institute unequal punishments for equal crimes.**

“There really should not be many different results in your cases. But you will have a better understanding of the law because of the insights economics offers, and that will help you be **better judges.”** — Henry Manne

*"I'm trying to change your view of the world, to show you that what you thought was **bad** really may not be."* (Alchian)

Antitrust

*"You could make a case that lower-income people are being benefited. .. **price discrimination which encourages more production is good**"* (Klein)

"If the price of bread gets too high, cake will compete with it." (Demsetz)

"the consumer who is supposed to benefit .. isn't represented; he isn't there in front of you with his lawyer" (Demsetz on standing)

Damages/Deterrence

"The plaintiffs may wait a long time before they complain, because they want damages to pile up" (Demsetz on moral hazard of damages)

*"not likely to be caught, [so] the threat of **simple damages may not be a tough enough deterrent**"* (Demsetz on increasing sanctions)

Environment/Labor

*"Give me a capsule that will magically clean all the air in Los Angeles .. Beg me to crush it. .. **I won't crush the capsule. Because, if I do, poor blacks will have to pay \$20 a month more for land rental. .. the black in Watts, already used to living with bad air, loses his discount for doing that.**"* (Alchian on environmental law)

*"you **should** be asking questions like, '**Is it more likely to be this than that?**'"* (Feldstein on equal opportunity and discrimination)

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Judge Williams, then fresh out of the center's program, .. included a diagram of marginal- and average-cost curves "the first significant opinion in history to do that"

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▶ e.g., voting against regulatory agency

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- ▶ Differences-in-differences model:

$$Y_{ijct} = \alpha_j + \alpha_{ct} + \gamma Z_{jt} + \mathbf{X}_j' \lambda_t + \epsilon_{ijct} \quad (1)$$

- ▶ α_j = judge fixed effect
- ▶ α_{ct} = court-year fixed effect (case randomization block)
- ▶ $Z_{jt} = 1$ for years after judge j attended Manne program.

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- ▶ Event-study model:

$$Y_{ijct} = \alpha_j + \alpha_{ct} + \sum_{k \in K} \gamma_k Z_{jt}^k + \mathbf{X}'_j \lambda_t + \epsilon_{ijct} \quad (2)$$

- ▶ Z_{jt}^k = leads and lags of Manne attendance, excluding year before attendance.

Regressions weighted to account for caseload differences across courts/years. Standard errors clustered by judge.

Selection into the program

Judges were not specifically recruited; enrollment was on a first-come first-serve basis.

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- ▶ Republicans attended more often, but conditional on attendance, did not attend sooner.
- ▶ Program was often oversubscribed, with later applicants bumped to next class.
 - ▶ → reduced opportunities for selection in response to short-run changes in judge beliefs/attitudes.

Addressing Selection Issues

Selection into the program:

- ▶ $\mathbf{X}'_j \lambda_t$ = ML-selected judge covariates, fully interacted with year fixed effects.
 - ▶ variables that are most predictive of the timing of Manne attendance.
 - ▶ selected by elastic net (lasso + L2/ridge penalty)
 - ▶ mostly judge birth cohort; does not include judge party
 - ▶ similar robustness to adding covariates that predict the outcome.

List of Selected Covariates

Addressing Selection Issues

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 - ▶ selected by elastic net (lasso + L2/ridge penalty)
 - ▶ mostly judge birth cohort; does not include judge party [List of Selected Covariates](#)
 - ▶ similar robustness to adding covariates that predict the outcome.

Selection into types of cases:

- ▶ [Manne Program had no effect on assignment/authorship in economics cases](#)
- ▶ results robust to dropping circuits where Levy and Chilton (2015) find non-random assignment of cases to judges.
- ▶ results robust to absorbing legal topic fixed effects.

Diagnostic for Staggered Treatment

- ▶ We have staggered treatment: different treated judges attend the program at different times.
 - ▶ the standard two-way fixed-effects estimator might not capture average treatment effect due to the potential for negative weights, when previously treated judges are present in the comparison group (e.g. Goodman-Bacon, 2018).

Diagnostic for Staggered Treatment

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- ▶ We perform the diagnostic methods from De Chaisemartin and d'Haultfoeuille (2020) and Jakiela (2021) show that issues of negative weights and heterogeneity are minimal in our two-way fixed effects regressions. [Table](#)
 - ▶ Therefore our estimates can be validly interpreted as average treatment effects.

Outline

Background

Econometrics

Results

- Effect on Economics Language in Opinions

- Effect on Circuit Court Decisions

- Effect on District Court Sentencing

Discussion and Conclusion

Measuring Economics Language in Case Text

Starting point: Lexicon of phrases used by Ellickson (2000) to identify law-and-economics articles in a law journal corpus:

{capital, chicago_school, cost*_benefit*, **deterren***, efficien*,
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- ▶ can't use counts over this lexicon as language outcome because it is too sparse Figure

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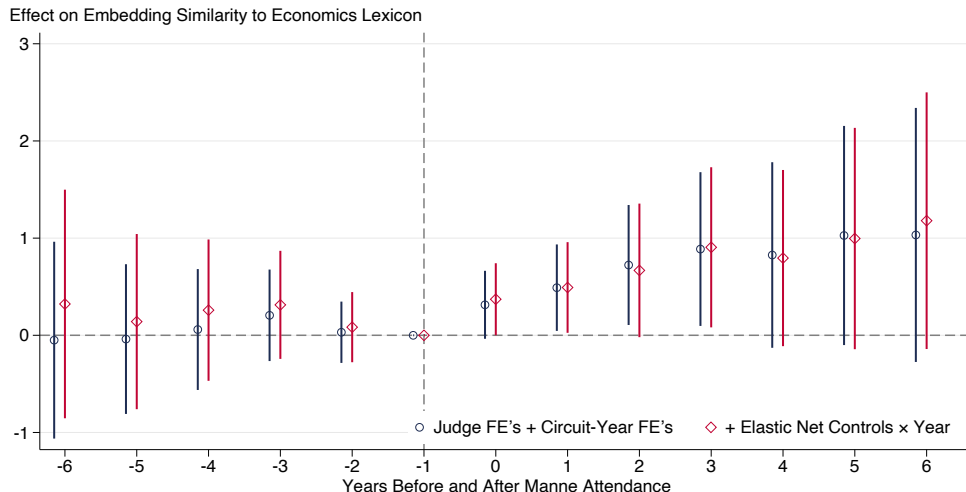
{capital, chicago_school, cost*_benefit*, **deterren***, efficien*,
externalit*, game_theor*, marketplace, transaction_cost*}

▶ can't use counts over this lexicon as language outcome because it is too sparse [Figure](#)

Word embeddings: a tool from machine translation that represents words in a geometric space, where directions encode meaning/concepts (e.g. Mikolov et al 2013). [Word embeddings](#)

Effect of Manne Program on Economics Language

Effect of Manne Program on Economics Language



Notes. Event study effect of Manne attendance on Word Embedding Similarity to Law-and-Economics Lexicon. Sample is limited to case authors. Regressions include judge and circuit-year fixed effects (blue circles), with additional specifications adding quadratic in judge years on court (red diamonds), plus elastic-net-selected controls interacted with year fixed effects (green triangles). Observations are weighted to treat judge-years equally. Error spikes give 95% confidence intervals, with standard errors clustered by judge.

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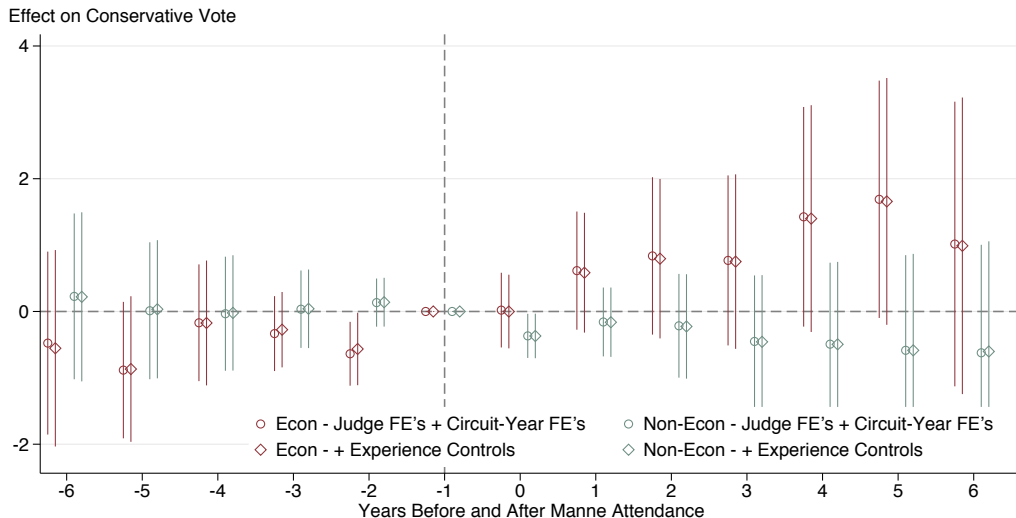
Appeals Decision Outcomes (using metadata)

1. Conservative vote direction (hand-coded 5% sample from Songer database)
2. Voting against regulatory agencies (labor/environmental)
3. Antitrust rulings (new annotated dataset on voting for/against mergers)

Summary Statistics

Effect of Manne Program on (Hand-Coded) Conservative Vote Direction

Effect of Manne Program on (Hand-Coded) Conservative Vote Direction



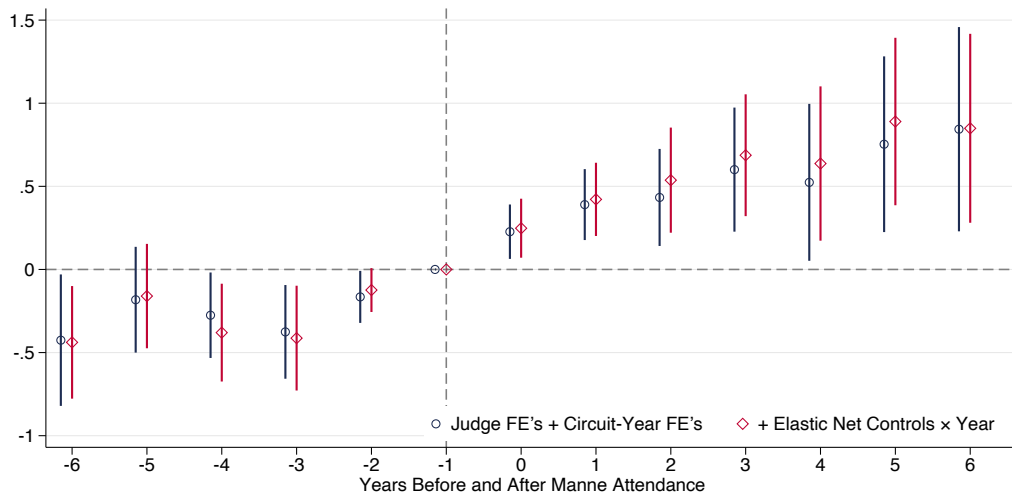
Notes. Event study effect on conservative vote in economics cases (regulation and labor; in red) and non-economics cases (in teal). Baseline specification (left dot in pair) includes judge and circuit-year fixed effects. Second specification (right dot in pair) includes controls for judge experience. Observations are weighted to treat judge-years equally. Error spikes give 95% confidence intervals, with standard errors clustered by judge.

[Regression Table](#)

Effect of Manne Program on Ruling Against Labor/Environment Agencies

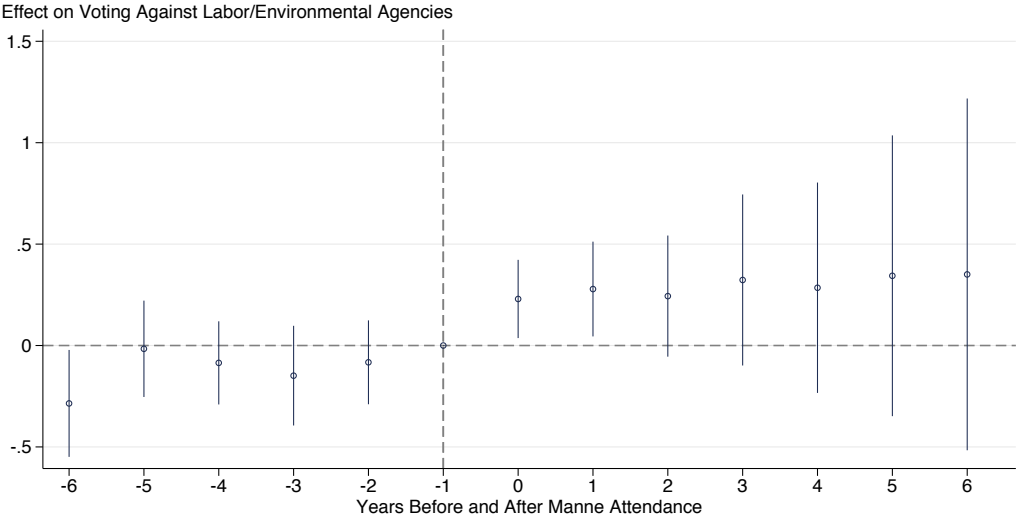
Effect of Manne Program on Ruling Against Labor/Environment Agencies

Effect on Voting Against Labor/Environmental Agencies



Notes. Event study effects on voting against government agency on labor and environmental issues, relative to year before attendance at Manne economics training. The baseline specification (blue circles) includes judge and circuit-year fixed effects. Additional specifications add experience controls (red diamonds) and elastic-net-selected controls interacted with year fixed effects (green triangles). Observations are weighted to treat judge-years equally. Error spikes give 95% confidence intervals, with standard errors clustered by judge.

Labor/EPA Event Study (with Judge-Specific Trends)



Notes. Event study effects on voting against government agency on labor and environmental issues, relative to year before attendance at Manne economics training. Includes judge fixed effects, circuit-year fixed effects, and judge-specific trends. Observations are weighted to treat judge-years equally. Error spikes give 95% confidence intervals, with standard errors clustered by judge.

Effect on Conservative Antitrust Decision (small sample of cases)

Effect on Conservative Antitrust Decision (small sample of cases)

| | Voting in Favor of Mergers | | |
|------------------------|----------------------------|-------------------|-------------------|
| | (1) | (2) | (3) |
| Post-Manne | 0.129 (0.0850) | 0.314* (0.128) | 0.271+ (0.147) |
| N (Votes) | 656 | 656 | 656 |
| adj. R-sq. | 0.437 | 0.321 | 0.255 |
| Ever Attenders | X | X | X |
| All Judges | | | |
| Circuit-Year FE | X | X | X |
| Judge FE | X | X | X |
| Experience Vars | | | X |
| Party \times Year FE | | | X |
| E-net \times Year FE | | X | X |

Notes. Effect of Manne economics training on conservative voting in antitrust cases. Experience Vars includes quadratic in judge years on court. Party refers to party of judge nominating president. E-net refers to elastic-net selected controls for predicting timing of Manne attendance. Event Study includes cases with Manne judges, within six years before/after attendance. Ever Attenders includes cases of Manne judges for all years of their career. All Judges includes all cases. Standard errors clustered by judge. Observations are weighted to treat judge-years equally.

+ $p < .1$, * $p < 0.05$, ** $p < .01$.

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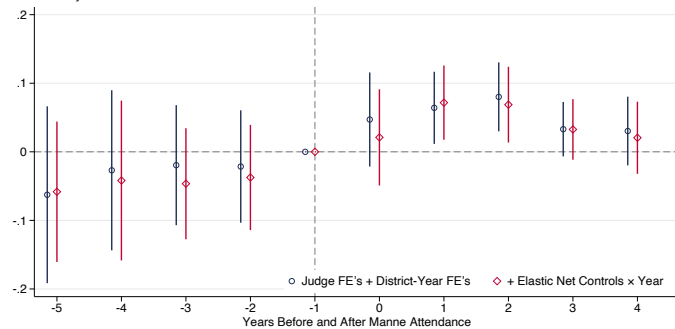
Effect on Economics Language in Opinions

Effect on Circuit Court Decisions

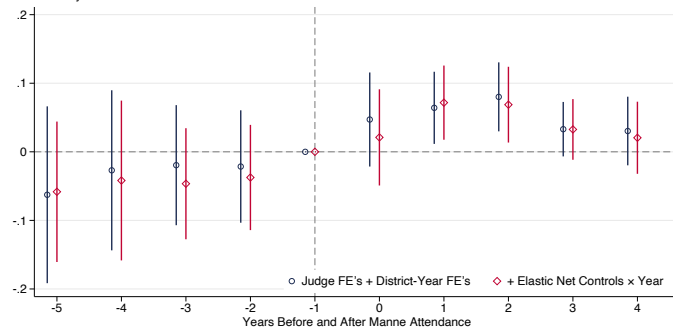
Effect on District Court Sentencing

Discussion and Conclusion

Effect on Any Prison Given



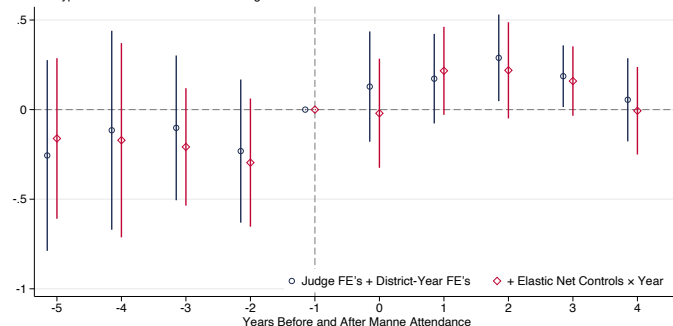
Effect on Any Prison Given



Notes. Event study effect of Manne attendance on criminal sentencing outcomes in district courts, 1992-2003. Panel (a): Outcome is any prison given. Panel (b): Outcome is log of prison sentence in days (plus one, to allow for zeros). Regressions include judge and district-year fixed effects (blue circles), plus quadratic in judge years on court (red diamonds), plus elastic-net-selected controls interacted with year fixed effects (green triangles). Observations are weighted to treat judge-years equally. Error spikes give 95% confidence intervals.

Regression Table

Inverse Hyperbolic Sine Prison Sentence Length



Sentencing Guidelines and *Booker* (2005)

Appendix Figure 1: United States Sentencing Guidelines Grid

| Sentencing Table (in months of imprisonment) | | Criminal History Category (Criminal History Points) | | | | | |
|--|----|---|----------------|------------------|-----------------|-------------------|--------------------|
| Offense Level | | I (0 or 1) | II (2 or 3) | III (4, 5, 6) | IV (7, 8, 9) | V (10, 11, 12) | VI (13 or more) |
| Zone A | 1 | 0-6 | 0-6 | 0-6 | 0-6 | 0-6 | 0-6 |
| | 2 | 0-6 | 0-6 | 0-6 | 0-6 | 0-6 | 1-7 |
| | 3 | 0-6 | 0-6 | 0-6 | 0-6 | 2-8 | 3-9 |
| | 4 | 0-6 | 0-6 | 0-6 | 2-8 | 4-10 | 6-12 |
| | 5 | 0-6 | 0-6 | 1-7 | 4-10 | 6-12 | 9-15 |
| | 6 | 0-6 | 1-7 | 2-8 | 6-12 | 9-15 | 12-18 |
| | 7 | 0-6 | 2-8 | 4-10 | 8-14 | 12-18 | 15-21 |
| | 8 | 0-6 | 4-10 | 6-12 | 10-16 | 15-21 | 18-24 |
| | 9 | 4-10 | 6-12 | 8-14 | 12-18 | 18-24 | 21-27 |
| Zone B | 10 | 6-12 | 8-14 | 10-16 | 15-21 | 21-27 | 24-30 |
| Zone C | 11 | 8-14 | 10-16 | 12-18 | 18-24 | 24-30 | 27-33 |
| | 12 | 10-16 | 12-18 | 15-21 | 21-27 | 27-33 | 30-37 |
| Zone D | 13 | 12-18 | 15-21 | 18-24 | 24-30 | 30-37 | 33-41 |
| | 14 | 15-21 | 18-24 | 21-27 | 27-33 | 33-41 | 37-46 |
| | 15 | 18-24 | 21-27 | 24-30 | 30-37 | 37-46 | 41-51 |
| | 16 | 21-27 | 24-30 | 27-33 | 33-41 | 41-51 | 46-57 |
| | 17 | 24-30 | 27-33 | 30-37 | 37-46 | 46-57 | 51-63 |
| | 18 | 27-33 | 30-37 | 33-41 | 41-51 | 51-63 | 57-71 |
| | 19 | 30-37 | 33-41 | 37-46 | 46-57 | 57-71 | 63-78 |
| | 20 | 33-41 | 37-46 | 41-51 | 51-63 | 63-78 | 70-87 |
| | 21 | 37-46 | 41-51 | 46-57 | 57-71 | 70-87 | 77-96 |
| | 22 | 41-51 | 46-57 | 51-63 | 63-78 | 77-96 | 84-105 |
| | 23 | 46-57 | 51-63 | 57-71 | 70-87 | 84-105 | 92-115 |
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| | 25 | 57-71 | 63-78 | 70-87 | 84-105 | 100-125 | 110-137 |
| | 26 | 63-78 | 70-87 | 78-97 | 92-115 | 110-137 | 120-150 |
| | 27 | 70-87 | 78-97 | 87-108 | 100-125 | 120-150 | 130-162 |
| | 28 | 78-97 | 87-108 | 97-121 | 110-137 | 130-162 | 140-175 |
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| | 30 | 97-121 | 108-135 | 121-151 | 135-168 | 151-188 | 168-210 |
| | 31 | 108-135 | 121-151 | 135-168 | 151-188 | 168-210 | 188-235 |
| | 32 | 121-151 | 135-168 | 151-188 | 168-210 | 188-235 | 210-262 |
| | 33 | 135-168 | 151-188 | 168-210 | 188-235 | 210-262 | 235-293 |
| | 34 | 151-188 | 168-210 | 188-235 | 210-262 | 235-293 | 262-327 |
| | 35 | 168-210 | 188-235 | 210-262 | 235-293 | 262-327 | 292-365 |
| | 36 | 188-235 | 210-262 | 235-293 | 262-327 | 292-365 | 324-405 |
| | 37 | 210-262 | 235-293 | 262-327 | 292-365 | 324-405 | 360-life |
| | 38 | 235-293 | 262-327 | 292-365 | 324-405 | 360-life | 360-life |
| | 39 | 262-327 | 292-365 | 324-405 | 360-life | 360-life | 360-life |
| | 40 | 292-365 | 324-405 | 360-life | 360-life | 360-life | 360-life |
| | 41 | 324-405 | 360-life | 360-life | 360-life | 360-life | 360-life |
| | 42 | 360-life | 360-life | 360-life | 360-life | 360-life | 360-life |
| | 43 | Life | Life | Life | Life | Life | Life |

- A 2005 Supreme Court Case, *United States v. Booker*, loosened the U.S. Sentencing Guidelines, which beforehand were mandatory.

Sentencing Guidelines and *Booker* (2005)

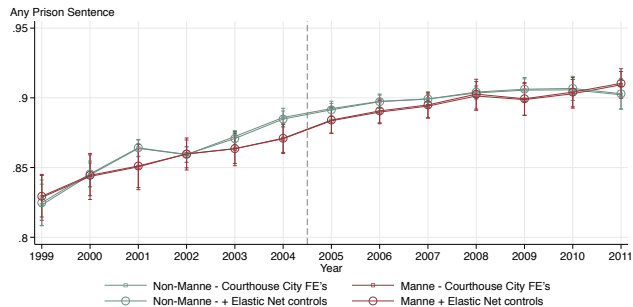
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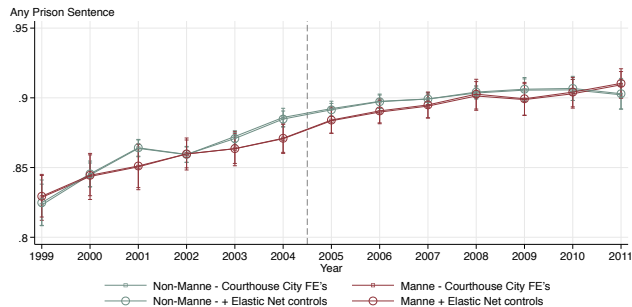
- ▶ A 2005 Supreme Court Case, *United States v. Booker*, loosened the U.S. Sentencing Guidelines, which beforehand were mandatory.
- ▶ We estimate the relative effect of *Booker* on Manne-trained District Judges.
 - ▶ Later dataset (1999-2011) has more detailed info on crime type.

Estimating Equation

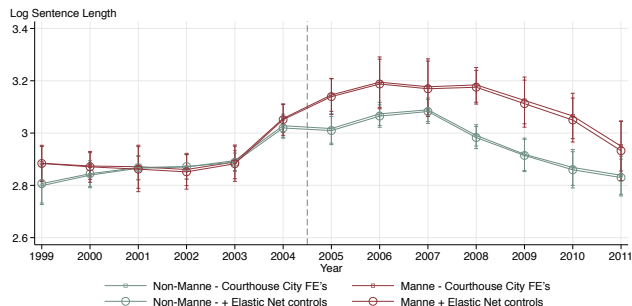
Manne Training and *Booker*



Manne Training and *Booker*



Notes. Margins plots for differences between Manne and non-Manne judges in sentencing outcomes over time. Panel (a): indicator variable for any prison given; Panel (b): log of one plus prison sentence length (in months). Regressions include fixed effects for courthouse, month, day-of-the-week, crime category, and investigating agency. Spikes give 95% confidence intervals.



| | <u>Any Prison</u> | | | <u>Log of Total Sentence</u> | | |
|--|-----------------------|----------------------------------|----------------------------------|----------------------------------|-----|-----|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| <i>Booker</i> (≥ 2005) | 0.0350** (0.00504) | 0.0692 (0.0825) | -0.182** (0.0654) | 0.114+ (0.0660) | | |
| Econ Training | -0.00141 (0.00725) | -0.0448 (0.0622) | -0.0403 (0.0468) | . | . | |
| Econ Training * Booker (≥ 2005) | 0.00887 (0.00621) | 0.199* (0.0835) | 0.154* (0.0736) | 0.166* (0.0675) | | |
| N | 882543 | 882543 | 781362 | 882940 | | |
| adj. R-sq | 0.033 | 0.038 | 0.084 | 0.048 | | |
| Sample | All | All | Sentence > 0 | All | | |
| Court FE | X | X | X | X | | |
| Calendar FE | X | X | X | X | | |
| Judge FE | | | | X | | |

Notes. Estimates for impact of *Booker*, Manne economics training, and their interaction on sentencing outcomes. Calendar FE includes day-of-week and year-month . Standard errors clustered by district in parentheses. + $p < .1$, * $p < 0.05$, ** $p < .01$. Results are similar with fully interacted Republican dummies.

- ▶ Effects on some other related outcomes
 - ▶ no effect on using academic language (based on similarity to law reviews) or use of statistical/quantitative language
 - ▶ no effect on citing U.S. Constitution or Bill of Rights
 - ▶ no effect on citing judges appointed by Reagan or Bush Sr.

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 - ▶ no effect on citing judges appointed by Reagan or Bush Sr.
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- ▶ Robustness Checks:
 - ▶ dropping circuits that seem to violate random assignment (Levy and Chilton 2015)
 - ▶ alternative clustering (e.g. by panel or by circuit-year)
 - ▶ with/without weighting
 - ▶ dropping judges with smallest and largest caseloads
 - ▶ fixed effects for legal topics or crime types
 - ▶ judge-specific trends

The Prejudices of Economic Ideology

- In “Covert Racism in Economics,” for example, Komlos (2022) argues that mainstream economics is replete with implications that feed into structural racism and maintains assumptions that contribute to ongoing dispossession and exploitation of racialized groups (Greenhouse, 2020; Small and Pager, 2020)
 - ▶ Even ostensibly anti-racist agendas that effectively reproduce racial inequalities (Bobo, Kluegel and Ryan, 1996; Bonilla-Silva and Eduardo, 2006)
 - ▶ Program content described in its newsletters are replete with implied racism
 - ★ Rationalization of disproportionately harsh sentencing for Black defendants: “Professor Goetz spoke on ‘Unequal’ Punishment for ‘Equal Crime’, arguing that discrimination in punishment can be analyzed in terms of economic efficiency. . . leading to the conclusion that society will institute unequal punishments for equal crimes.”
 - ★ Even more explicit, Fortune magazine quoting an instructor, “Give me a capsule that will magically clean all the air in Los Angeles .. Beg me to crush it. .. I won’t crush the capsule. Because, if I do, poor blacks will have to pay \$20 a month more for land rental. .. the black in Watts, already used to living with bad air, loses his discount for doing that.”

The Prejudices of Economic Ideology

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The Prejudices of Economic Ideology

- Theoretically ambiguous

- ▶ Less biased since they are guided by cost-benefit analysis, not interpretation
- ▶ School-of-thought thinking conforms to norms and they may be less flexible in decision making, less attentive, and more prone to their own implicit biases
- ▶ Even when making attentive decisions, economics trained judges might prefer longer sentences for a certain race or gender, if more cost-efficient
- ▶ Outline
 - ★ Impact of assigning an economics-trained judge
 - ★ Impact of assigning economics-trained judge relative to Republicans
 - ★ Mechanism: Offense level manipulation
 - ★ judges are provided with discretionary powers to recommend changes to the assigned offense levels
 - ★ Heterogeneity: case type & experience

The Prejudices of Economic Ideology

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- ▶ Outline
 - ★ Impact of assigning an economics-trained judge
 - ★ Impact of assigning economics-trained judge relative to Republicans
 - ★ Mechanism: Offense level manipulation
 - ★ judges are provided with discretionary powers to recommend changes to the assigned offense levels
 - ★ Heterogeneity: case type & experience

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Random Assignment of Judges by Defendant Characteristics

| | <u>Manne</u> | <u>Republican</u> | <u>White</u> | <u>Female</u> |
|------------------------------|-------------------|-------------------|--------------------|-------------------|
| Minority Defendant | 0.004 (0.004) | -0.009 (0.005) | -0.013* (0.006) | 0.010* (0.005) |
| Female Defendant | -0.000 (0.002) | -0.002 (0.003) | -0.010* (0.004) | 0.002 (0.003) |
| Defendant Age | 0.000 (0.000) | -0.000 (0.000) | -0.000 (0.000) | 0.000 (0.000) |
| Guilty Plea | -0.003 (0.003) | -0.002 (0.005) | -0.009 (0.005) | 0.002 (0.005) |
| Defendant New Citizen | -0.004 (0.003) | -0.010 (0.005) | -0.015 (0.010) | 0.008 (0.008) |
| Education = High School | 0.001 (0.002) | 0.001 (0.002) | 0.003 (0.003) | 0.002 (0.005) |
| Education = Some College | 0.001 (0.003) | -0.001 (0.004) | 0.002 (0.003) | 0.004 (0.006) |
| Education = College Graduate | -0.003 (0.005) | -0.003 (0.005) | -0.000 (0.004) | 0.013* (0.006) |
| Court x Sentencing Year FE | Y | Y | Y | Y |
| N | 605684 | 603512 | 589619 | 589619 |
| adj. R-sq | 0.244 | 0.196 | 0.289 | 0.151 |
| F | 1.409 | 0.887 | 1.152 | 1.682 |
| Joint Significance | 0.196 | 0.54 | 0.335 | 0.105 |

Offense Level Manipulation by Judges (Schulhofer and Nagel 1997)

| | <u>Criminal History Rating</u> | <u>Base Offense Level</u> | <u>Final Offense Level</u> |
|----------------------------------|--------------------------------|---------------------------|----------------------------|
| Manne Judge x Minority Defendant | 0.094* (0.036) | 0.473*** (0.110) | 0.610*** (0.116) |
| Manne Judge x Female Defendant | 0.006 (0.024) | -0.267* (0.103) | -0.280** (0.100) |
| Judge x Sentencing Year FE | Yes | Yes | Yes |
| Defendant Controls | Yes | Yes | Yes |
| Case Controls | Yes | Yes | Yes |
| N | 603702 | 599608 | 600757 |
| Adjusted R-squared | 0.260 | 0.759 | 0.492 |
| Mean Dependant Variable | 2.471 | 18.14 | 19.36 |

Standard errors clustered by court are shown within parentheses. Defendant controls include the defendant's age, no. of dependents in the household, education level, citizenship status and whether they plead guilty or not. The case controls include the offense type classification. (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$)

- Manne judges appear to manipulate the offense levels for minority defendants leading to an increase of around 0.61 points for final offense level which corresponds to about a 3.1% increase over the sample mean.
- Females received 0.26 point decrease in their final offense level (1.5% of sample mean)
- This is over 4x larger than the manipulation by Republican judges (in Cohen and Yang 2019)

Race and Gender Disparities due to Economics Training

| | Sentence Length (in months) | | |
|----------------------------------|-----------------------------|-----------------------|-----------------------|
| Minority Defendant | 6.545*** (0.521) | 7.153*** (0.524) | 6.559*** (0.522) |
| Manne Judge x Minority Defendant | 4.268*** (0.968) | | 4.169*** (0.954) |
| Female Defendant | -11.919*** (0.472) | -11.590*** (0.504) | -11.643*** (0.501) |
| Manne Judge x Female Defendant | | -2.435** (0.916) | -2.100* (0.885) |
| Judge X Sentencing Year FE | Yes | Yes | Yes |
| Defendant Controls | Yes | Yes | Yes |
| Case Controls | Yes | Yes | Yes |
| N | 603702 | 603702 | 603702 |
| Adjusted R-squared | 0.418 | 0.418 | 0.418 |

Standard errors clustered by courts are shown within parentheses. Defendant controls include the defendant's age, no. of dependents in the household, education level, citizenship status and whether they plead guilty or not. Case controls include the offense type classification and criminal history rating. (* $p < 0.05$, ** $p < 0.01$. *** $p < 0.001$)

- Manne judges tend to give harsher sentences to minority defendants by about 4 months longer which is equal to 8% over the sample mean of 50 months.
- Manne judges tend to give lenient sentences to female defendants by about 2 months shorter which is about 4% under the sample mean.

Republican Judge Interactions with Race and Gender

| | Sentence Length (in months) | | |
|----------------------------------|-----------------------------|---------|----------|
| Manne Judge x Minority Defendant | 4.258*** | | 4.165*** |
| | (0.961) | | (0.946) |
| Republican x Minority Defendant | -0.292 | | -0.306 |
| | (0.631) | | (0.619) |
| Manne Judge x Female Defendant | | -2.316* | -1.988* |
| | | (0.946) | (0.917) |
| Republican x Female Defendant | | -0.206 | -0.215 |
| | | (0.676) | (0.658) |
| Court x Sentencing Year FE | No | No | No |
| Judge x Sentencing Year FE | Yes | Yes | Yes |
| Defendant Controls | Yes | Yes | Yes |
| Case Controls | Yes | Yes | Yes |
| N | 601839 | 601839 | 601839 |
| Adjusted R-squared | 0.407 | 0.407 | 0.407 |

Standard errors clustered by courts are shown within parentheses. Defendant controls include the defendant's age, no. of dependents in the household, education level, citizenship status and whether they plead guilty or not. The case controls include the offense type classification and criminal history rating. Republican us a dummy variable indicating whether the judges were appointed by a Republican President. (* $p < 0.05$, ** $p < 0.01$. *** $p < 0.001$)

Race and Gender Disparities with Offense Level control

| | | | |
|----------------------------------|----------------------|----------------------|----------------------|
| Minority Defendant | 3.833*** (0.301) | 3.949*** (0.283) | 3.836*** (0.301) |
| Manne Judge x Minority Defendant | 0.816 (0.469) | | 0.794 (0.462) |
| Female Defendant | -5.029*** (0.326) | -4.958*** (0.358) | -4.968*** (0.358) |
| Manne Judge x Female Defendant | | -0.531 (0.611) | -0.467 (0.601) |
| Court X Sentencing Year FE | No | No | No |
| Judge X Sentencing Year FE | Yes | Yes | Yes |
| Defendant Controls | Yes | Yes | Yes |
| Case Controls | Yes | Yes | Yes |
| N | 600661 | 600661 | 600661 |
| Adjusted R-squared | 0.740 | 0.740 | 0.740 |

Standard errors clustered by courts are shown within parentheses. Defendant controls include the defendant's age, no. of dependents in the household, education level, citizenship status and whether they plead guilty or not. Case controls include the offense type classification, criminal history rating and final offense level rating for the case. (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$).

Heterogeneity by Offense Type

| | Sentence Length (in months) | | | | | | |
|--------------------|-----------------------------|--------------------|-------------------|-------------------|-------------------|--------------------|------------------|
| Manne x Minority | 4.593 (4.132) | 5.138** (1.780) | 3.076 (1.909) | -1.374 (1.333) | -1.808 (1.076) | -6.280 (14.302) | 0.412 (0.641) |
| Manne x Female | 5.790 (4.389) | -4.063* (2.011) | -4.073 (3.718) | -0.247 (1.806) | -1.702 (2.001) | -2.166 (19.735) | 1.238 (0.720) |
| Offense Type | violent | drugs | firearms | theft | immigration | sex offense | white collar |
| Judge x S Year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Defendant Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Case Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 23248. | 230143 | 73917 | 13082 | 97369. | 1408 | 102573 |
| Adjusted R-sq. | 0.424 | 0.424 | 0.314 | 0.426 | 0.442 | 0.280 | 0.266 |

Standard errors clustered by courts are shown within parentheses. Defendant controls include the defendant's age, no. of dependents in the household, education level, citizenship status and whether they plead guilty or not. Case controls include the offense type classification and criminal history rating. (* $p < 0.05$, ** $p < 0.01$. *** $p < 0.001$)

- This is consistent with the economic thought where drug-related crimes can be viewed as expensive due to its reach and implications within the society and therefore spurring a more intensive deterrent mechanism targeting minority defendants in such cases.
- Likewise it also explains the more lenient sentencing for the female defendants in such crimes since it is relatively less harmful or more beneficial to the society or dependants at home if they were to be incarcerated for a shorter time period.

Heterogeneity by Judge Experience

| Sample | Sentence Length (in months) | |
|----------------------------------|--------------------------------------|--------------------------------------|
| | <u>Above Median Judge Experience</u> | <u>Below Median Judge Experience</u> |
| Manne Judge x Minority Defendant | 4.243*** (1.014) | 6.653*** (1.755) |
| Manne Judge x Female Defendant | -1.952* (0.927) | -3.188 (1.859) |
| Judge x Sentencing Year FE | Yes | Yes |
| Defendant Controls | Yes | Yes |
| Case Controls | Yes | Yes |
| Observations | 309326 | 294376 |
| Adjusted R-squared | 0.414 | 0.423 |

Standard errors clustered by courts are shown within parentheses. Defendant controls include the defendant's age, no. of dependents in the household, education level, citizenship status and whether they plead guilty or not. Case controls include the offense type classification and criminal history rating. Judge experience defined at the time of hearing as being above or below the sample median (* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$)

- Manne judges tend to be relatively less disparate with experience.
- Could be explained by experienced judges are more attentive to implicit biases thereby mitigating the disparate effects of economic thinking on their sentencing decisions

The Prejudices of Economic Ideology

- The rationale behind awarding harsher sentences for minority defendants and lenient sentencing for female defendants could be considered to be consistent with the ideologies of economic thought.
 - ▶ The idea of deterrence being a more cost-effective approach for minority defendants who have reportedly higher arrest rates and the female defendants being relatively more economically productive in the society could have been the driving forces behind the implicit or explicit bias observed in the sentencing decisions among the Manne judges.
 - ▶ From a cognitive perspective, it could be argued that the judges were motivated by the economic aspects of the case leading to them paying lesser attention to implicit biases in their decision making (Clair and Winter, 2016).

WHERE DO WE GO FROM HERE?

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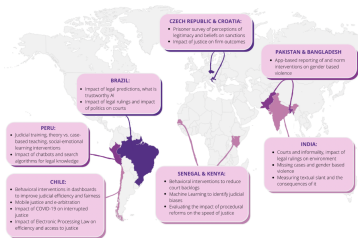
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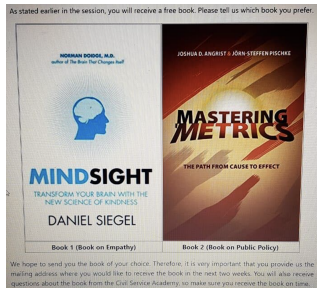
WHERE DO WE GO FROM HERE?

A Friendlier Economics?

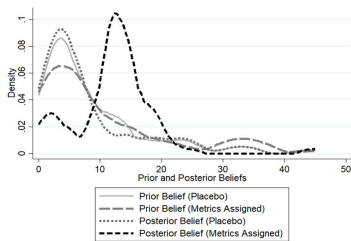
AMICUS (Analytical Metrics for Informed Courtroom Understanding & Strategy)



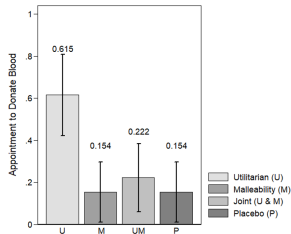
Training deputy ministers in a school of thought



Econometrics Training Increased Responsiveness to Causal Evidence



Effective Altruism Training Increased Altruism in Action



How Can We Train Judges to Improve Rule of Law?

- The training of public officials is one of the key dimensions governments use to improve bureaucratic performance
- For example, in 2017 alone, the U.S. allocated approximately 4% of its annual budget for personnel compensation and benefits, or around \$10 billion, towards training civil servants (Credibility Engine 2021; USA Spending)
- Despite its significance, there is limited empirical research on effective methods to improve the training of public officials using RCTs
- Particularly relevant in the judiciary, as slow and unreliable justice systems represent a key barrier to economic growth

Do economic ideas impact decision-making?

- Closest study: randomly assigned law profs w/ econ phds (Fisman, Kariv, Markovits 2009)
 - Curricula \Rightarrow 10-20% shift in free market **attitudes** (Cantoni et al. JPE 2014)
 - Redistributive **preferences** (Alesina et al. AER 2007)
 - Less **redistributive** of potential lottery winnings (Selten and Ockenfels JEBO 1998)
 - Decline in self-reported **honest** behavior (Frank et al. JEP 2003)
 - Favor **profit** maximization in business vignette (Rubinstein EJ 2006)
 - Surge **prices** viewed more fairly, with any econ experience (Frey et al. EI 2003)
 - **8 hours** of high school training impacts economic preferences (Sutter, etc. 201x)
 - **<1 hour** of economics increases PD defection by 20% (Ifcher, etc. JBEE 2018)
- Narratives/text as product of discrete choice (Shiller 2017)
 - **Economic NLP, LASSO on Congressional Speech** (Gentzkow et al. 2015)
 - Classify economics text as conservative or liberal (Jelveh et al. 2016)
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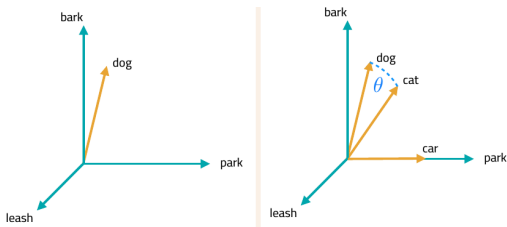
Law-and-Economics Vectors

- Want to measure take up of economic ideas in written opinions
- Cosine distance of word and document embeddings to:
 - externalit*, transaction_costs, efficien*, deterr*, cost_benefit, capital, game_theo, chicago_school, marketplace (Law & economics words - Ellickson 2000)



Predict the surrounding words given a current word in a current document

Words as Vectors

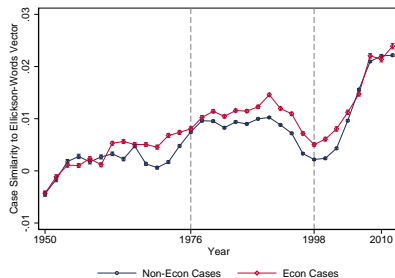
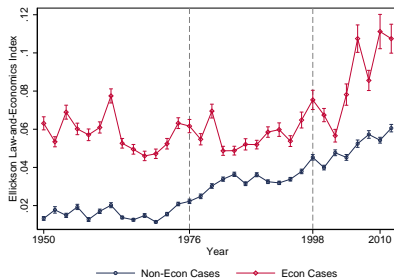


- Use cosine similarity as a measure of relatedness:

$$\cos \theta = \frac{v_1 \cdot v_2}{\|v_1\| \|v_2\|}$$

- Every word gets represented as a 300-dimensional vector
 - Similar words tend to co-locate

Increasing Economic Orientation in Federal Judiciary



- **Interviews** of courts and **orthogonality checks** of observables
 - (1) 2-3 weeks before oral argument, computer:
 - randomly assigns available judges including visiting judges
 - ensures judges are not sitting together repeatedly
 - senior judges reduced frequency entered into the program
 - (2) randomly assign panels on yearly basis, then randomly assign cases
 - judges can occasionally recuse
 - panel sees case again on remand
 - exceptions for specialized cases like death penalty
- **Omnibus test:** how similar string of panel assignments is to random strings
 - Not accounting for vacation, sick leave, senior status, en banc, remand, and recusal can lead to the inference that judges are not randomly assigned.
 - We assume these deviations from randomness are Rubin-ignorable.

Judge Randomization Check

| | <u>Economics Case</u> | | | |
|-----------------|-----------------------|------------------------|-----------------------|----------------------|
| | (1) | (2) | (3) | (4) |
| Econ Training | 0.00788 (0.00807) | -0.000716 (0.00454) | -0.00512 (0.00893) | 0.00540 (0.00416) |
| N | 123519 | 115561 | 500266 | 389105 |
| adj. R-sq | 0.115 | 0.024 | 0.112 | 0.023 |
| Circuit-Year FE | Y | Y | Y | Y |
| Sample | Author | Author | On Panel | On Panel |
| Sample | Year < 1976 | Year > 1991 | Year < 1976 | Year > 1991 |

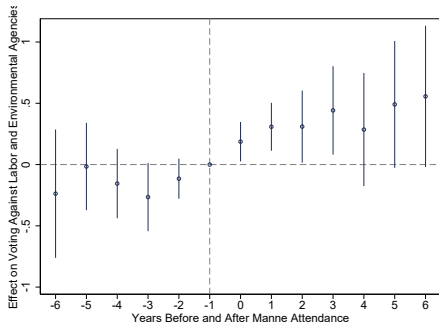
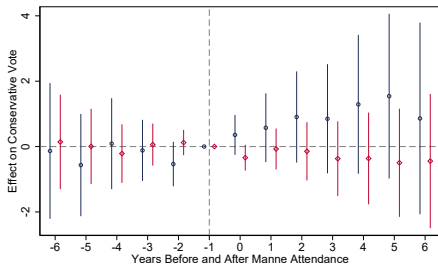
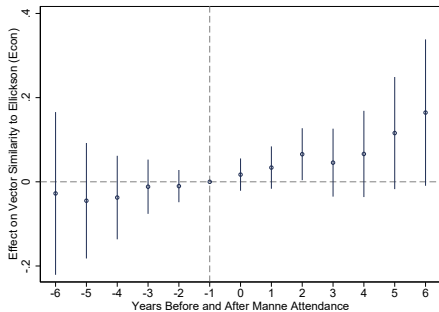
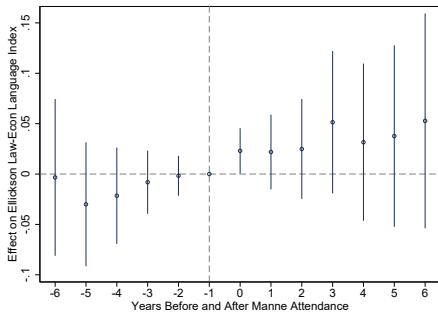
Omnibus check: No endogenous settlement or selection of cases.

Outline

- 1 Manne Program
- 2 Event Studies**
- 3 Discretion
- 4 Peer Effects
- 5 Language
- 6 Long-Difference Impact of Economics Judges
- 7 Impact of Economics Training on Criminal Cases
- 8 General Equilibrium Impacts of Economics Training
- 9 Concluding Remarks and Bonus Slides

$$Y_{ijct} = \theta_{ct} + \theta_j + \sum_{n=-6}^{0..6} \beta_{t-n} \text{Manne}_{ct-n} + \eta X_{jt} + \varepsilon_{ijct}$$

- case i , judge j , court c , year t , for $n \in [-6, 6]$
- 95% CI; j clusters; jt weighted equally



○ Non-Econ Cases ♦ Econ Cases

Manne Attendance on

◀ Conservative votes

| | <u>Conservative Vote (+1/0/-1)</u> | | |
|-----------------------|------------------------------------|-----------------------|-----------------------|
| | (1) | (2) | (3) |
| Econ Case | -0.203*** (0.0304) | -0.194*** (0.0286) | -0.187*** (0.0194) |
| Post-Manne | -0.118 (0.0739) | -0.0481 (0.0750) | -0.104* (0.0544) |
| Econ Case * | 0.315** | 0.193* | 0.190** |
| Post-Manne | (0.135) | (0.114) | (0.0768) |
| N | 28092 | 27799 | 25882 |
| adj. R-sq | 0.115 | 0.254 | 0.124 |
| Circuit-Year FE | X | X | X |
| Judge FE | | X | X |
| E-net-Vars ## Year FE | | | X |
| Sample | 1970-2002 | 1970-2002 | 1970-2002 |

Judges shift by 10% the direction of their votes.

◀ 30-70 distribution of economics and non-economics cases

Manne Attendance on Government Regulations

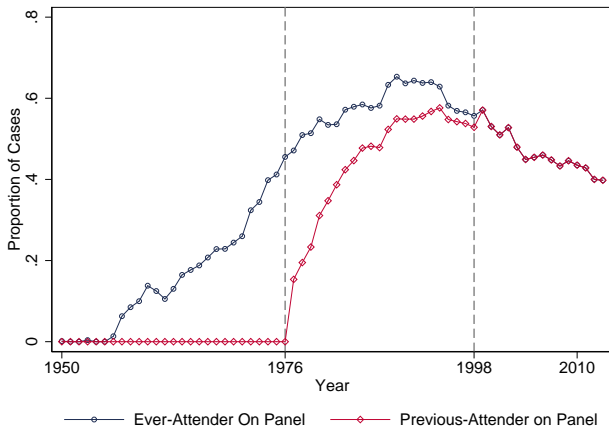
| | <u>Voting Against Government Regulations</u> | | | |
|-----------------------|--|-----------------|-----------------|-----------------|
| | (1) | (2) | (3) | (4) |
| Post-Manne | 0.0734** | 0.0698** | 0.117*** | 0.116*** |
| | (0.0345) | (0.0334) | (0.0393) | (0.0416) |
| N | 68597 | 68597 | 68597 | 68597 |
| adj. R-sq | 0.230 | 0.235 | 0.238 | 0.234 |
| Circuit-Year FE | X | X | X | X |
| Judge FE | X | X | X | X |
| Party-Year FE | | X | X | |
| Ever-Attend-Year FE | | | X | |
| E-net Vars ## Year FE | | | | X |

Judges are 7-12% more likely to vote against government regulations after economics training.

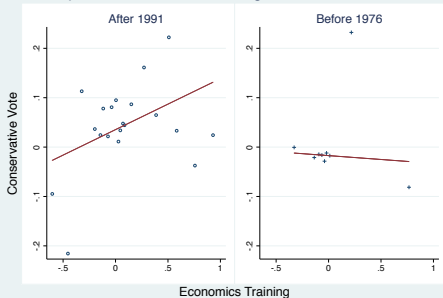
Long-Difference – Specification

$$Y_{ijct} = \alpha_{ct} + \gamma Z_{ijt} + X_j' \beta + \varepsilon_{ijct}$$

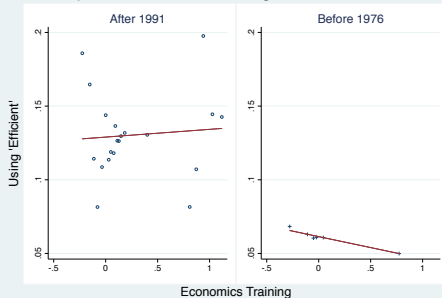
- case i , judge j , court c , year t , for $n \in [-6, 6]$
- 95% CI; j clusters; jt weighted equally
- Z_{ijt} , economics training (1976-1999)



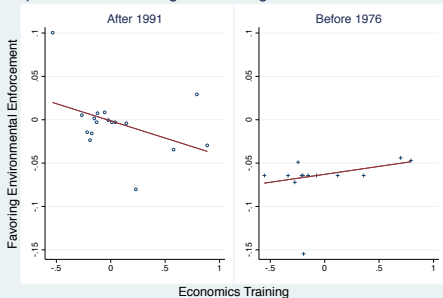
Impact of Economics Training on Economics Cases



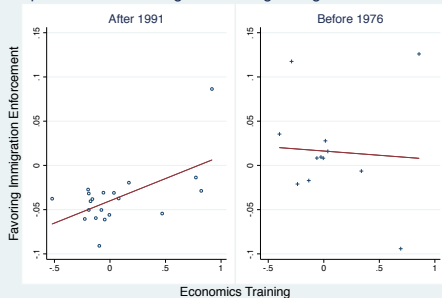
Impact of Economics Training on Use of 'Efficient'



Impact of Econ Training on Favoring Environment Enforcement



Impact of Econ Training on Favoring Immigration Enforcement



Heterogeneity by Instructor

"Friedman always started on legalization of recreational drugs" (Butler 10/2017)

Milton Friedman taught in 1976, 1978, 1979, 1980

| | <u>Rejecting Criminal Appeal (Habeas Corpus)</u> | | | |
|--------------------------|--|-----------------|-----------------|-----------------|
| | (1) | (2) | (3) | (4) |
| Manne Training | 0.0608* | | -0.251** | |
| | (0.0286) | | (0.0922) | |
| Friedman Training | -0.0921* | -0.102 | 0.131 | 0.243** |
| | (0.0437) | (0.0615) | (0.107) | (0.0819) |
| N | 12173 | 1269 | 13895 | 753 |
| adj. R-sq | 0.140 | 0.233 | 0.264 | 0.393 |
| Circuit-Year FE | Y | Y | Y | Y |
| Sample | Post 1991 | | Pre 1976 | |
| Judges | All | Attend < 1986 | All | Attend < 1986 |

Economics Trained Judges vote to reject appeal of unlawful detention or imprisonment, unless Friedman taught.

Heterogeneity by Instructor

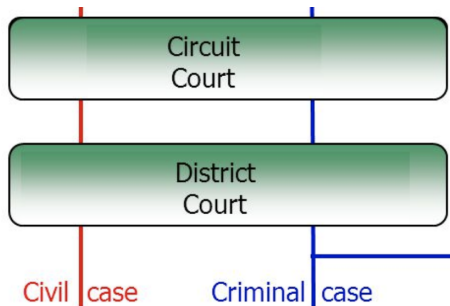
"Friedman always started on legalization of recreational drugs" (Butler 10/2017)

Milton Friedman taught in 1976, 1978, 1979, 1980

| | <u>Rejecting Criminal Appeal (Habeas Corpus)</u> | | | |
|--------------------------|--|-----------------|-----------------|-----------------|
| | (1) | (2) | (3) | (4) |
| Manne Training | 0.0608* | | -0.251** | |
| | (0.0286) | | (0.0922) | |
| Friedman Training | -0.0921* | -0.102 | 0.131 | 0.243** |
| | (0.0437) | (0.0615) | (0.107) | (0.0819) |
| N | 12173 | 1269 | 13895 | 753 |
| adj. R-sq | 0.140 | 0.233 | 0.264 | 0.393 |
| Circuit-Year FE | Y | Y | Y | Y |
| Sample | Post 1991 | | Pre 1976 | |
| Judges | All | Attend < 1986 | All | Attend < 1986 |

Economics Trained Judges vote to reject appeal of unlawful detention or imprisonment, unless Friedman taught.

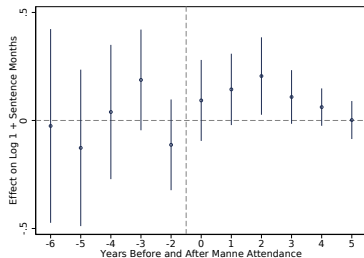
Federal Criminal Justice Setting



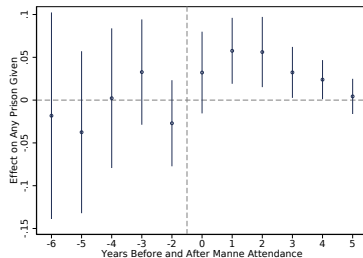
Federal courts handle the most serious criminal cases (8% of US prison population).

◀ Randomization check of district judges

Manne Attendance on Sentencing Decisions



Sentence Length



Any Sentence

$$Y_{ijct} = \theta_{ct} + \theta_j + \sum_{n=-6..-2}^{0..6} \beta_{t-n} \text{Manne}_{ct-n} + \eta X_{jt} + \varepsilon_{ijct} \quad \text{for } n \in [-6, 6]$$

95% CI; j clusters; 1992-2003

Manne Attendance on Sentencing Decisions

| | <u>Manne Effect on Sentencing Outcomes</u> | | | |
|----------------------|--|-----------------|---------------------|------------------|
| | (1) | (2) | (3) | (4) |
| | <u>Log Sentence Length</u> | | <u>Any Sentence</u> | |
| Post-Manne | 0.0833** | 0.0655* | 0.0212** | 0.0186** |
| | (0.0366) | (0.0395) | (0.00920) | (0.00944) |
| N | 1027409 | 978445 | 1029800 | 980735 |
| adj. R-sq | 0.067 | 0.063 | 0.075 | 0.072 |
| Circuit-Year FE | X | X | X | X |
| Judge FE | X | X | X | X |
| E-net-Vars x Year FE | | X | | X |

Judges increase sentence lengths by 7% and any sentences by 2%.

Outline

- 1 Manne Program
- 2 Event Studies
- 3 Discretion**
- 4 Peer Effects
- 5 Language
- 6 Long-Difference Impact of Economics Judges
- 7 Impact of Economics Training on Criminal Cases
- 8 General Equilibrium Impacts of Economics Training
- 9 Concluding Remarks and Bonus Slides

Sentencing Guidelines in District Courts

Appendix Figure 1: United States Sentencing Guidelines Grid

Sentencing Table (in months of imprisonment)

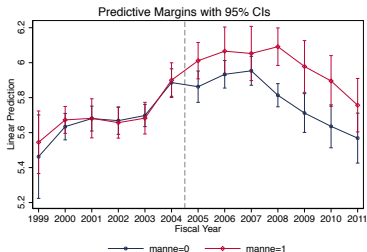
| Offense Level | | Criminal History Category (Criminal History Points) | | | | | |
|---------------|----|---|----------------|------------------|-----------------|-------------------|--------------------|
| | | I (0 or 1) | II (2 or 3) | III (4, 5, 6) | IV (7, 8, 9) | V (10, 11, 12) | VI (13 or more) |
| Zone A | 1 | 0-6 | 0-6 | 0-6 | 0-6 | 0-6 | 0-6 |
| | 2 | 0-6 | 0-6 | 0-6 | 0-6 | 0-6 | 1-7 |
| | 3 | 0-6 | 0-6 | 0-6 | 0-6 | 2-8 | 3-9 |
| | 4 | 0-6 | 0-6 | 0-6 | 2-8 | 4-10 | 6-12 |
| | 5 | 0-6 | 0-6 | 1-7 | 4-10 | 6-12 | 9-15 |
| | 6 | 0-6 | 1-7 | 2-8 | 6-12 | 9-15 | 12-18 |
| | 7 | 0-6 | 2-8 | 4-10 | 8-14 | 12-18 | 15-21 |
| | 8 | 0-6 | 4-10 | 6-12 | 10-16 | 15-21 | 18-24 |
| Zone B | 9 | 4-10 | 6-12 | 8-14 | 12-18 | 18-24 | 21-27 |
| | 10 | 6-12 | 8-14 | 10-16 | 15-21 | 21-27 | 24-30 |
| Zone C | 11 | 8-14 | 10-16 | 12-18 | 18-24 | 24-30 | 27-33 |
| | 12 | 10-16 | 12-18 | 15-21 | 21-27 | 27-33 | 30-37 |
| | 13 | 12-18 | 15-21 | 18-24 | 24-30 | 30-37 | 33-41 |
| | 14 | 15-21 | 18-24 | 21-27 | 27-33 | 33-41 | 37-46 |
| | 15 | 18-24 | 21-27 | 24-30 | 30-37 | 37-46 | 41-51 |

Sentencing Guidelines in District Courts

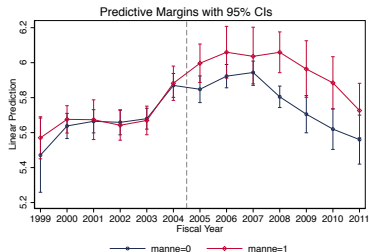
Appendix Figure 1: United States Sentencing Guidelines Grid
Sentencing Table (in months of imprisonment)

| Offense Level | Criminal History Category (Criminal History Points) | | | | | |
|---------------|---|----------------|------------------|-----------------|-------------------|--------------------|
| | I (0 or 1) | II (2 or 3) | III (4, 5, 6) | IV (7, 8, 9) | V (10, 11, 12) | VI (13 or more) |
| Zone A | 1 | 0-6 | 0-6 | 0-6 | 0-6 | 0-6 |
| | 2 | 0-6 | 0-6 | 0-6 | 0-6 | 1-7 |
| | 3 | 0-6 | 0-6 | 0-6 | 2-8 | 3-9 |
| | 4 | 0-6 | 0-6 | 2-8 | 4-10 | 6-12 |
| | 5 | 0-6 | 0-6 | 1-7 | 4-10 | 6-12 |
| | 6 | 0-6 | 1-7 | 2-8 | 6-12 | 9-15 |
| | 7 | 0-6 | 2-8 | 4-10 | 8-14 | 12-18 |
| Zone B | 8 | 0-6 | 4-10 | 6-12 | 10-16 | 15-21 |
| | 9 | 4-10 | 6-12 | 8-14 | 12-18 | 18-24 |
| | 10 | 6-12 | 8-14 | 10-16 | 15-21 | 21-27 |
| Zone C | 11 | 8-14 | 10-16 | 12-18 | 18-24 | 24-30 |
| | 12 | 10-16 | 12-18 | 15-21 | 21-27 | 27-33 |
| Zone D | 13 | 12-18 | 15-21 | 18-24 | 24-30 | 30-37 |
| | 14 | 15-21 | 18-24 | 21-27 | 27-33 | 33-41 |
| | 15 | 18-24 | 21-27 | 24-30 | 30-37 | 37-46 |
| | 16 | 21-27 | 24-30 | 27-33 | 33-41 | 41-51 |
| | 17 | 24-30 | 27-33 | 30-37 | 37-46 | 46-57 |
| | 18 | 27-33 | 30-37 | 33-41 | 41-51 | 51-63 |
| | 19 | 30-37 | 33-41 | 37-46 | 46-57 | 57-71 |
| | 20 | 33-41 | 37-46 | 41-51 | 51-63 | 63-78 |
| | 21 | 37-46 | 41-51 | 46-57 | 57-71 | 70-87 |
| | 22 | 41-51 | 46-57 | 51-63 | 63-78 | 77-96 |
| | 23 | 46-57 | 51-63 | 57-71 | 70-87 | 84-105 |
| | 24 | 51-63 | 57-71 | 63-78 | 77-96 | 92-115 |
| | 25 | 57-71 | 63-78 | 70-87 | 84-105 | 100-125 |
| | 26 | 63-78 | 70-87 | 78-97 | 92-115 | 110-137 |
| | 27 | 70-87 | 78-97 | 87-108 | 100-125 | 120-150 |
| | 28 | 78-97 | 87-108 | 97-121 | 110-137 | 130-162 |
| | 29 | 87-108 | 97-121 | 108-135 | 121-151 | 140-175 |
| | 30 | 97-121 | 108-135 | 121-151 | 135-168 | 151-188 |
| | 31 | 108-135 | 121-151 | 135-168 | 151-188 | 168-210 |
| | 32 | 121-151 | 135-168 | 151-188 | 168-210 | 188-235 |
| | 33 | 135-168 | 151-188 | 168-210 | 188-235 | 210-262 |
| | 34 | 151-188 | 168-210 | 188-235 | 210-262 | 235-293 |
| | 35 | 168-210 | 188-235 | 210-262 | 235-293 | 262-327 |
| | 36 | 188-235 | 210-262 | 235-293 | 262-327 | 292-365 |
| | 37 | 210-262 | 235-293 | 262-327 | 292-365 | 324-405 |
| | 38 | 235-293 | 262-327 | 292-365 | 324-405 | 360-life |
| | 39 | 262-327 | 292-365 | 324-405 | 360-life | 360-life |
| | 40 | 292-365 | 324-405 | 360-life | 360-life | 360-life |
| | 41 | 324-405 | 360-life | 360-life | 360-life | 360-life |
| | 42 | 360-life | 360-life | 360-life | 360-life | 360-life |
| | 43 | Life | Life | Life | Life | Life |

Impact of Economics Judges, Pre and Post *Booker*



Raw Correlation



with Elastic Net x Year FE

After allowing judicial discretion, Economics Trained Judges increase sentencing severity in District Courts.

- In *U.S. v. Booker* (Jan 12, 2005) the Supreme Court declared existing guidelines violated Constitution. *Booker* motivated by judges' desire to depart below guidelines, which seems to be a long-term trend.
- *Booker* ↑ variance (Yang 2014); Republicans 13% harsher for 5 yrs (Cohen and Yang AEJ 2017) Results hold with fully interacted Republican (as w/ Circuit), seem persistent. Note: could be non-econ effect.

Impact of Economics Judges, Pre and Post *Booker*

| | <u>Any Sentence</u> | <u>Log of Total Sentence</u> | | |
|--|-----------------------|------------------------------|----------------------|---------------------|
| | (1) | (2) | (3) | (4) |
| Econ Training | -0.00433 (0.00692) | -0.0336 (0.0594) | -0.00527 (0.0462) | -0.00795 (0.142) |
| Econ Training * | 0.0117* | 0.198** | 0.131* | 0.130* |
| Booker (≥ 2005) | (0.00631) | (0.0829) | (0.0731) | (0.0774) |
| N | 930448 | 930448 | 819881 | 889951 |
| adj. R-sq | 0.035 | 0.037 | 0.085 | 0.053 |
| Courthouse and Calendar FE | X | X | X | X |
| Judge FE | | | | X |
| Sample | All | All | Sentence > 0 | All |

To benchmark, blacks receive almost 10% longer sentences than comparable white defendants arrested for the same crimes (Rehavi and Starr JPE 2014).

Immigration Charges

| Lead Charge | Count | Rank | 1 yr ago | 5 yrs ago | 10 yrs ago | 20 yrs ago |
|---|--------|------|----------|-----------|------------|------------|
| 08 USC 1325 - Entry of alien at improper time or place; etc. | 35,367 | 1 | 1 | 1 | 2 | 3 |
| 08 USC 1326 - Reentry of deported alien | 28,930 | 2 | 2 | 2 | 1 | 1 |
| 08 USC 1324 - Bringing in and harboring certain aliens | 3,794 | 3 | 3 | 3 | 3 | 2 |
| 18 USC 1546 - Fraud and misuse of visas, permits, and other documents | 502 | 4 | 4 | 4 | 4 | 4 |
| 18 USC 1544 - Misuse of passport | 333 | 5 | 5 | 8 | 15 | 16 |
| 18 USC 1028 - Fraud and related activity - id documents | 165 | 6 | 6 | 5 | 6 | 7 |
| 18 USC 1542 - False statement in application and use of passport | 72 | 7 | 7 | 9 | 10 | 8 |
| 18 USC 922 - Firearms; Unlawful acts | 50 | 8 | 11 | 12 | 13 | 22 |
| 21 USC 841 - Drug Abuse Prevention & Control-Prohibited acts A | 45 | 9 | 10 | 14 | 14 | 11 |
| 18 USC 371 - Conspiracy to commit offense or to defraud US | 40 | 10 | 16 | 10 | 11 | 5 |

Immigration crime associated with limited liability and no 'rehabilitation' margin

Impact of Economics Judges, by Crime Type

| | <u>Log of Total Sentence</u> | | | | |
|----------------------------|------------------------------|----------------------|---------------------|---------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Econ Training | -0.0695 (0.0839) | -0.00621 (0.0347) | -0.0369 (0.0559) | -0.0213 (0.0619) | -0.0226 (0.0599) |
| Econ Training * | 0.245** | 0.0467 | 0.200** | 0.184** | 0.219** |
| Booker (≥ 2005) | (0.100) | (0.0411) | (0.0856) | (0.0903) | (0.0900) |
| N | 600010 | 697844 | 798823 | 838643 | 786472 |
| adj. R-sq | 0.043 | 0.044 | 0.051 | 0.037 | 0.043 |
| Courthouse and Calendar FE | Y | Y | Y | Y | Y |
| Drop Crime | Drug | Immigration | Fraud | Weapon | Other |

Largest effects of economic training found in immigration crimes

Coarse Communication

- Use of stereotypes under information constraints (*Bordalo et al. QJE 2016*)
- Communication constraint works as a magnifier of correlation (*Kweik 2013*)

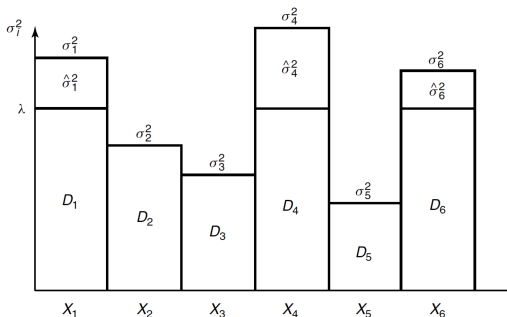


FIGURE 10.7. Reverse water-filling for independent Gaussian random variables.

Elements of Information Theory (Cover and Thomas 1991)

- No bits used to describe information with variance less than a constant
- Results in exaggerating pre-existing correlations

Impact of Economics Judges on Racial Gaps

| | <u>Life</u> | <u>Months</u> | <u>Life</u> | <u>Months</u> |
|-----------------|--------------------------|---------------------|-------------------------|---------------------|
| | (1) | (2) | (3) | (4) |
| <i>Minority</i> | 0.00395*** (0.000770) | 20.84*** (1.979) | 0.00388*** (0.00102) | 20.34*** (2.170) |
| * Economics | 0.00401** (0.00157) | 5.413*** (2.044) | 0.00379** (0.00170) | 3.180* (1.910) |
| * Republican | | | 0.000641 (0.00103) | 4.096** (1.723) |
| * Minority J | | | -0.00119 (0.00135) | -7.451** (3.167) |
| N | 156650 | 155977 | 154920 | 154253 |
| adj. R-sq | 0.015 | 0.102 | 0.015 | 0.102 |
| Judge FE | Y | Y | Y | Y |
| Sample | All | All | All | All |

Economics Trained Judges harsher to minorities (1992-2003 30% merge to USSC)

Impact of Economics Judges on Gender Gaps

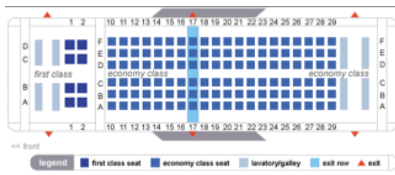
| | <u>Life</u> | <u>Months</u> | <u>Life</u> | <u>Months</u> |
|---------------|-------------|---------------|-------------|---------------|
| | (1) | (2) | (3) | (4) |
| <i>Female</i> | -0.00397*** | -31.01*** | -0.00395*** | -29.84*** |
| | (0.000562) | (1.676) | (0.000718) | (2.127) |
| * Economics | -0.00247** | -5.083*** | -0.00227* | -4.120** |
| | (0.00113) | (1.717) | (0.00116) | (1.617) |
| * Republican | | | -0.000372 | -2.549* |
| | | | (0.000678) | (1.456) |
| * Female J | | | 0.000697 | 0.145 |
| | | | (0.000750) | (1.218) |
| N | 160402 | 159713 | 158634 | 157951 |
| adj. R-sq | 0.014 | 0.109 | 0.015 | 0.109 |
| Judge FE | Y | Y | Y | Y |
| Sample | All | All | All | All |

Economics Trained Judges more lenient to females (1992-2003 30% merge to USSC)

Outline

- 1 Manne Program
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Identification of Learning & Memetic Effects



Impact of law-and-economics exposure $a_{i-\ell}$ on

- case i , judge j , court c , year t

$$F_{ijct} = \sum_{\ell=0}^{L_s} \beta_s^\ell s_{i-\ell} a_{i-\ell} + \sum_{\ell=0}^{L_d} \beta_t^\ell t_{i-\ell} a_{i-\ell} + \mu_j + \xi_{ct} + \varepsilon_{ijct}$$

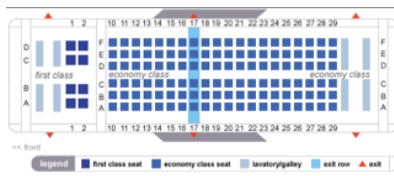
- $s_{i-\ell}$: exogenous seat network, $t_{i-\ell}$: time network, $c_{i-\ell}$: citation network
- β_s^ℓ : Impact of Economics Training on Previous Case of this Judge
- β_t^ℓ : Impact of Economics Training on Previous Case in this Circuit

Separately identify within- (β_{sT}^ℓ) vs. across-topic (β_s^ℓ) impacts:

- β_{sT}^ℓ : Impact of Economics Training on Previous Case of Judge on Topic
- β_{tT}^ℓ : Impact of Economics Training on Previous Case of Circuit on Topic

Active v. Passive Persuasion (Was previous case divided? $\beta(\text{citation, reversal, dissent})$)

Identification of Learning & Memetic Effects



Impact of law-and-economics exposure $a_{i-\ell}$ on

- case i , judge j , court c , year t

$$F_{ijct} = \sum_{\ell=0}^{L_s} \beta_s^\ell s_{i-\ell} a_{i-\ell} + \sum_{\ell=0}^{L_d} \beta_t^\ell t_{i-\ell} a_{i-\ell} + \mu_j + \xi_{ct} + \varepsilon_{ijct}$$

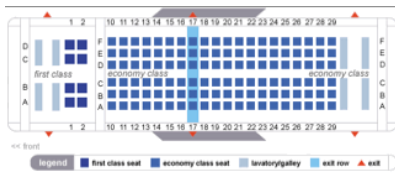
- $s_{i-\ell}$: exogenous seat network, $t_{i-\ell}$: time network, $c_{i-\ell}$: citation network
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Active v. Passive Persuasion (Was previous case divided? $\beta(\text{citation, reversal, dissent})$)

Identification of Learning & Memetic Effects



Impact of law-and-economics exposure $a_{i-\ell}$ on

- case i , judge j , court c , year t

$$F_{ijct} = \sum_{\ell=0}^{L_s} \beta_s^\ell s_{i-\ell} a_{i-\ell} + \sum_{\ell=0}^{L_d} \beta_t^\ell t_{i-\ell} a_{i-\ell} + \mu_j + \xi_{ct} + \varepsilon_{ijct}$$

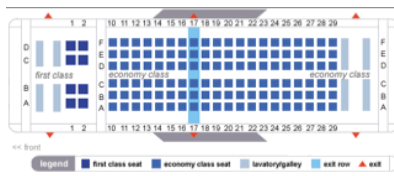
- $s_{i-\ell}$: exogenous seat network, $t_{i-\ell}$: time network, $c_{i-\ell}$: citation network
- β_s^ℓ : Impact of Economics Training on Previous Case of this Judge
- β_t^ℓ : Impact of Economics Training on Previous Case in this Circuit

Separately identify within- (β_{sT}^ℓ) vs. across-topic (β_s^ℓ) impacts:

- β_{sT}^ℓ : Impact of Economics Training on Previous Case of Judge on Topic
- β_{tT}^ℓ : Impact of Economics Training on Previous Case of Circuit on Topic

Active v. Passive Persuasion (Was previous case divided? $\beta(\text{citation, reversal, dissent})$)

Identification of Learning & Memetic Effects



Impact of law-and-economics exposure $a_{i-\ell}$ on

- case i , judge j , court c , year t

$$F_{ijct} = \sum_{\ell=0}^{L_s} \beta_s^\ell s_{i-\ell} a_{i-\ell} + \sum_{\ell=0}^{L_d} \beta_t^\ell t_{i-\ell} a_{i-\ell} + \mu_j + \xi_{ct} + \varepsilon_{ijct}$$

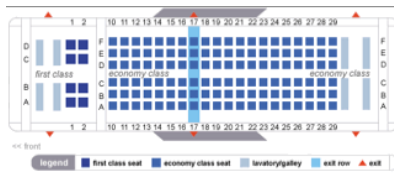
- $s_{i-\ell}$: exogenous seat network, $t_{i-\ell}$: time network, $c_{i-\ell}$: citation network
- β_s^ℓ : Impact of Economics Training on **Previous Case of this Judge**
- β_t^ℓ : Impact of Economics Training on **Previous Case in this Circuit**

Separately identify within- (β_{sT}^ℓ) vs. across-topic (β_s^ℓ) impacts:

- β_{sT}^ℓ : Impact of Economics Training on **Previous Case of Judge on Topic**
- β_{tT}^ℓ : Impact of Economics Training on **Previous Case of Circuit on Topic**

Active v. Passive Persuasion (Was previous case divided? $\beta(\text{citation, reversal, dissent})$)

Identification of Learning & Memetic Effects



Impact of law-and-economics exposure $a_{i-\ell}$ on

- case i , judge j , court c , year t

$$F_{ijct} = \sum_{\ell=0}^{L_s} \beta_s^\ell s_{i-\ell} a_{i-\ell} + \sum_{\ell=0}^{L_d} \beta_t^\ell t_{i-\ell} a_{i-\ell} + \mu_j + \xi_{ct} + \varepsilon_{ijct}$$

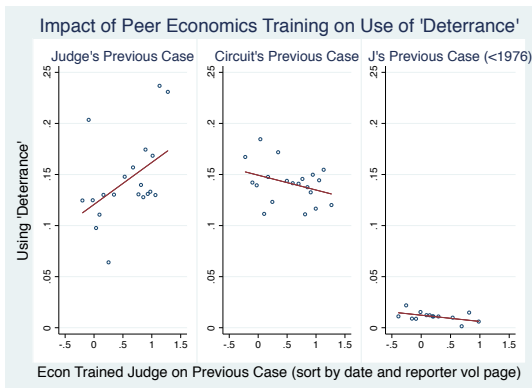
- $s_{i-\ell}$: exogenous seat network, $t_{i-\ell}$: time network, $c_{i-\ell}$: citation network
- β_s^ℓ : Impact of Economics Training on **Previous Case of this Judge**
- β_t^ℓ : Impact of Economics Training on **Previous Case in this Circuit**

Separately identify within- (β_{sT}^ℓ) vs. across-topic (β_s^ℓ) impacts:

- β_{sT}^ℓ : Impact of Economics Training on **Previous Case of Judge on Topic**
- β_{tT}^ℓ : Impact of Economics Training on **Previous Case of Circuit on Topic**

Active v. Passive Persuasion (Was previous case divided? $\hat{\rho}(\text{citation, reversal, dissent})$)

Impact of Peer Econ Judges on Criminal Case Reasoning



Previous judge case (median) 9 days ago; previous circuit case (median) 2 days ago. Exclude same day cases.

Identifying Memetic Economic Phrases, All Cases

| | | <u># Uses of “Deterrence”</u> | | |
|----------------------|-----------------------|-------------------------------------|------------------------------------|------------------------------------|
| Econ Training on | (1) | (2) | (3) | (4) |
| Next Case | -0.00412 (0.00730) | | | |
| This Case | | 0.0161** (0.00683) | | |
| Previous Case | | | 0.0127* (0.00692) | |
| Two Cases Ago | | | | 0.0120* (0.00678) |
| N | 353981 | 355504 | 354695 | 353928 |
| adj. R-sq | 0.009 | 0.010 | 0.010 | 0.010 |
| Circuit-Year FE | Y | Y | Y | Y |
| Circuit Order | Y | Y | Y | Y |
| Sample | Year > 1991 | Year > 1991 | Year > 1991 | Year > 1991 |
| Order within | Judge | Judge | Judge | Judge |
| Cluster | Judge | Judge | Judge | Judge |

Identifying Memetic Economic Phrases, All Cases

| | <u># Uses of "Law and Economics"</u> | | | |
|----------------------|--------------------------------------|--|--|---------------------------------------|
| Econ Training on | (1) | (2) | (3) | (4) |
| Next Case | 0.000206 (0.000259) | | | |
| This Case | | 0.000537** (0.000243) | | |
| Previous Case | | | 0.000574** (0.000252) | |
| Two Cases Ago | | | | 0.000536* (0.000280) |
| N | 353981 | 355504 | 354695 | 353928 |
| adj. R-sq | 0.002 | 0.005 | 0.005 | 0.005 |
| Circuit-Year FE | Y | Y | Y | Y |
| Circuit Order | Y | Y | Y | Y |
| Sample | Year > 1991 | Year > 1991 | Year > 1991 | Year > 1991 |
| Order within | Judge | Judge | Judge | Judge |
| Cluster | Judge | Judge | Judge | Judge |

Identifying Memetic Economic Phrases, All Cases

Uses of “Deterrence” on [N] cases later

| Econ Training on | [N] = (-1) | (0) | (1) | (2) | (3) | (4) |
|------------------|-----------------------|-------------------------------------|------------------------------------|------------------------------------|-------------------------------------|-------------------------------------|
| [N] cases later | -0.00412 (0.00730) | 0.0161** (0.00683) | 0.0127* (0.00692) | 0.0120* (0.00678) | 0.0142** (0.00647) | 0.0156** (0.00625) |
| N | 353981 | 355504 | 354695 | 353928 | 353192 | 352477 |
| adj. R-sq | 0.009 | 0.010 | 0.010 | 0.010 | 0.010 | 0.010 |
| Circuit-Year FE | Y | Y | Y | Y | Y | Y |
| Circuit Order | Y | Y | Y | Y | Y | Y |
| Sample | Year > 1991 | Year > 1991 | Year > 1991 | Year > 1991 | Year > 1991 | Year > 1991 |
| Order within | Judge | Judge | Judge | Judge | Judge | Judge |
| Cluster | Judge | Judge | Judge | Judge | Judge | Judge |

4 cases later = 43 days later on average

Identifying Memetic Economic Phrases, All Cases

| Econ Training on | <u>Ellickson Average</u> | | | |
|----------------------|--------------------------|--------------------------------------|-------------------------------------|--------------------------------------|
| | (1) | (2) | (3) | (4) |
| Next Case | -0.000957 (0.00231) | | | |
| Next Case | -0.000231 (0.00192) | | | |
| This Case | | 0.00585** (0.00271) | | |
| Previous Case | | | 0.00379* (0.00212) | |
| Previous Case | | | 0.00385* (0.00223) | |
| Same Topic | | | | |
| Two Cases Ago | | | | -0.000710 (0.00303) |
| Two Cases Ago | | | | 0.00689** (0.00272) |
| Same Topic | | | | |
| N | 327844 | 355504 | 338739 | 327821 |
| adj. R-sq | 0.017 | 0.011 | 0.014 | 0.016 |

Peer Impacts on Never-Attendees

| | <u>Ellickson Average</u> | |
|-------------------------|--------------------------|--------------------|
| | (1) | (2) |
| Econ Case | 0.0300*** | 0.0294*** |
| | (0.00524) | (0.00249) |
| Post-Manne | 0.0141** | |
| | (0.00630) | |
| Econ Case * | 0.00170 | |
| Post-Manne | (0.00919) | |
| Econ Training on | -0.00559 | 0.00513* |
| Previous Case | (0.0106) | (0.00292) |
| N | 143144 | 486673 |
| adj. R-sq | 0.042 | 0.042 |
| Circuit-Year FE | X | X |
| Judge FE | X | X |
| Sample | Ever-Manne | Never-Manne |

◀ Transmission seems generalized, somewhat greater when panel is unified

Transmission from Regulatory to Criminal Cases

| Econ Training | <u>Ellickson Average</u> | | | | | |
|--|--------------------------|-----|------------------|-------------|------------------|-----------------|
| | [N] = (-1) | (0) | (1) | (2) | (3) | (4) |
| <u>[N] Cases Ago is Regulation, Current Case is Criminal</u> | | | | | | |
| [N] cases later | 0.0119 | - | 0.0304*** | -0.00639 | 0.0180* | 0.0253** |
| | (0.0114) | - | (0.0103) | (0.0146) | (0.00951) | (0.0117) |
| N | 17314 | - | 17238 | 17714 | 17658 | 17723 |
| adj. R-sq | 0.035 | - | 0.314 | 0.119 | 0.078 | 0.209 |
| <u>[N] Case Ago is Criminal, Current Case is Regulation</u> | | | | | | |
| [N] cases later | -0.00277 | - | -0.00371 | 0.0110 | -0.0383 | -0.0243 |
| | (0.00981) | - | (0.0136) | (0.00990) | (0.0242) | (0.0246) |
| N | 17176 | - | 17355 | 17552 | 17731 | 17636 |
| adj. R-sq | 0.042 | - | 0.080 | 0.034 | 0.047 | 0.072 |
| Circuit-Year FE | Y | - | Y | Y | Y | Y |
| Circuit Order | Y | - | Y | Y | Y | Y |
| Sample | Year > 1991 | - | Year > 1991 | Year > 1991 | Year > 1991 | Year > 1991 |
| Order within | Judge | - | Judge | Judge | Judge | Judge |
| Cluster | Judge | - | Judge | Judge | Judge | Judge |

Transmission from Regulatory to Criminal Cases

| Econ Training | # Uses of "Deterrence" | | | | | |
|--|------------------------|-----|-----------------|-----------------|-------------|-------------|
| | [N] = (-1) | (0) | (1) | (2) | (3) | (4) |
| <u>[N] Cases Ago is Regulation, Current Case is Criminal</u> | | | | | | |
| [N] cases later | -0.0145 | - | 0.122** | 0.0340* | -0.0234 | 0.0245 |
| | (0.0179) | - | (0.0580) | (0.0189) | (0.0259) | (0.0178) |
| N | 17314 | - | 17238 | 17714 | 17658 | 17723 |
| adj. R-sq | 0.066 | - | 0.180 | 0.141 | 0.077 | 0.111 |
| <u>[N] Case Ago is Criminal, Current Case is Regulation</u> | | | | | | |
| [N] cases later | 0.0172 | - | 0.0114 | 0.00765 | 0.00637 | -0.00926 |
| | (0.0169) | - | (0.0216) | (0.0172) | (0.0126) | (0.0124) |
| N | 17176 | - | 17355 | 17552 | 17731 | 17636 |
| adj. R-sq | 0.097 | - | 0.065 | 0.208 | 0.035 | 0.046 |
| Circuit-Year FE | Y | - | Y | Y | Y | Y |
| Circuit Order | Y | - | Y | Y | Y | Y |
| Sample | Year > 1991 | - | Year > 1991 | Year > 1991 | Year > 1991 | Year > 1991 |
| Order within | Judge | - | Judge | Judge | Judge | Judge |
| Cluster | Judge | - | Judge | Judge | Judge | Judge |

Peer Behavior Effects, Labor/Environmental

| <u>Voting Against Environmental or Labor Agency [N] cases later</u> | | | | | | |
|---|-------------------|----------|----------|------------------|-----------|----------|
| Econ Training on | [N] = (-1) | (0) | (1) | (2) | (3) | (4) |
| [N] cases later | -0.00338 | - | -0.00438 | 0.0192** | 0.00929 | -0.00420 |
| | (0.0111) | - | (0.0100) | (0.00887) | (0.00995) | (0.0101) |
| Circuit-Year FE | Y | - | Y | Y | Y | Y |
| [N] cases later | -0.00811 | | -0.00544 | 0.0236** | 0.0113 | -0.0145 |
| | (0.0160) | | (0.0136) | (0.0120) | (0.0128) | (0.0139) |
| Circuit-Year FE | Y | - | Y | Y | Y | Y |
| Judge FE | Y | - | Y | Y | Y | Y |
| Circuit Order | Y | - | Y | Y | Y | Y |
| Order within | Judge | - | Judge | Judge | Judge | Judge |
| Cluster | Judge | - | Judge | Judge | Judge | Judge |

Outline

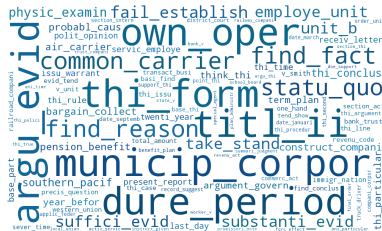
- 1 Manne Program
- 2 Event Studies
- 3 Discretion
- 4 Peer Effects
- 5 Language**
- 6 Long-Difference Impact of Economics Judges
- 7 Impact of Economics Training on Criminal Cases
- 8 General Equilibrium Impacts of Economics Training
- 9 Concluding Remarks and Bonus Slides

Law-and-Economics Language (N-gram)

- All JSTOR economics articles (1960-) JEL K (1990-) JLE (1960-)
 - Highest and lowest frequencies for two-grams in ≥ 1000 cases:

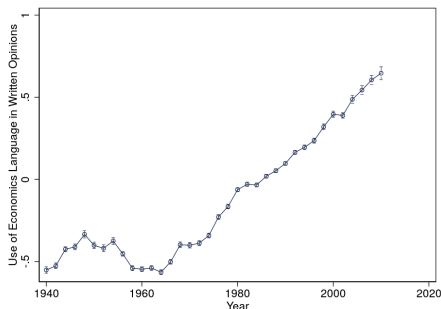


Most similar to Law-Econ Corpus



Least similar to Law-Econ Corpus

- Law-Econ: deterrent effect, cost-benefit, public goods, bargaining power, litigation costs
 - violent crime, criminal behavior, capital punishment, illegal immigration
- Non-LE: find reason, find fact, fail establish, substantive / sufficient / argue evidence
 - evidence and other constitutional theories of interpretation seem less salient



- E : vector of phrase frequencies in economics corpus
- F_i : vector of frequencies in case i
- Economics Style of case i is cosine similarity to economics corpus:

$$z_i = \frac{F_i \cdot E}{\|F_i\| \|E\|}$$

- A case that has terms exactly in the same proportions as they appear in economics articles will have a score of 1.

Law-and-Economics Vectors

- externalit*, transaction_costs, efficien*, deterr*, cost_benefit, capital, game_theo, chicago_school, marketplace, law1economic, law2economic identified by Ellickson (2000)



- Document vectors for each case using Le and Mikolov (2014)
 - forms an embedding for each word and each document in a common space, where words and documents that are related to each other are located near to each other in the vector space.
 - One of the sentences that is closest to “economics” in our corpus is: “The discussion then turned to economics.”
 - ◀ Ellickson Vector Increasing Over Time

Word Embeddings

- (obama speaks media illinois) is orthogonal to (president greets press chicago) according to **cosine similarity**
- But **word embeddings** capture contextual similarities between words

1. Finding the degree of similarity between two words.

```
model.similarity('woman','man')  
0.73723527
```

2. Finding odd one out.

```
model.doesnt_match('breakfast cereal dinner  
lunch';.split())  
'cereal'
```

3. Amazing things like woman+king-man =queen

```
model.most_similar(positive=  
['woman','king'],negative=['man'],topn=1)  
queen: 0.508
```

4. Probability of a text under the model

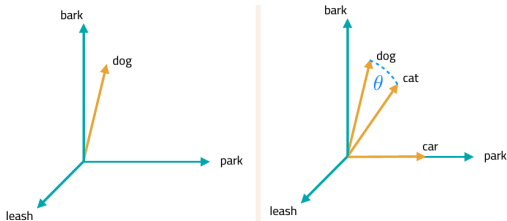
```
model.score(['The fox jumped over the lazy  
dog'.split()])  
0.21
```

- Each word is mapped to one vector, often hundreds of dimensions
 - Contrast to 2B N-grams for sparse word representations
- If we know the words having similar meanings in different languages, word embeddings can be used to (Google) translate!

Relatedness between words

How does it work? Predict the surrounding words given a current word

Words as Vectors



- Use cosine similarity as a measure of relatedness:

$$\cos \theta = \frac{v_1 \cdot v_2}{||v_1|| ||v_2||}$$

- Google translate
 - “he/she is a doctor”(turkish) -> “he is a doctor” (english)
 - “he/she is a nurse”(turkish) -> “she is a nurse” (english)

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(“The Great AI Awakening”, New York Times, Dec 14, 2016)

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Word Embeddings

- Skip-gram - predict the surrounding words given a current word
 - Skip-gram model can capture two semantics for a single word. i.e it will have two vector representations of Apple (i.e. company and fruit).
- Uses neural networks
- Moment conditions
 - In 2SLS, orthogonality of instruments and prediction error
 - In structural econometrics, means of the data
 - In word embeddings, multi-class predictions of context

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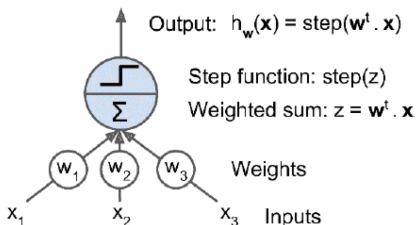
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Neural network



- In a perceptron, an individual neuron (called an LTU, or linear threshold unit) is defined by

$$h(\mathbf{x}) = \text{step}(\omega' \mathbf{x})$$

where $\text{step}(\cdot)$ is the step function.

- The neuron computes a linear combination of the inputs; if result exceeds threshold, output positive class, otherwise negative class.

- ▶ An DNN with a single hidden layer can be written as

$$y = \alpha_2 + g(\alpha_1 + x'\omega_1)'\omega_2$$

- ▶ α_1 and ω_1 , the intercept and coefficients in the input layer
 - ▶ ω_1 is a $d_0 \times d_1$ matrix, where d_0 is the dimension of the input and d_1 is the number of neurons in the hidden layer.
- ▶ $g(\cdot)$, the non-linear activation function.
 - ▶ without this, the DNN could only represent linear transformations of the input.
- ▶ α_2 and ω_2 , the intercept and coefficients in the hidden layer.
 - ▶ ω_2 is a $d_1 \times d_2$ matrix, where d_2 is the dimensionality of the output.

- ▶ Similarly, with two hidden layers we have

$$y = \alpha_3 + g_2(\alpha_2 + g_1(\alpha_1 + x'\omega_1)'\omega_2)'\omega_3$$

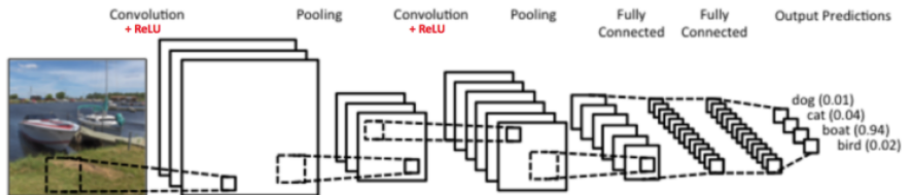
- ▶ $g_1(\cdot)$ and $g_2(\cdot)$, activation functions for the first and second layers.
- ▶ α_3 and ω_3 , intercepts and coefficients for the second hidden layer.

- ▶ An embedding layer can be represented as

$$\underbrace{x}_{n \times 1} = \underbrace{\Omega'}_{n \times m} \underbrace{w}_{m \times 1}$$

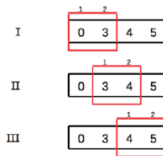
- ▶ w , a categorical variable, a one-hot-encoded vector that is all zeros, with a single item equaling one.
 - ▶ The input to the embedding layer.
- ▶ x , a dense representation of the variable.
 - ▶ The output of the embedding layer.
- ▶ An embedding matrix Ω .
 - ▶ the model learns the weights of this matrix.

Neural network



- CNNs are a special category of deep neural nets that have been especially effective at image classification.

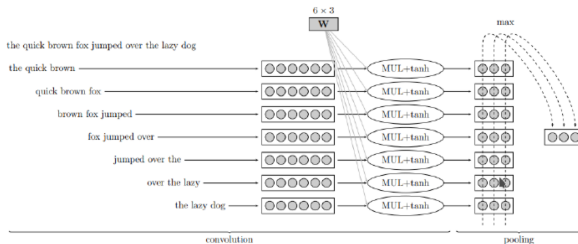
Neural network



- ▶ CNN's generate filters, such as the $\{1, 2\}$ here, and slides the filters across the input sequence.
- ▶ At each window, take the dot product:
 - ▶ $[0 \ 3] * [1 \ 2] = 6$, $[3 \ 4] * [1 \ 2] = 11$, $[4 \ 5] * [1 \ 2] = 14$
 - ▶ output = $\{6, 11, 14\}$
- ▶ CNN learns the weights for the filter $\{w_1, w_2\}$, to try to match the output ($w_1 = 1$ and $w_2 = 2$ in this example).
 - ▶ complicated CNNs have more filters, and different filter window sizes.

Neural network

- ▶ CNNs are useful for classification tasks where we expect to find strong local clues regarding class membership, but where the clues could appear in different places in the input documents.



- ▶ The sliding window of length n learns to identify informative n -grams.

Most similar words to dog, depending on window size

| | 2-word window | 30-word window | |
|-------------------|---------------|----------------|------------------|
| More paradigmatic | | <u>kennel</u> | More syntagmatic |
| | cat | puppy | |
| | horse | pet | |
| | fox | bitch | |
| | pet | terrier | |
| | rabbit | rottweiler | |
| | pig | canine | |
| | animal | cat | |
| | mongrel | bark | |
| | sheep | alsatian | |
| | pigeon | | |

- Small windows pick up substitutable words; large windows pick up topics.

Reinterpreting NLP as Discrete Choice

- Utility for judge i at year t :

$$u_{it} = \tilde{\alpha}_t + \mathbf{x}'_{it} \tilde{\gamma}_t + \tilde{\varphi}_t \mathbf{1}_{i \in R_t},$$

- Utility for judge i at year t :

$$u_{it} = \tilde{\alpha}_t + \mathbf{x}'_{it} \tilde{\gamma}_t + \sum_{(c,c') \in G_j \times G_j: c \neq c'} \tilde{v}_{c,c',t} \mathbf{1}_{i \in R_t},$$

- Arbitrary pattern of complements/substitution across phrases
 - \Rightarrow word embeddings
 - joint choice to write and use a set of words

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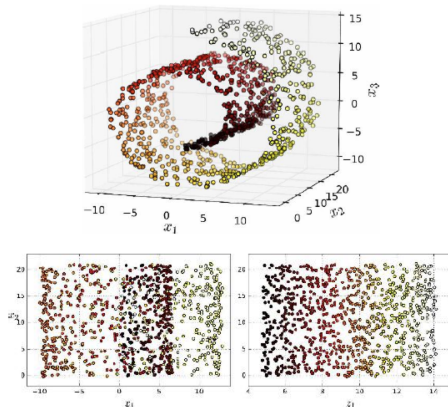
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 - joint choice to write and use a set of words

Importance of dimension reduction



- The dimension reduction process matters: projecting down to two dimensions directly (left panel) might not isolate the variation we are interested in (as done in the right panel, which unrolls the Swiss Roll)

From Bag of Words (N-grams) to Word Embeddings

The Skip-gram Model

As an example, let's consider the dataset

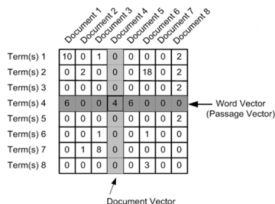
the quick brown fox jumped over the lazy dog

We first form a dataset of words and the contexts in which they appear. We could define 'context' in any way that makes sense, and in fact people have looked at syntactic contexts (i.e. the syntactic dependents of the current target word, see e.g. [Levy et al.](#)), words-to-the-left of the target, words-to-the-right of the target, etc. For now, let's stick to the vanilla definition and define 'context' as the window of words to the left and to the right of a target word. Using a window size of 1, we then have the dataset

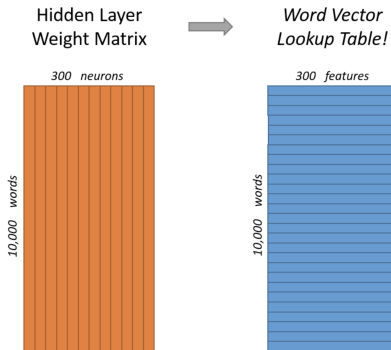
([the, brown], quick), ([quick, fox], brown), ([brown, jumped], fox), ...

of (context, target) pairs. Recall that skip-gram inverts contexts and targets, and tries to predict each context word from its target word, so the task becomes to predict 'the' and 'brown' from 'quick', 'quick' and 'fox' from 'brown', etc. Therefore our dataset becomes

(quick, the), (quick, brown), (brown, quick), (brown, fox), ...



Neural network with single hidden layer



- Objective function: given a word in a sentence, predict probability for every word in our vocabulary of being in the context of the word
- Word embeddings are the weights of the hidden layer

Relatedness between documents

Embeddings - dimension-reduction approach in deep learning models for prediction

- identify closest documents
- allows vector math
 - *Everson vs. Board of Education* is to *Engel v. Vitale* as
 - *Griswold v. Connecticut* is to *Roe v. Wade*
 - application of the constitutional principle articulated in the former case.

Word embeddings isolate directions for gender, time, plural, etc.

- isolating directions for legal and political concepts
 - liberal vs. conservative, procedural vs. substantive, originalists vs. pragmatists, or economic analysis

◀ Judges Most Textually Similar to Posner

New objective

- Predict context *and* N-gram representation of whole document

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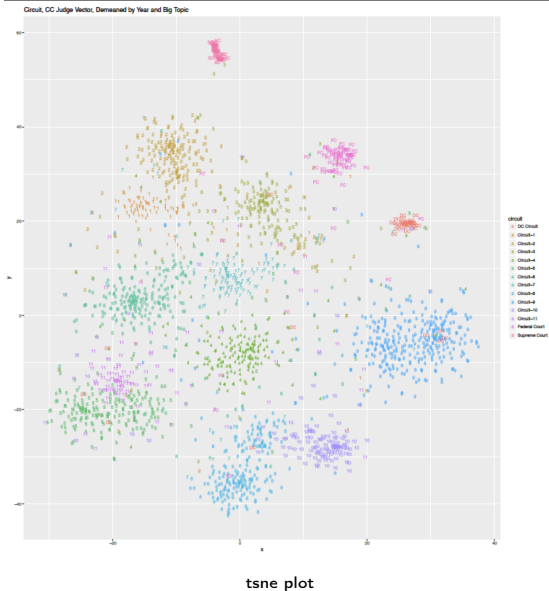
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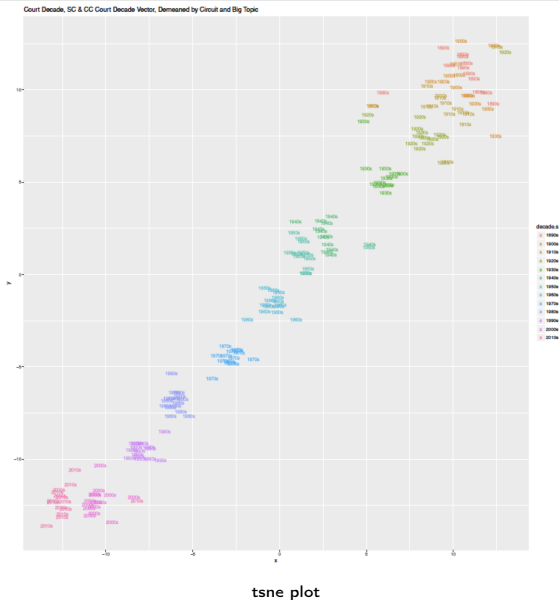
Visual Structure of Case Vectors by Circuit

Figure 1: Centered by Topic-Year, Averaged by Judge, Labeled by Court



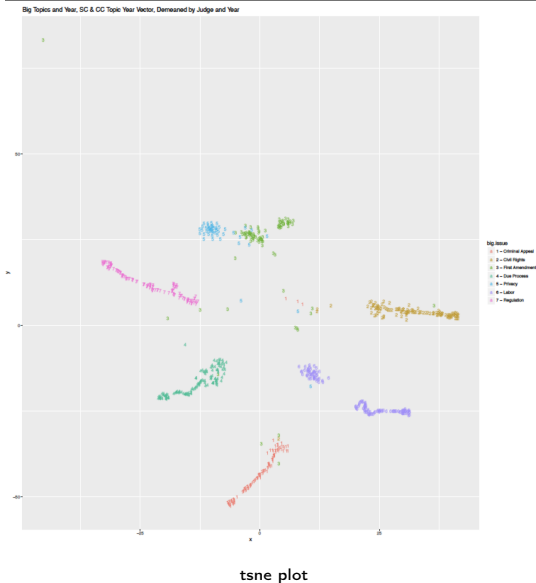
Visual Structure of Case Vectors by Decade

Figure 2: Centered by Court-Topic, Averaged by Court-Year, Labeled by Decade



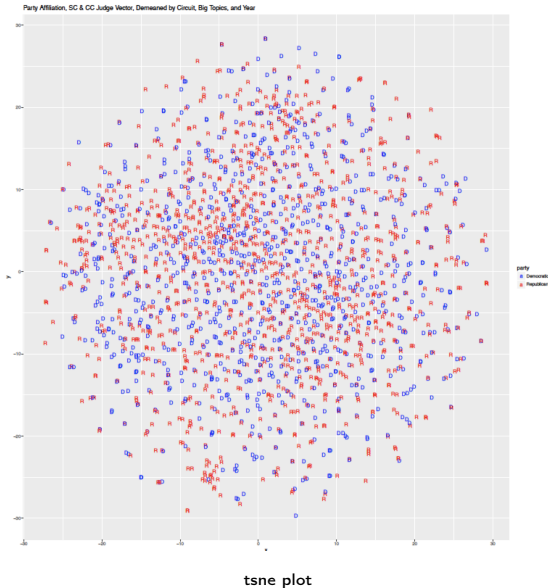
Visual Structure of Case Vectors by Topic

Figure 3: Centered by Judge-Year, Averaged by Topic-Year, Labeled by Topic



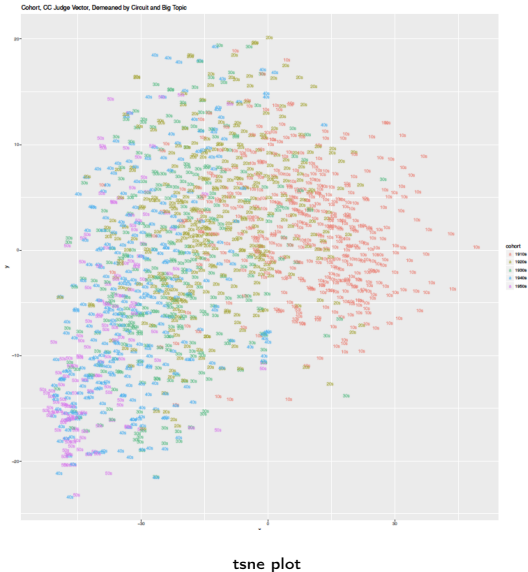
Visual Structure of Case Vectors by Party

Figure 4: Centered by Court-Topic-Year, Averaged by Judge, Labeled by Political Party



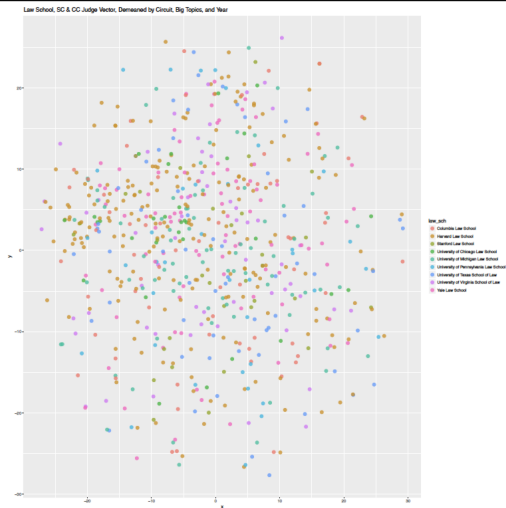
Visual Structure of Case Vectors by Birth Cohort

Figure 5: Centered by Court-Topic-Year, Averaged by Judge, Labeled by Judge Birth Cohort



Visual Structure of Case Vectors by Law School

Figure 6: Centered by Court-Topic-Year, Averaged by Judge, Labeled by Law School Attended



◀ Judges Most Textually Similar to Posner

Relatedness between judges

| Circuit Judge Name | Similarity | Rank | Circuit Judge Name | Similarity | Rank |
|-------------------------|------------|------|--------------------------|------------|------|
| POSNER, RICHARD A. | 1.000 | 1 | TONE, PHILIP W. | 0.459 | 16 |
| EASTERBROOK, FRANK H. | 0.663 | 2 | SIBLEY, SAMUEL | 0.459 | 17 |
| SUTTON, JEFFREY S. | 0.620 | 3 | SCALIA, ANTONIN | 0.456 | 18 |
| NOONAN, JOHN T. | 0.596 | 4 | COLLTON, STEVEN M. | 0.445 | 19 |
| NELSON, DAVID A. | 0.592 | 5 | DUNIWAY, BENJAMIN | 0.438 | 20 |
| CARNES, EDWARD E. | 0.567 | 6 | GIBBONS, JOHN J. | 0.422 | 21 |
| FRIENDLY, HENRY | 0.566 | 7 | BOGGS, DANNY J. | 0.420 | 22 |
| KOZINSKI, ALEX | 0.563 | 8 | BREYER, STEPHEN G. | 0.414 | 23 |
| GORSUCH, NEIL M. | 0.559 | 9 | GOODRICH, HERBERT | 0.412 | 24 |
| CHAMBERS, RICHARD H. | 0.546 | 10 | LOKEN, JAMES B. | 0.410 | 25 |
| FERNANDEZ, FERDINAND F. | 0.503 | 11 | WEIS, JOSEPH F. | 0.408 | 26 |
| EDMONDSON, JAMES L. | 0.501 | 12 | SCALIA, ANTONIN (SCOTUS) | 0.406 | 27 |
| KLEINFELD, ANDREW J. | 0.491 | 13 | BOUDIN, MICHAEL | 0.403 | 28 |
| WILLIAMS, STEPHEN F. | 0.481 | 14 | RANDOLPH, A. RAYMOND | 0.397 | 29 |
| KETHLEDGE, RAYMOND M. | 0.459 | 15 | MCCONNELL, MICHAEL W. | 0.390 | 30 |

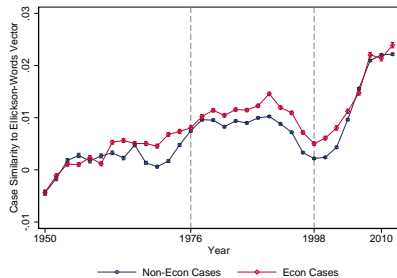
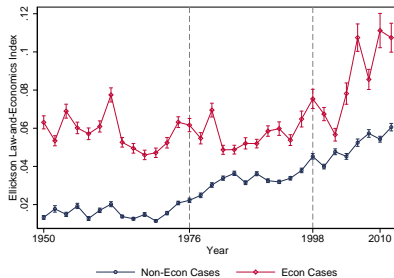
Document vectors demeaned by court, year, and topic, then aggregated by judge.

◀ Natural Laboratory

◀ Sentencing Event Study

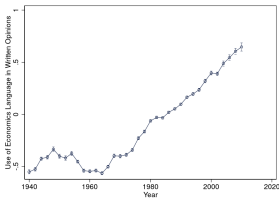
◀ Ellickson Vector Increasing Over Time

Increasing Economic Orientation in Federal Judiciary

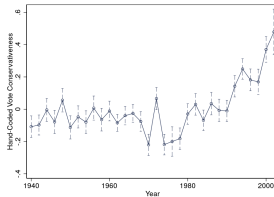


Increasing Economic Orientation in Federal Judiciary

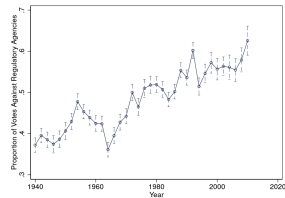
Economics style



Conservative vote share



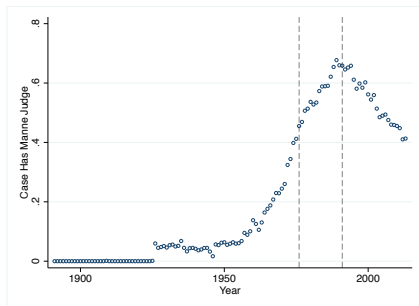
Voting against government regulation



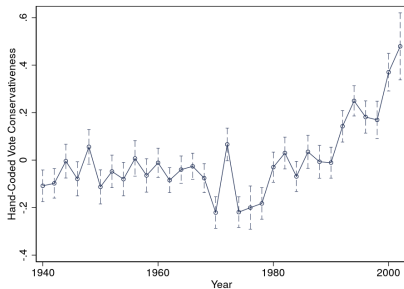
Methodology

Program Evaluate Economics Training

Long-Difference (Long-Run) Impact of Training



on conservatism?



Robust to cutoffs besides 1991; measurement error biases

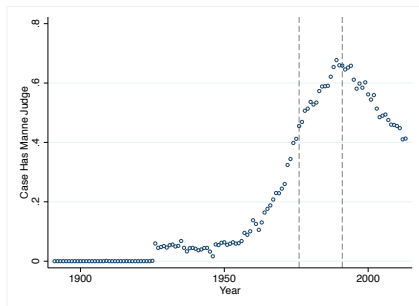
estimates downwards; also (**Short-Run**) event study.

◀ Placebo Period

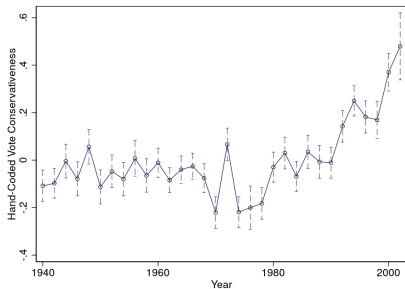
◀ Highlights

Program Evaluate Economics Training

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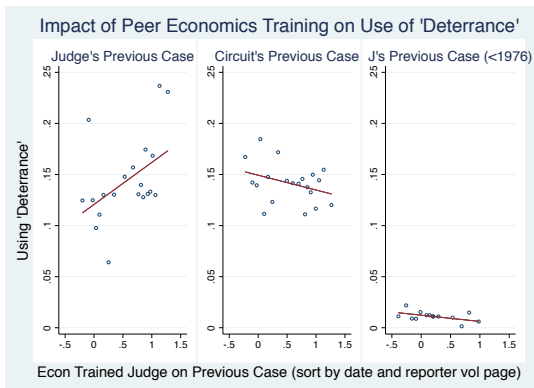
◀ Placebo Period

◀ Highlights

Outline

- 1 Manne Program
- 2 Event Studies
- 3 Discretion
- 4 Peer Effects
- 5 Language
- 6 Long-Difference Impact of Economics Judges**
- 7 Impact of Economics Training on Criminal Cases
- 8 General Equilibrium Impacts of Economics Training
- 9 Concluding Remarks and Bonus Slides

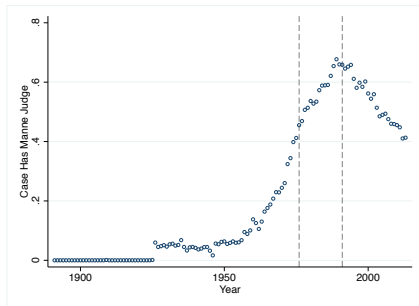
Impact of Peer Econ Judges on Criminal Case Reasoning



Previous judge case (median) 9 days ago; previous circuit case (median) 2 days ago. Exclude same day cases.

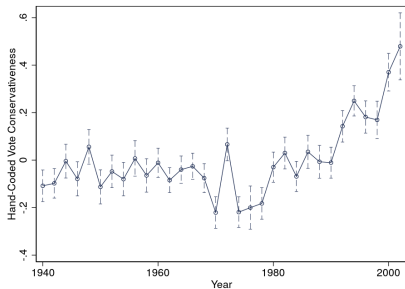
Long-Difference – Approach

Long-Difference (**Long-Run**) Impact of Training



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Long-Difference – Highlights (and Recap)

- ① Rejection of environmental regulations
 - ◀ Opposite shifts by regulatory agency Ideological Reversals
- ② Conservative votes in economics cases
 - ◀ Long difference
- ③ Use of economics language
 - e.g., ◀ Efficiency
- ④ Rejection of criminal appeals
 - ◀ unless Milton Friedman taught
- ⑤ In partial equilibrium, ◀ Manne can account for one third of great transformation
- ⑥ Additional ◀ Impacts on Criminal Cases

Long-Difference – Specification

- The coefficient γ gives the causal effect of judge-assignment

- case i , judge j , court c , year t ◀ randomization check

$$Y_{ijct} = \alpha_{ct} + \gamma Z_{ijt} + X_j' \beta + \varepsilon_{ijct}$$

- Outcome Y_{ijct} measured four ways:

- (1) 1 = conservative vote, -1 = liberal vote (Songer-Auburn 5%, hand-labeled)
- (2) Voting against government regulatory agencies (100%, machine-coded)
- (3) Rejecting criminal appeals (100%, machine-coded)

- from gov't in title of case, Π vs. Δ , for (2) Economics, Labor, and (3) Criminal Appeals cases

- (4) Length of criminal sentence (100%, FOIA requested to include judge identity)

- Z_{ijt} , law-and-economics thinking of judge j :

- Economics Style (leave-one-out mean $Z_{ijt} = \sum_{k \in J_i^j} \frac{Z_k}{|J_i^j|}$)

- Economics Training (1976-1999) ◀ Evaluate

- Treatment is judge; so cluster by judge; weight to treat judge-years equally

- Controls

- α_{ct} : court-year fixed effects ◀ Methodology

- X_j : judge covariates, e.g. Republican (benchmark for Economics Training)

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Impact of Economics Judges – Additional Highlights

1 Summary Correlations

- Economics Training correlated with Economics Style
 - ◀ Both are independently correlated (but not synonymous) with Republican Party
- Economics Trained Judges vote against regulation
 - ◀ Economics is more predictive than Republican Party
 - Heterogeneity by regulatory agency: ◀ for immigration enforcement
- Economics Trained Judges reject criminal appeals
 - ◀ unless Milton Friedman taught

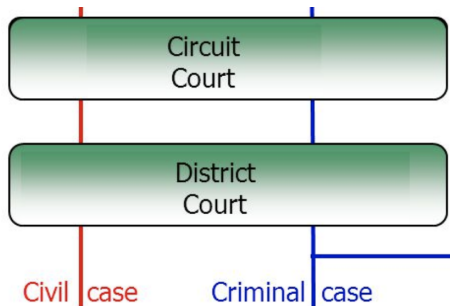
2 Economics Judges Impact on Economics Cases

- ◀ Economics judges render conservative votes in economics cases
- Economics judges render conservative votes in economics cases after training
 - ◀ Long difference
 - ◀ Opposite shifts by regulatory agency Ideological Reversals
 - ◀ Efficiency
 - ◀ Manne can account for one third of great transformation

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Federal Criminal Justice Setting



Federal courts handle the most serious criminal cases (8% of US prison population).

◀ Randomization check of district judges

Impacts on Criminal Cases – Highlights

- 1
 - ◀ Discretion
 - ◀ increases sentencing gaps from economics training
 - ◀ primarily for immigration crimes
- 2
 - ◀ Economics trained judges increase racial and gender disparities

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General Equilibrium Effects – Highlights

- ◀ Recap

- We see treatment effects, what about general equilibrium effects?

- panel verdicts

- peers

- **psychological**

- ◀ Textual implicit bias not correlated with economics training ◀ but with Republicans
 - ◀ Economics judges unaffected by defendant birthdays ◀ but non-economics judges are

- **precedent**

- ◀ Economics judges increase citations and dissents after training
 - ◀ Appeals to Supreme Court increase ◀ but not reversals
 - ◀ Greater consequentialist reasoning over time and in dissents

- **paradigm shift**

- ◀ Identifying memes across citation network
 - ◀ Exposure to sameness increase dissents and attendance

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- (1) Economics language in academic articles being adopted in judicial opinions
- (2) Economics-trained judges changing their decisions and impacting their peers
- (3) Economics language travelling from judge to judge and across legal topics
 - Economics likely changed how they perceived the consequences of their decisions
 - In economics cases, economics training changed by 10% the direction of their votes
 - If you teach judges markets work, they deregulate government
 - If you teach judges deterrence works, they become harsher to criminal defendants
 - In District Courts, when judges had sentencing discretion, economics trained judges immediately rendered 20% longer sentences than non-economics judges
 - Economics training accounts for substantial portion of great transformation of law

Next steps

- FOIA exact day of application & cancellations (RDD “first-come, first-served” around quota)
- General equilibrium (measure impacts along citation edge, centrality & network analysis)
- Information acquisition (how education affects search, predictability)
- High-dimensional data (word2vec, document and judge embeddings)

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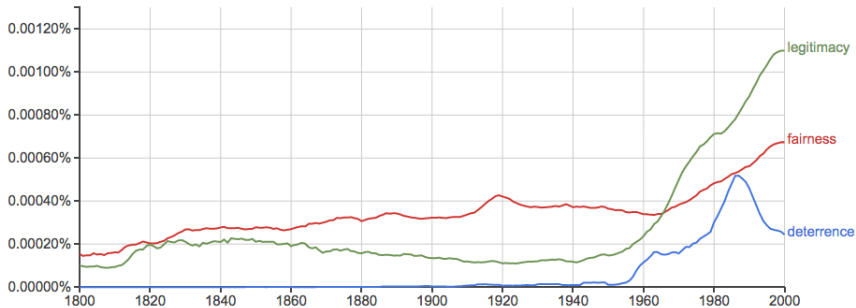
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What's Next?

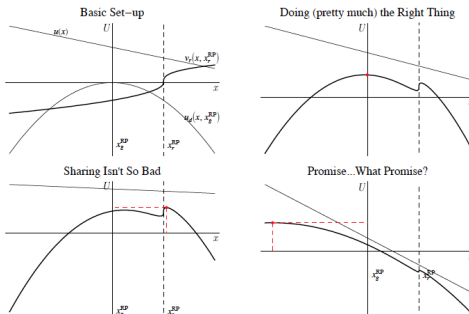


- ~~retribution, rehabilitation~~, deterrence, legitimacy, fairness

Legitimacy and Perceived Indifference

Justice: equal treatment before the law ($y = f(X) + \varepsilon, a \rightarrow X$)
equality based on recognition of difference
($y \perp W, \text{var}(\varepsilon) \perp W, a \not\rightarrow W$)

Sympathy and Empathy



(Recognition-Respect theory)

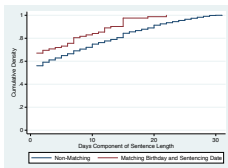
“settings where people are closer to *indifference* among options are more likely to lead to detectable effects [of behavioral biases] outside of it.” (Simonsohn 2011)

Courts as Natural Incubator of Social Preferences

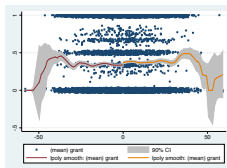
Cultural roots of social preferences (courts as “natural incubator”)

- Reference points, **empathy**, emotional theory of mind (punishment)
- Identity, **egotism**, dissimulation, curvature of moral costs (duties)
- Memes, **implicit bias from judicial corpora**, grammar of law (4 terabytes data)

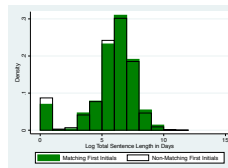
Leniency on Defendant Birthdays



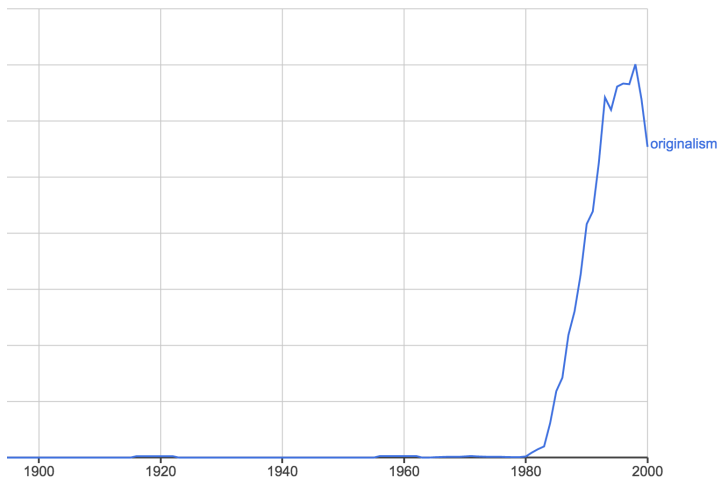
after NFL football wins



not matching first initials

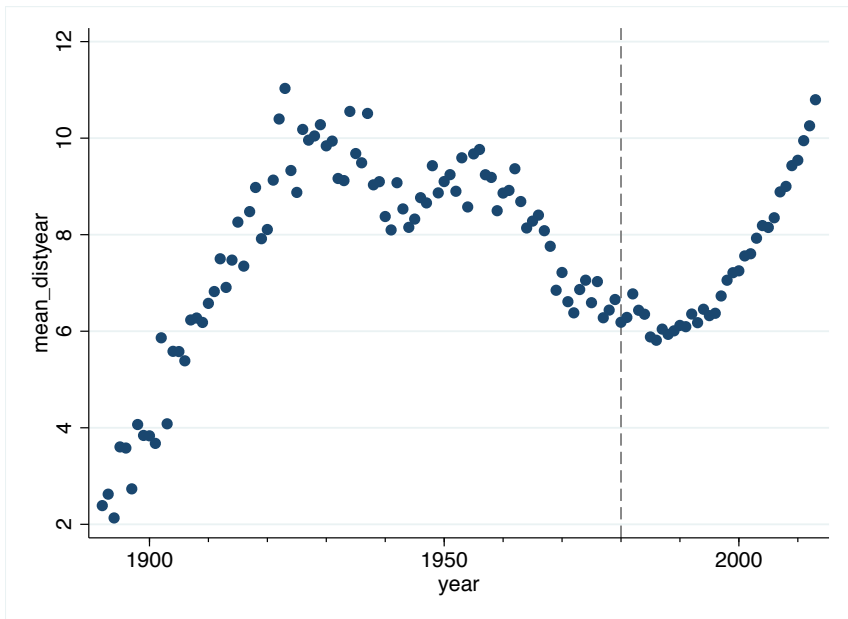


Originalism



- The word "originalism" was coined by Paul Brest in 1980.
- Here is the famous passage: *"By "originalism" I mean the familiar approach to constitutional adjudication that accords binding authority to the text of the Constitution or the intentions of its adopters."*

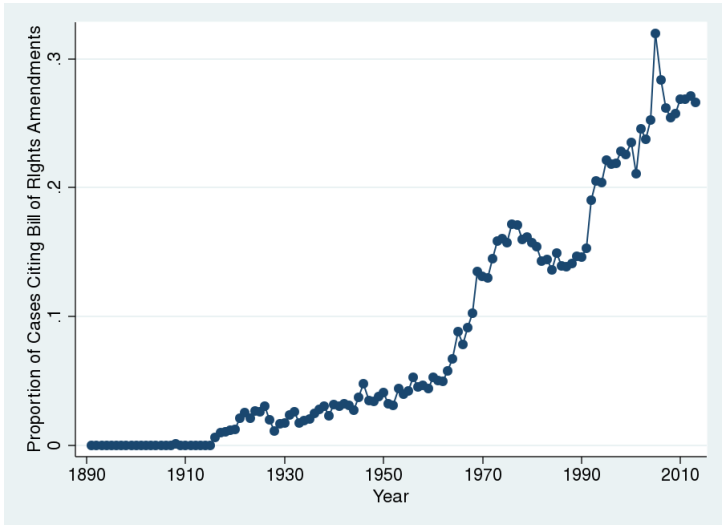
Measuring Originalism



Measuring Originalism

- “We are all Originalists now”

Figure: Trend in Citing Bill of Rights Amendments



Most Originalist Circuit Court Judges

| Rank | Judge | Originalism Score |
|------|--------------------|-------------------|
| 1 | DUNCAN, ALLYSON | 6.76 |
| 2 | RAWLINSON, JOHN | 6.08 |
| 3 | SYKES, DIANE S. | 5.29 |
| 4 | SCALIA, ANTONIN | 5.13 |
| 5 | PARKER, BARRINGTON | 4.76 |
| 6 | MARCUS, STANLEY | 4.33 |
| 7 | LINN, RICHARD | 3.88 |
| 8 | LEMMON, DAL | 3.78 |
| 9 | GRABER, SUSAN | 3.43 |
| 10 | HARDIMAN, THOMAS | 3.36 |
| 11 | WESLEY, RICHARD | 3.19 |
| 12 | SACK, ROBERT DAVID | 3.17 |
| 13 | CLEVENGER, RAYMOND | 3.13 |
| 14 | MCKEAGUE, DAVID | 2.77 |
| 15 | GARLAND, MERRICK | 2.67 |
| 16 | KETHLEDGE, RAYMOND | 2.30 |
| 17 | GORSUCH, NEIL M. | 2.28 |
| 18 | CLAY, ERIC L. | 2.24 |
| ... | | |
| | SOTOMAYOR, SONIA | 0.26 |
| | POSNER, RICHARD A. | -0.4 |

Consequentialist Reinterpretation of Duty

Efficient Breach Theory in Contracts

- **Duty posits a general obligation to keep promises** vs.
- a party should be allowed to breach a contract and pay damages, if doing so would be more **economically efficient** than performing under the contract.
- Posner in *Lake River Corp. v. Carborundum Co.*, 769 F.2d 1284 (7th Cir. 1985)

Least Cost Avoider in Torts

- **Duty of care** is breached when $PL > B$
- P is the probability of loss (L) * L is the gravity of loss
- B is the cost (burden) of taking precautions

Expected Deterrence in Criminal Law

- $\text{Pr}(\text{detection}) * \text{sanction} = \mathbb{E}[\text{sanction}]$
- Costs of detection \gg cost of sanction
- Approach as social planner

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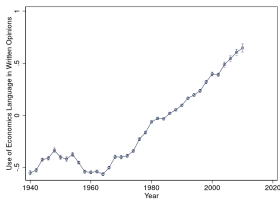
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 - ◀ Natural Laboratory
 - ◀ Judges Most Textually Similar to Posner
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 - Becker’s analysis of crime & punishment (Posner 2004; Harcourt 2011)
 - “Rational criminals” **went against prevailing wisdom** re mental illness
 - ~~retribution, rehabilitation,~~ deterrence, legitimacy, fairness
 - Antitrust laws
 - Economic analysis **has attained near complete consensus.** (Judge Ginsburg)
 - Should promote economic efficiency and consumer welfare, rather than shield individuals from competitive market forces or redistribute income.
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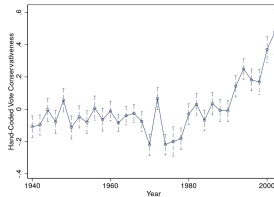
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Increasing pro-market orientation in U.S. judiciary

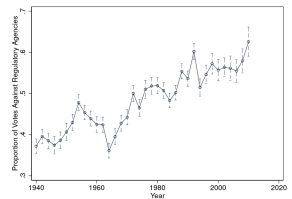
Economics style



◀ Conservative vote share



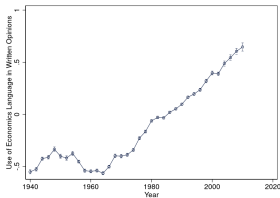
Voting against government regulation



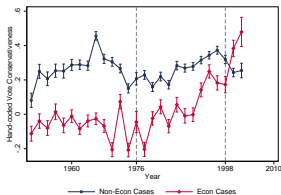
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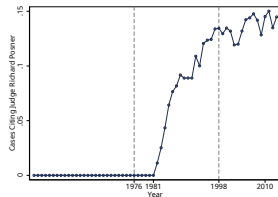
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Citation to Richard Posner



◀ Natural Laboratory

Federal Cases

- Abortion example:

- 5th Circuit **invalidated** a Mississippi statute *requiring its doctors to obtain admitting privileges at local hospitals* but allowed an identical Texas statute, resulting in one-third of Texas abortion clinics shutting down
 - Reasoned on potential **consequences** on abortion access for women.
- A new Texas statute *requires abortion clinics to meet the building standards of ambulatory surgery centers*; this statute was **allowed** by the 5th Circuit.
 - This statute would reduce the number of centers in TX to fewer than 10.

- Labor example:

- Shift from **reasonable person** standard to **reasonable woman** standard for what constitutes sexual harassment.
- **Waiving need to prove emotional harm** in court by plaintiff (to a jury).

- Circuit Courts only decide “issues of new law”

◀ Common Law

- Consequentialist (utilitarian) v. deontological (duties and rights) modes of reasoning

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Legitimacy: Democratic will of the people (Breyer 2006)

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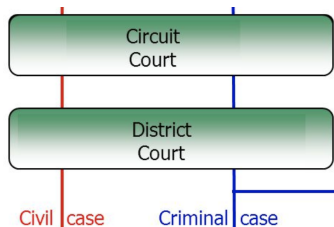
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US Federal Courts as “Natural Laboratory”



- Incremental common-law space; new rules, distinctions (Gennaioli et al. 2007)
 - Random assignment to cases & panels of 3 (in Circuit courts, no juries)
 - Appointed for life (179 Circuit judges in 12 C; 678 District judges in 94 D)
 - 327K cases/yr in D \Rightarrow 67K cases/yr in C \Rightarrow 100 cases/yr in Supreme Ct
- Influential and controversial economics training program for judges
 - “Big Corporations Bankroll Seminars For US Judges” (*Washington Post*, 1/20/1980)
 - By 1990, 40% of federal judges had attended economics training (Butler 1999)
 - Despite “swamped with criminal cases .. not seeing relevance of economics”
- Sentencing has undergone several moral revolutions (~~retribution~~, ~~rehabilitation~~,
 - Deterrence: **severity substitutes for low detection probability** (Becker 1968)
 - One justification for massive build-up of prisons in 1980s and 1990s [◀ WhatWeDo](#)
 - Mass incarceration as “new Jim Crow” (Davis 1998, Gilmore 2007)

What We Find

- Judges who use **economics** language (in cases other than the current)
 - vote for and author **conservative verdicts**, especially for economics cases
 - reject government **regulation** and **criminal appeals**
- Judges **trained** in economics
 - use **economics language** (e.g. “efficiency”, “deterrence”)
 - render **conservative verdicts** (especially for economics jurisprudence)
 - reject government **regulation**
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 - Not prior to 1976 Manne program inception
 - 20% gap after *Booker* made previously mandatory guidelines “advisory”
- Judges **trained** in economics impact panelists
 - **influence** criminal appeals verdicts when not the author
 - **increase** use of “deterrence” in panelists’ subsequent opinion
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- Judges **trained** in economics
 - increase **citation impact** and **dissents** (proxy for legal innovation)
 - Not prior to 1976 Manne program inception
 - render racial and gender **sentencing disparities**
 - More so than Republican or ingroup judges
 - but do not show more **implicit race or gender bias** in their opinions
 - Unlike Republican and ingroup judges
- Exposure to ideological sameness
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 - Being in ideological minority increases ingroup conformity
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Validating the N-grams

Predicting Liberal vs. Conservative decisions ~ facts or reasonings salient to judge ~ not just words

| | | |
|--------------------|--|---|
| Campaign Finance | advertis influenc outcom vote, argument appel consid definit, challeng present, case controversi district, disclosur sourc | Expens, inform elector mean provis, compel court went histori, buckley court limit |
| Capital Punishment | duti make reason, Involuntari, materi reason probabl, mental health | consid mitig, Attack, Inelig, counti jail |
| EPA | act impos, board character, Chevron, Elimin, interst transport hazard wast | factor demonstr, id statut silent ambigu respect, requir provis |

(Buckley held that election spending limits are unconstitutional)

◀ WhatWeDo

◀ Manne Program

◀ ModelFit

Validating the N-grams

- Predict hand-coded cases
- Delete N-grams which appear in no more than a threshold based on the number of observations in each individual legal field
- Logistic AUC
 - better for imbalanced data - plots true positive over false positive rate

Validating the N-grams

| AUC | Logistic Regression with tf-idf |
|--------------------|---------------------------------|
| 11th Abrogation | 0.845 |
| Abortion | 0.642 |
| ADA | 0.751 |
| Affirmative Action | 0.653 |
| Campaign Finance | 0.876 |
| Capital Punishment | 0.650 |
| EPA | 0.72 |
| FCC | 0.96 |
| First Amend | 0.695 |
| Homosexual Rights | 0.873 |
| NEPA | 0.783 |
| NLRB | 0.715 |
| Obscenity | 0.855 |
| Piercing Corp Veil | 0.719 |
| Sex Discrimination | 0.752 |
| Title 7 | 0.78 |

Validating the N-grams

| Legal Field | Positive | Negative |
|--------------------|---|--|
| 11th Abrogation | accru plaintiff knew known, amend constitut unit state, argu eleventh amend, compel undertak approach, congress unequivoc express, congruent proport | cite discrimin public, compet privat enterpris doe mean, congress articl, enact statut, plaintiff appel argument exact relief seek |
| Abortion | appeal concern, Life health, court held proper function legislatur, health servic, pregnant minor | mother result, clinic district court abus discret, plaintiff deni, |
| ADA | Administr, Distress, punit damag, rehabilit act claim | medic condit, Dispar, extend |
| Affirmative Action | black candid, board compli, racial balanc, impermiss | Arbitrari, argu constitut, Conscienc, constitut violat |

Validating the N-grams

capital punishment: involuntary, mental health v. attack

| | | |
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| Campaign Finance | advertis influenc outcom vote, argument appel consid definit, challeng present, case controversi district, disclosur sourc | Expens, inform elector mean provis, compel court went histori, buckley court limit |
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| | | |
|-------------------|---|--|
| First Amend | materi fact, purpos regul, mater fact, purpos regul | concur result reach judg hall opinion analysi amend, direct narrowli, essenti curti content statut inclus, provid ineffect remot support govern |
| Homosexual Rights | claim revers, equal protect claus fourteenth amend, homosexu engag consensu sodomi court state great, prohibit homosexu conduct, sexual prefer | know corps, militari matter difficult think clearer, |
| NEPA | accord proper forest servic fish, area plan, increas risk, litig cost save, nativ | caprici violat. result destruct, project narrowli |
| NLRB | animus design rid compani financi, care includ critic, complaint alleg violat section mention, Limit, involv face simpl jurisdict question doe | alleg february precis interrog employe threaten employe, allow mason van atter time acclim posit, expens attribut unit employ communis worker financi |

Validating the N-grams

obscenity: constitutionally protected v. core pornographic [◀ TextAsData](#)

| | | |
|--------------------|---|--|
| Obscenity | appel court, constitut protect, regard invalid major opinion miller recogn | core pornographi, materi public, sexual relat |
| Piercing Corp Veil | oblig make, issu liabil, refund | agreement district, alleg complaint, court review |
| Sex Discrimination | district court grant summari judgment favor, dismiss complaint, complain, opinion | deni, discrimin, evid |
| Title 7 | Faith, Reason trier fact, conclud | prima faci case racial discrimin, discrimin retali |

"the instruction was far more intense than the Florida sun. .. my enduring appreciation." (Justice Ruth Bader Ginsburg, SCOTUS)

"I don't believe I have ever attended a seminar that involved such intensive study and discussion. My wife, who accompanied me, commented, 'I don't see any more of you here than I do at home.' .. one of my fellow judges .. said, 'I can't believe how much I have learned, but I'm glad I didn't have to take this course in college.'" (Judge Curran, U.S.D.C. Eastern Wisconsin)

"a principled basis for deciding close cases." (Judge Michel, Federal Circuit)

"a sound theoretical and rational structure for my decisions.. the potential effects and foreseeable impact of imposing a duty" (Judge Jolly, Fifth Circuit)

"I regard myself as a social progressive and all the economists in attendance, from my perspective, had Neanderthal views on race and social policy. The basic lesson I learned .. is that social good comes at a price, a social and economic cost. I had never thought that through before being exposed to Henry's teachings. .. has led me to measure the cost of the social good being furthered against the gain to be achieved." (Judge Carter, S.D.N.Y.)

"there is a wide area of decision entrusted to us where the result can go either way, depending on how we view the evidence. That area is called 'judicial discretion.' This is the area that is most affected by these seminars .. as a result of what I have learned at these seminars, I have become a much better judge" (Judge Alaimo, U.S.D.C. Southern Georgia)

"Henry and his LEC colleagues were of a conservative persuasion. .. the class wanted to express our gratitude on the final day. The person who rose to speak was Judge Hall from West Virginia .. Without doubt he was a Democrat going back to New Deal days. He was fervent in his appreciation" (Judge Griesa, S.D.N.Y.)

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LEC is seeking funds to make a double offering of the Institute in 1978 as a means of reducing the backlog.

In letters to LEC, federal judges who attended the Institute last December uniformly gave it high marks, one saying, "The exposure to microeconomic theory was truly mind-expanding."

Said another:

"Needless to say, I was extraordinarily stimulated by my exposure to the discipline of economics and indeed how disciplined a profession it is. I really know of no other which so relentlessly applies logic and deductive thinking. Nor one which unceasingly works out the facts underlying the premises upon which the theory is based. . . . One lasting impression was received. Never again will I

"The subject matter was too concentrated and too complex for me honestly to claim to know very much about economics. But it has caused me to see some of the fallacies that are presented in political-economic proposals. For example, in one case, a criminal antitrust case, my experience at the institute made my work a little more difficult. Prior to my attendance at the institute, I might have finessed some hard thinking and accepted a simplistic answer to a complex problem. After the institute, my conscience has forced me to do some serious work on questions which otherwise I might have bypassed. So, has the institute made my work easier? No. But it has made it more interesting. The institute also has made me feel more confident in my ability to cope with questions that have economic implications."

Such comments are common in the sheaf of evaluatory letters, and the assertion is frequent: "I have (or shall) recommend the institute to my colleagues."

After the first institute, ~100 applied per seminar, some 7 months in advance; First-come first-served, quota of ~25

● Instrument for attendance:

- Bartik-type shock: leave-Circuit-out share of judges from same birth decade and law-school type who have attended Manne
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Other Instructors (from [◀ Syllabi](#))

| Year | Alchian | Ashenfelter | Demsetz | Friedman | Goetz | Haddock | Manne | Markham | Samuelson | Feldstein | MacAvoy | Klein | Benston | Butler | Hoffmann |
|------|---------|-------------|---------|----------|-------|---------|-------|---------|-----------|-----------|---------|-------|---------|--------|----------|
| 1976 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 1977 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 |
| 1978 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 |
| 1979 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | 0 |
| 1979 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| 1980 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1980 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 |
| 1981 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 0 | 0 |
| 1982 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 |
| 1983 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1984 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1985 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1986 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1987 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 |
| 1988 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 |
| 1989 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 |
| 1990 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1991 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 1 |
| 1992 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1993 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1994 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1995 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| 1996 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1997 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1998 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |

| Year | Fielding | Giacomini | Priest | Smith | Johnsen | Fischel | Henderson | Lash | Hartfield | Grady | Cooter | Williams | Brady | Hoberman |
|------|----------|-----------|--------|-------|---------|---------|-----------|------|-----------|-------|--------|----------|-------|----------|
| 1976 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1977 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1978 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1979 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1979 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1980 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1980 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1981 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1982 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1983 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1984 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1985 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1986 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1987 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1988 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 |
| 1989 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1990 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1991 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1992 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1993 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1994 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1995 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1996 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 1997 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| 1998 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 |

During one of the earliest Economics Institutes, Paul Samuelson developed a tradition of starting his first session with the judges by emphasizing that the reason he participated in the program was to provide “ideological balance” to a program that was otherwise dominated by *laissez faire* economists. Samuelson then proceeded to discuss his views on several non-ideological areas, including finance theory and personal financial investments. He also launched a strong defense of free international trade. Not surprisingly, many judges thought his views were fairly conservative. Indeed, the evening roundtable discussions attended by Samuelson invariably included a judge’s request that he identify the concepts taught by Alchian and other scholars that Samuelson found objectionable. Samuelson was not about to challenge the legitimacy of the neoclassical price theory taught by the rest of the team, so his response was usually some vague reference to their differences about the proper role of government in a market economy. When confronted, he admitted that their differences were on the normative implications, not on the positive analysis of how markets actually work.

Butler 10/2017 comments: “Alchian went into excruciating detail on marginal analysis, consumer choice and demand, production costs and supply, market equilibrium; Demsetz on team production, theory of the firm, I.O. Structure Conduct Performance paradigm, Manne on corporate governance and market for corporate control; Samuelson on whatever the heck he wanted to, usually personal investment strategies; Friedman always started on legalization of recreational drugs; Ashenfelter used climate to predict quality and prices of wine, followed by wine tasting”

| | | | | |
|--|-----------------------|---|--|--|
| | | | Probability Theory | Orley Ashenfelter <i>Industrial Relations, Princeton University</i> |
| | | | Statistical Analysis | Orley Ashenfelter |
| Does Immigration Help or Hurt? | George Borjas | Harvard University Kennedy School | A Consumer's Guide to Econometrics | Eric Rasmusen <i>School of Business, Indiana University</i> |
| What Can We Do about Crime? | James Q. Wilson | Pepperdine University, Public Policy | Regression Analysis: A How-to Guide | Eric Rasmusen |
| Family and Society | James Q. Wilson | | Empirical Application: Crime | James Q. Wilson <i>Public Policy, Pepperdine University</i> |
| Why Families Matter | David Popenoe | Rutgers University, Sociology | Empirical Application: A Nation at Risk? | Paul Peterson <i>Kennedy School, Harvard University</i> |
| The Social Significance of Families | Jennifer Roback Morse | Writer | Empirical Application: The Gun Debate | John Lott <i>American Enterprise Institute</i> |

Borjas was a repeat-instructor; Jennifer Morse founded
Ruth Institute designated as anti-LGBT hate group

Different empirical professors

Efficiency Concerns Crowding Out Equity Concerns

Criminal sentencing

- disparate impacts ('efficient')
- crowd out constitutional theories of minority protection
- females for raising families

Immigration

- a conservative stance
- evaluate in terms of crime (Miles and Cox 2014; Treyger, Chalfin, Loeffler 2014)
- or national security (Trebilcock 2005)

1970s Law & Economics \approx Economics 101 (not 102, 103, ...)

- Simplest price theory arguments may render conservative conclusions
- So what about Law & Economics in 1990s & 2000s?

◀ Methodology

◀ Event Studies

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Predictors of Attendance (OLS and Elastic Net) (1 of 2)

| | (1) | (2) | | (1) | (2) | | (1) | |
|---------------------|----------|----------|---------------|----------|-----------|--------------------|----------|-------|
| Unified Appoint | -0.0237 | -0.0386 | Black | 0.0469 | | U.S. Senator | 0.0136 | C |
| | (0.0231) | (0.0221) | | (0.0583) | | | (0.0634) | |
| Cross-Party Appoint | -0.0226 | | Cohort: 1910s | 0.108*** | | State Atty General | -0.00437 | Distr |
| | (0.0407) | | | (0.0298) | | | (0.0366) | |
| Republican | 0.0508** | 0.0379* | Cohort: 1920s | 0.308*** | 0.267*** | Private Practice | 0.0544 | Cou |
| | (0.0191) | (0.0186) | | (0.0508) | (0.0499) | | (0.0435) | |
| U.S. Attorney | 0.0166 | | Cohort: 1930s | 0.249*** | 0.205*** | Mayor | 0.0783 | Cit |
| | (0.0413) | | | (0.0498) | (0.0482) | | (0.0959) | |
| Solicitor General | -0.144** | -0.162* | Cohort: 1940s | 0.126** | 0.0841* | State Senator | 0.0439 | Assi |
| | (0.0536) | (0.0664) | | (0.0389) | (0.0391) | | (0.0814) | |
| Solicit Gen Office | 0.176 | 0.193 | Cohort: 1950s | 0.0229 | | State Lower Ct | -0.0287 | Att |
| | (0.126) | (0.133) | | (0.0249) | | | (0.0310) | |
| Local Court | 0.0696 | 0.0515 | Bnkcy Judge | 0.135 | 0.140 | State Supr Court | 0.0469 | U. |
| | (0.0543) | (0.0522) | | (0.183) | (0.182) | | (0.0372) | |
| Asst Dist Atty | 0.109* | 0.109* | Magistr Judge | -0.166** | -0.174*** | State House | 0.0192 | Any |
| | (0.0530) | (0.0482) | | (0.0556) | (0.0483) | | (0.0427) | |

Predictors of Attendance (OLS and Elastic Net) (2 of 2)

| | (1) | (2) | (1) | (2) | (1) | (2) |
|--------------------|----------|-------------------|----------|------------------|----------|----------|
| U.S. Senator | 0.0136 | Governor | -0.0156 | Constant | -0.0745 | 0.0342 |
| | (0.0634) | | (0.0711) | | (0.0626) | (0.0212) |
| State Atty General | -0.00437 | District Attorney | -0.00409 | All Variables | X | |
| | (0.0366) | | (0.0406) | Post Elastic Net | | X |
| Private Practice | 0.0544 | County Comm | 0.0548 | N | 699 | 699 |
| | (0.0435) | | (0.0948) | adj. R-sq | 0.124 | 0.129 |
| Mayor | 0.0783 | City Council | -0.0946 | | | |
| | (0.0959) | | (0.0697) | | | |
| State Senator | 0.0439 | Assit U.S. Atty | 0.00629 | | | |
| | (0.0814) | | (0.0348) | | | |
| State Lower Ct | -0.0287 | Atty General | -0.104 | | | |
| | (0.0310) | | (0.118) | | | |
| State Supr Court | 0.0469 | U.S. House | -0.0367 | | | |
| | (0.0372) | | (0.0531) | | | |
| State House | 0.0192 | Any Govt Exper | 0.00160 | | | |
| | (0.0427) | | (0.0394) | | | |

Predictors of Attendance Year (OLS and Elastic Net) (1 of 2)

| | (1) | (2) | | (1) | (2) | | (1) | |
|---------------------|----------|----------|---------------|----------|-----------|--------------------|---------|-------|
| Unified Appoint | 1.392 | | Black | 1.270 | | U.S. Senator | 4.779** | C |
| | (2.360) | | | (1.543) | | | (1.493) | |
| Cross-Party Appoint | 3.857 | | Cohort: 1910s | 0 | -8.496*** | State Atty General | -0.613 | Distr |
| | (2.395) | | | (.) | (1.265) | | (1.911) | |
| Republican | 1.768 | | Cohort: 1920s | 3.769* | -4.853*** | Private Practice | -2.576 | Cou |
| | (2.303) | | | (1.440) | (1.403) | | (2.891) | |
| U.S. Attorney | -1.481 | | Cohort: 1930s | 8.038*** | | Mayor | -4.548 | Ass |
| | (1.703) | | | (1.775) | | | (2.919) | |
| Solicitor General | 1.950 | | Cohort: 1940s | 14.48*** | 5.504*** | State Senator | -1.693 | Assi |
| | (2.753) | | | (1.852) | (1.525) | | (1.351) | |
| Solicit Gen Office | 0 | | Cohort: 1950s | 17.28*** | | State Lower Ct | -1.609 | Att |
| | (.) | | | (3.250) | | | (1.384) | |
| Local Court | 3.149* | 3.112 | Bnkcty Judge | -2.896 | | State Supr Court | 2.775 | U. |
| | (1.575) | (2.028) | | (2.734) | | | (1.473) | |
| City Council | 11.17*** | 10.29*** | Magistr Judge | 0 | | State House | 1.223 | Any |
| | (2.340) | (0.797) | | (.) | | | (1.309) | |

Predictors of Attendance Year (OLS and Elastic Net) (2 of 2) [◀ Syllabi](#)

| | (1) | (2) | | (1) | (2) | | (1) | (2) |
|--------------------|---------|-----|-------------------|---------|-----|------------------|-----------|-----------|
| U.S. Senator | 4.779** | | Governor | 0 | | Constant | 1980.0*** | 1986.6*** |
| | (1.493) | | | (.) | | | (3.500) | (1.167) |
| State Atty General | -0.613 | | District Attorney | -0.890 | | All Variables | X | |
| | (1.911) | | | (1.751) | | Post Elastic Net | | X |
| Private Practice | -2.576 | | County Comm | -1.751 | | N | 85 | 85 |
| | (2.891) | | | (2.295) | | adj. R-sq | 0.464 | 0.497 |
| Mayor | -4.548 | | Asst Dist Atty | -0.803 | | | | |
| | (2.919) | | | (1.677) | | | | |
| State Senator | -1.693 | | Assit U.S. Atty | 0.914 | | | | |
| | (1.351) | | | (2.295) | | | | |
| State Lower Ct | -1.609 | | Atty General | 0 | | | | |
| | (1.384) | | | (.) | | | | |
| State Supr Court | 2.775 | | U.S. House | 3.087 | | | | |
| | (1.473) | | | (3.077) | | | | |
| State House | 1.223 | | Any Govt Exper | -1.534 | | | | |
| | (1.309) | | | (2.252) | | | | |

Predictors of Attendance (Elastic Net in DCT) (1 of 1)

| | (1) | | (1) | | (1) |
|--------------------|-----------------------|-----------------|-----------------------|------------------|----------------------|
| Unified Appoint | -0.00925 (0.0106) | Mayor | -0.0251 (0.0290) | Cohort: 1910s | 0.0776** (0.0152) |
| Republican | 0.0393** (0.00989) | Local Court | 0.0272 (0.0253) | Cohort: 1920s | 0.236** (0.0246) |
| State Supr Court | -0.0244 (0.0285) | U.S. House | -0.0447** (0.0137) | Cohort: 1930s | 0.260** (0.0266) |
| State House | -0.00554 (0.0219) | Assit U.S. Atty | 0.0426* (0.0190) | Cohort: 1940s | 0.114** (0.0187) |
| U.S. Senator | -0.0430 (0.0263) | Atty General | 0.424 (0.267) | | |
| State Atty General | -0.0395 (0.0237) | Magistr Judge | -0.0492 (0.0254) | | |
| District Attorney | -0.0104 (0.0170) | City Council | -0.0848* (0.0387) | Post Elastic Net | X |
| Black | 0.0423 (0.0318) | Any Govt Exper | 0.0416** (0.0147) | N | 2276 |
| | | | | adj. R-sq | 0.117 |

Predictors of Attendance Year (Elastic Net in DCT) (1 of 1)

| | (1) | | (1) |
|---------------------|----------|------------------|----------|
| Cross-Party Appoint | -1.121 | Black | 1.038 |
| | (1.092) | | (1.012) |
| U.S. Attorney | -1.049 | Cohort: 1910s | -7.247** |
| | (0.631) | | (0.644) |
| State Senator | -2.155* | Cohort: 1920s | -3.947** |
| | (0.877) | | (0.685) |
| State House | 1.648 | Cohort: 1940s | 4.518** |
| | (1.073) | | (0.768) |
| Solicitor General | 6.424** | Cohort: 1950s | 7.536** |
| | (0.465) | | (1.307) |
| State Atty General | -1.752 | Magistr Judge | 1.069 |
| | (1.049) | | (1.405) |
| Governor | -4.824** | | |
| | (1.066) | Post Elastic Net | X |
| Asst Dist Atty | -0.717 | N | 350 |
| | (0.652) | adj. R-sq | 0.468 |

◀ Syllabi

1 Measuring Law-and-Economics Thinking

- ◀ Economics style is cosine distance to economics articles

2 Empirical Approach

- ◀ Estimate causal effect of assigning economics judges

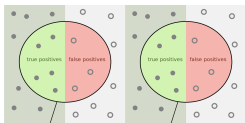
3 (Polanyian) Great Transformation of American Law

- ◀ Increasing economic orientation in federal judiciary
- ◀ Evaluate economics training via event studies, post-elastic net, Bartik IV, long-diff, and placebos

Bartik Shifter for economics training

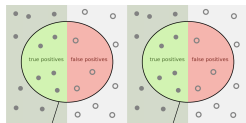
%Year_t votes by judges born in your decade × law school type that attended economics training
excluding your Circuit cases

Born in 1930s (L) or 1940s (R)



1991

Born in 1930s (L) or 1940s (R)



1992

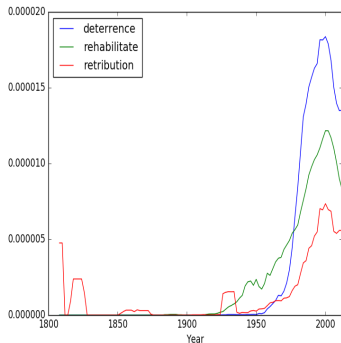
Word-of-mouth mechanism: (0.78, $p < 0.001$, Circuit) (0.92, $p < 0.001$, District)

Placebo Period

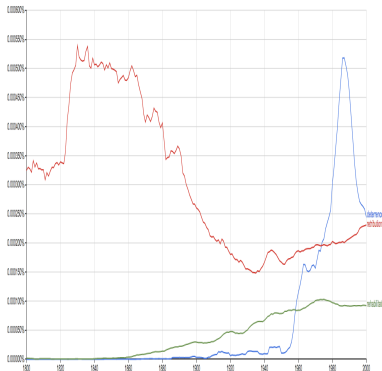
Some placebo analyses rely on pre-1976 period, where we focus on

- **votes and verdicts** (avoids endogeneity of authorship) [← Methodology](#)
- **lay words like “efficient” and “deterrence”** (already present in 1960s)

Avoids issue of scarce economics terminology pre-1976, when checking long-diffs



Word Frequency in State Court Opinions



Word Frequency in Google Books

- **Interviews** of courts and **orthogonality checks** of observables
 - (1) 2-3 weeks before oral argument, computer:
 - randomly assigns available judges including visiting judges
 - ensures judges are not sitting together repeatedly
 - senior judges reduced frequency entered into the program
 - (2) randomly assign panels on yearly basis, then randomly assign cases
 - judges can occasionally recuse
 - panel sees case again on remand
 - exceptions for specialized cases like death penalty
- **Omnibus test:** how similar string of panel assignments is to random strings
 - Not accounting for vacation, sick leave, senior status, en banc, remand, and recusal can lead to the inference that judges are not randomly assigned.
 - We assume these deviations from randomness are Rubin-ignorable.

Judge Randomization Check

| | <u>Economics Case</u> | | | |
|-----------------|-----------------------|------------------------|-----------------------|----------------------|
| | (1) | (2) | (3) | (4) |
| Econ Training | 0.00788 (0.00807) | -0.000716 (0.00454) | -0.00512 (0.00893) | 0.00540 (0.00416) |
| N | 123519 | 115561 | 500266 | 389105 |
| adj. R-sq | 0.115 | 0.024 | 0.112 | 0.023 |
| Circuit-Year FE | Y | Y | Y | Y |
| Sample | Author | Author | On Panel | On Panel |
| Sample | Year < 1976 | Year > 1991 | Year < 1976 | Year > 1991 |

Omnibus check: No endogenous settlement or selection of cases.

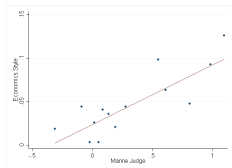
† Stylized Facts

Table: Distribution of Ideology

| Liberal and Conservative Votes | | | Party Membership | | |
|--------------------------------|--------|---------|----------------------|-----------|---------|
| Vote Valence | Freq. | Percent | Party of Appointment | Freq. | Percent |
| Liberal | 17,529 | 33.74 | Democrat | 515,418 | 44.56 |
| Neutral/Other | 8,355 | 16.08 | Other | 38,486 | 3.33 |
| Conservative | 26,076 | 50.18 | Republican | 602,836 | 52.12 |
| Total | 51,960 | 100.00 | Total | 1,156,740 | 100.00 |

- Hand-labeled vote valence for a random 5% sample by Songer-Auburn. [◀ Stylized Facts](#) [◀ Event Study](#)
- 0.7 correlation between conservative vote and ruling against regulatory agency in economics cases.
 - rejecting defendant in a criminal procedure case,
 - rejecting plaintiff asserting violation of First Amendment rights
 - rejecting Secretary of Labor who sues a corporation for violation of child labor regulations

Summary Correlations



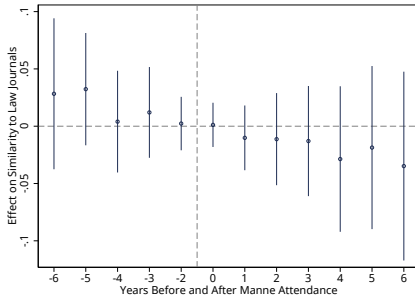
**Economics Training
correlated with Economics
Style**

| | <u>Republican</u> | | |
|--------------------|---------------------|---------------------|------------------------------|
| | (1) | (2) | (3) |
| Economics Style | 0.0367* (0.0146) | | 0.0563** (0.0191) |
| Economics Training | | 0.140** (0.0382) | 0.191** (0.0602) |
| N | 923866 | 410309 | 380085 |
| adj. R-sq | 0.137 | 0.082 | 0.099 |

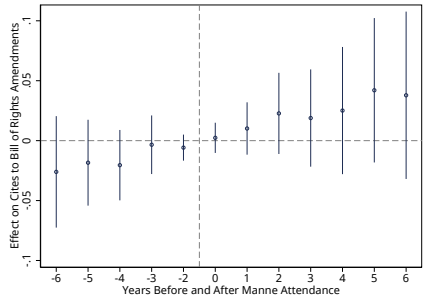
0.2 Correlation between Economics Training and Republican Party

◀ Additional Highlights

Manne Attendance on Law Journal Similarity & Originalism



Law journal similarity



Citations to Originalist Amendments

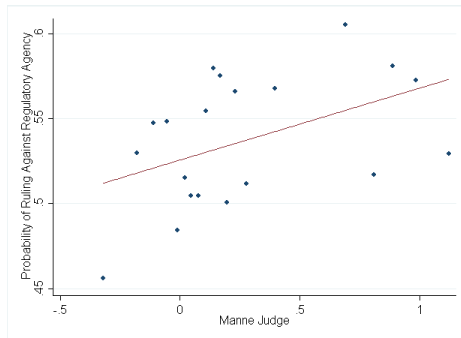
$$Y_{ijct} = \theta_{ct} + \theta_j + \sum_{n=-6..-2}^{0..6} \beta_{t-n} \text{Manne}_{ct-n} + \eta X_{jt} + \varepsilon_{ijct} \quad \text{for } n \in [-6, 6]$$

95% CI; j clusters; jt weighted equally; [authoring in economics cases](#)

Benchmark Effect of Economics (vs. Republican)

| | <u>Ruling Against Regulatory Agency</u> | | | |
|----------------------|---|------------------|-----------------|-----------------|
| | (1) | (2) | (3) | (4) |
| Econ Style | 0.00554** | 0.00533** | | |
| | (0.00245) | (0.00243) | | |
| Econ Training | | | 0.0364* | 0.0425** |
| | | | (0.0208) | (0.0212) |
| Republican | | -0.00752 | | -0.0333 |
| | | (0.00750) | | (0.0208) |
| N | 53977 | 53977 | 12320 | 12320 |
| adj. R-sq | 0.100 | 0.100 | 0.173 | 0.173 |
| Circuit-Year FE | Y | Y | Y | Y |
| Sample | All | All | Post 1991 | |

Benchmark Effect of Economics (vs. Republican)

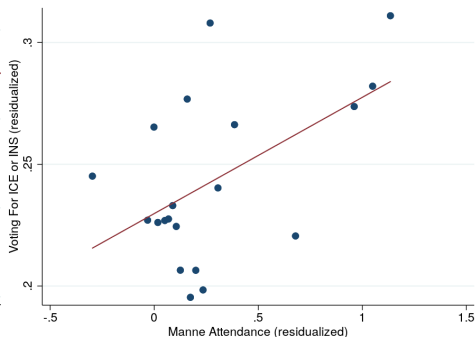
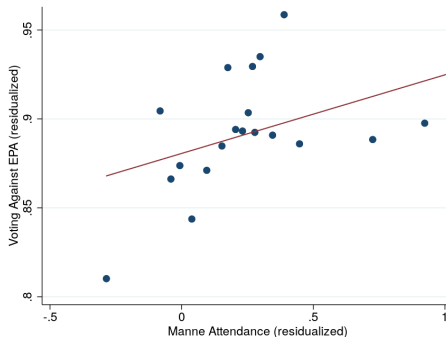


Economics Trained Judges vote against regulation

Binscatter: Probability vs. economics training, residualized on circuit-year fixed effects and Republican indicator

◀ Additional Highlights

Heterogeneity by Regulation



Economics Trained Judges vote **against** environmental

but for immigration enforcement (← cost benefit).

Binscatter: Probability vs. economics training, residualized on circuit-year fixed effects and Republican indicator

← Additional Highlights

Heterogeneity by Instructor

"Friedman always started on legalization of recreational drugs" (Butler 10/2017)

Milton Friedman taught in 1976, 1978, 1979, 1980

| | <u>Rejecting Criminal Appeal (Habeas Corpus)</u> | | | |
|--------------------------|--|-----------------|-----------------|-----------------|
| | (1) | (2) | (3) | (4) |
| Manne Training | 0.0608* | | -0.251** | |
| | (0.0286) | | (0.0922) | |
| Friedman Training | -0.0921* | -0.102 | 0.131 | 0.243** |
| | (0.0437) | (0.0615) | (0.107) | (0.0819) |
| N | 12173 | 1269 | 13895 | 753 |
| adj. R-sq | 0.140 | 0.233 | 0.264 | 0.393 |
| Circuit-Year FE | Y | Y | Y | Y |
| Sample | Post 1991 | | Pre 1976 | |
| Judges | All | Attend < 1986 | All | Attend < 1986 |

Economics Trained Judges vote to reject appeal of unlawful detention or imprisonment, unless Friedman taught.

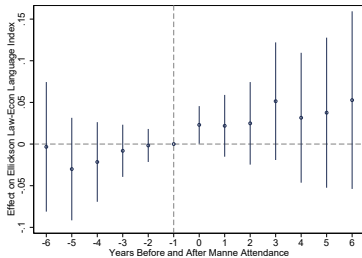
Impact of Economics Judges on Economics Cases

Table: Distribution of Case Topics

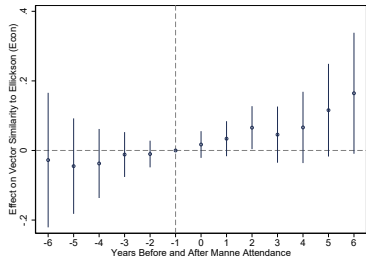
| Songer Topic | Freq. | Percent | Detailed Topic (partial list) | Freq. | Percent |
|------------------------|-----------|---------|-------------------------------|---------|---------|
| Economics | 332,553 | 29.69 | Criminal Law | 246,012 | 22.27 |
| Due Process | 259,845 | 23.20 | Civil Procedure | 194,391 | 17.6 |
| Criminal Appeal | 250,281 | 22.34 | Administrative Law | 51,900 | 4.7 |
| Miscellaneous | 149,322 | 13.33 | Tax & Accounting | 46,404 | 4.2 |
| Civil Rights | 67,350 | 6.01 | Bankruptcy Law | 40,773 | 3.69 |
| Labor | 54,681 | 4.88 | Constitutional Law | 34,575 | 3.13 |
| First Amendment | 5,268 | 0.47 | Habeas Corpus | 33,429 | 3.03 |
| Privacy | 927 | 0.08 | Contracts | 32,700 | 2.96 |
| Total | 1,120,227 | 100.0 | .. and 86 additional topics | | |

- Hand-labeled for 5% random sample by Songer-Auburn and for 100% and then aggregated to Songer topics.
- We might expect stronger effects for economics rather than non-economics cases.
 - Non-economics can include social issues like abortion or drug policy
 - The effect of economic thinking could be libertarian
- Libertarian would be coded as American “liberal” (by Songer-Auburn)

Manne Attendance on ◀ Ellickson Index and Vector



Ellickson Index

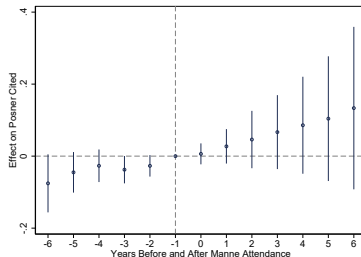


Ellickson Vector

$$Y_{ijct} = \theta_{ct} + \theta_j + \sum_{n=-6..-2}^{0..6} \beta_{t-n} \text{Manne}_{ct-n} + \eta X_{jt} + \varepsilon_{ijct} \quad \text{for } n \in [-6, 6]$$

95% CI; j clusters; jt weighted equally; [authoring in economics cases](#)

◀ decreases in law journal similarity

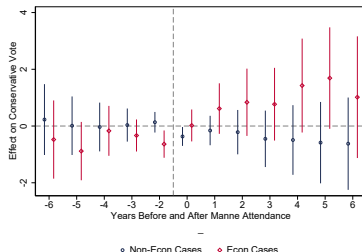


Citations to Richard Posner

$$Y_{ijct} = \theta_{ct} + \theta_j + \sum_{n=-6..-2}^{0..6} \beta_{t-n} \text{Manne}_{ct-n} + \eta X_{jt} + \varepsilon_{ijct} \quad \text{for } n \in [-6, 6]$$

95% CI; j clusters; jt weighted equally

| | <u>Ellickson Index</u> | <u>Ellickson Vector</u> | <u>Posner Cited</u> |
|-----------------|------------------------|-------------------------|------------------------|
| | (1) | (2) | (3) |
| Post-Manne | 0.0105** (0.00523) | 0.00525 (0.00342) | 0.00861** (0.00400) |
| N | 632799 | 623874 | 886988 |
| adj. R-sq | 0.060 | 0.075 | 0.194 |
| Circuit-Year FE | X | X | X |
| Judge FE | X | X | X |



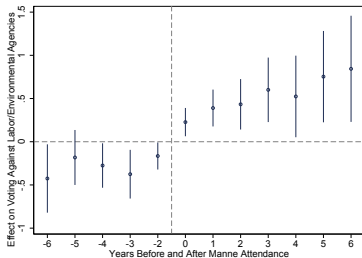
Econ vs Non-Economics Cases

$$Y_{ijct} = \theta_{ct} + \theta_j + \sum_{n=-6..-2} \beta_{t-n} \text{Manne}_{ct-n} + \eta X_{jt} + \varepsilon_{ijct} \quad \text{for } n \in [-6, 6]$$

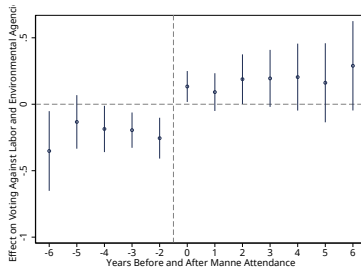
95% CI; j clusters; jt weighted equally; 5% SA sample

◀ 30-70 distribution of economics and non-economics cases

Manne Attendance on Labor/Environmental



Raw Correlation



with Elastic Net x Year FE

$$Y_{ijct} = \theta_{ct} + \theta_j + \sum_{n=-6..-2}^{0..6} \beta_{t-n} \text{Manne}_{ct-n} + \eta X_{jt} + \varepsilon_{ijct} \quad \text{for } n \in [-6, 6]$$

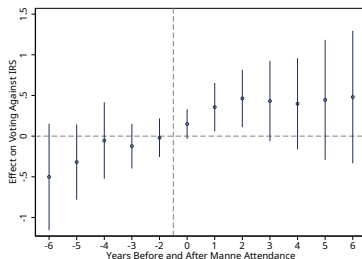
95% CI; j clusters; jt weighted equally

Manne Attendance on Labor/Environmental

| | <u>Voting Against Environmental or Labor Agency</u> | | | |
|-----------------------|---|-----------------|-----------------|-----------------|
| | (1) | (2) | (3) | (4) |
| Post-Manne | 0.101** | 0.0939** | 0.165** | 0.144** |
| | (0.0315) | (0.0298) | (0.0376) | (0.0305) |
| N | 19521 | 19521 | 19521 | 19521 |
| adj. R-sq | 0.307 | 0.311 | 0.319 | 0.337 |
| Circuit-Year FE | X | X | X | X |
| Judge FE | X | X | X | X |
| Party-Year FE | | X | X | |
| Ever-Attend-Year FE | | | X | |
| E-net Vars ## Year FE | | | | X |

Judges are 10-15% more likely to vote against environmental and labor regulations after economics training.

Manne Attendance on Tax Decisions



with Elastic Net \times Year FE

$$Y_{ijct} = \theta_{ct} + \theta_j + \sum_{n=-6..-2}^{0..6} \beta_{t-n} \text{Manne}_{ct-n} + \eta X_{jt} + \varepsilon_{ijct} \quad \text{for } n \in [-6, 6]$$

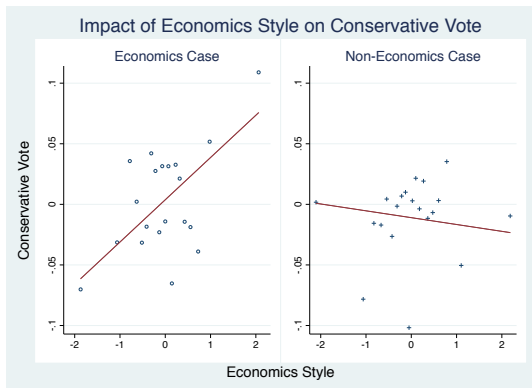
95% CI; j clusters; jt weighted equally

Manne Attendance on Tax Decisions

| | <u>Voting Against Internal Revenue Service</u> | | | |
|-----------------------|--|-----------------|-----------------|-----------------|
| | (1) | (2) | (3) | (4) |
| Post-Manne | 0.0840** | 0.0848** | 0.133** | 0.104** |
| | (0.0424) | (0.0413) | (0.0528) | (0.0506) |
| N | 19957 | 19957 | 19957 | 19957 |
| adj. R-sq | 0.312 | 0.317 | 0.327 | 0.319 |
| Circuit-Year FE | X | X | X | X |
| Judge FE | X | X | X | X |
| Party-Year FE | | X | X | |
| Ever-Attend-Year FE | | | X | |
| E-net Vars ## Year FE | | | | X |

Judges are 10% more likely to vote against IRS after economics training.

Impact of Economics Judges on Economics Cases



In Economics Cases, Economics Style Judges render Conservative Votes (normalized).

◀ Additional Highlights

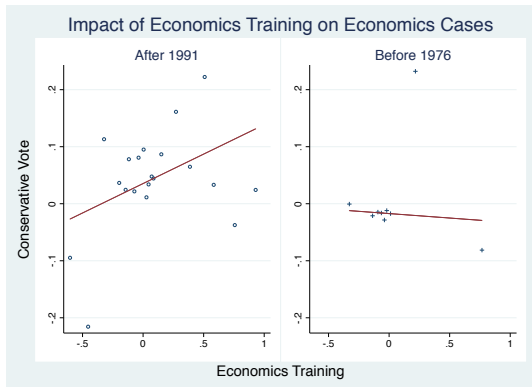
Impact of Economics Judges on Economics Cases

| | <u>Conservative Vote (+1/0/-1)</u> | | | | <u>Conservative Vote (+1/0/-1)</u> | | |
|---------------------|------------------------------------|-----------------------|-----------------------|---------------------|------------------------------------|-----------------------|-----------------------|
| | (1) | (2) | (3) | | (4) | (5) | (6) |
| Econ Style | -0.0116 (0.0102) | -0.0120 (0.0103) | -0.0125 (0.0111) | Republican | 0.00622 (0.0234) | 0.0113 (0.0147) | 0.00660 (0.0273) |
| Econ Case | -0.229*** (0.0138) | -0.241*** (0.0171) | -0.243*** (0.0167) | Econ Case | -0.262*** (0.0236) | -0.241*** (0.0171) | -0.274*** (0.0276) |
| Econ Style * | 0.0609*** | 0.0600*** | 0.0636*** | Republican * | 0.0678* | 0.0254 | 0.0806* |
| Econ Case | (0.0141) | (0.0140) | (0.0148) | Econ Case | (0.0370) | (0.0259) | (0.0434) |
| N | 48195 | 48195 | 33901 | N | 52215 | 48195 | 37921 |
| adj. R-sq | 0.089 | 0.089 | 0.100 | adj. R-sq | 0.123 | 0.089 | 0.138 |
| Circuit-Year FE | Y | Y | Y | Circuit-Year FE | Y | Y | Y |
| Control | N | Repub | N | Control | N | Econ Style | N |
| Sample | All | All | Non-Author | Sample | All | All | Non-Author |

Holds controlling for Republican and examining Non-Authors

Additional Highlights

Impact of Economics Judges on Economics Cases



After attendance, Economics Trained Judges render Conservative Votes (normalized).

◀ Highlights

Impact of Economics Judges on Economics Cases

| | Conservative Vote (+1/0/-1) | | | | | | |
|-----------------------------|-----------------------------|-----------------------|----------------|----------------|-----------------|------------|------------|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Econ Training * Econ Case | -0.129 | 0.257*** | 0.000178 | 0.246 | | | |
| | (0.126) | (0.0977) | (0.0581) | (0.139) | | | |
| Econ Training * Econ Case * | | | 0.207** | 0.254** | | | |
| Post 1991 | | | (0.103) | (0.116) | | | |
| Econ Training * Econ Case * | | | | | 0.625*** | 0.708*** | 0.427* |
| Post | | | | | (0.160) | (0.169) | (0.226) |
| N | 29153 | 9639 | 52215 | 51861 | 52215 | 26202 | 25975 |
| adj. R-sq | 0.146 | 0.106 | 0.271 | 0.220 | 0.302 | 0.355 | 0.320 |
| Circuit-Year FE | Y | Y | Y | Y | Y | Y | Y |
| E-Net Vars ## Econ ## Post | N | N | N | Y | N | N | N |
| Judge FE | N | N | Y | Y | Y | Y | Y |
| Sample | Year < 1976 | Year > 1991 | All | All | All | Rep | Dem |

Holds with fully interacted Republican and Judge trends. Rows omitted (but not regressors).

Impact of Economics Judges on Economics Cases (Bartik)

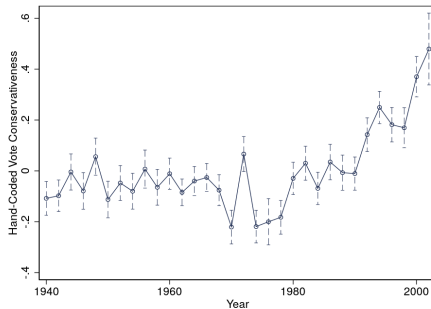
| | <u>Conservative Vote (+1/0/-1)</u> | |
|--------------------|------------------------------------|---------------------|
| | (1) | (2) |
| Econ Case | -0.254*** | -0.283*** |
| | (0.0177) | (0.0199) |
| Post-Manne | -0.0773 | -0.557** |
| | (0.0638) | (0.236) |
| Econ Case * | 0.240*** | 0.624*** |
| Post-Manne | (0.0667) | (0.157) |
| N | 51868 | 51868 |
| adj. R-sq | 0.2467 | 0.247 |
| Bartik | N | reduced form |
| Circuit-Year FE | Y | Y |
| Judge FE | Y | Y |
| Sample | All | All |

Bartik (leave-judge-out) is constructed from current year X decade of birth cohort

◀ Word of Mouth

◀ Additional Highlights

Impact of Economics Judges, Magnitudes



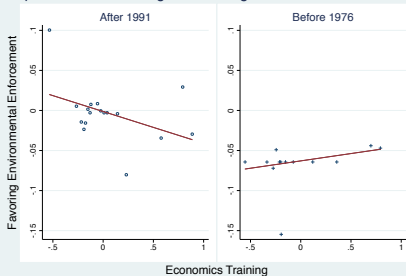
From 1976–2002, a rise of 0.2–0.3 likelihood to vote conservative, then Manne $\frac{0.2 \times 0.4}{0.3}$ accounts for 28–42% of rise.

Only accounts for **own attendance**; if **peers and precedent affect non-Manne** \Rightarrow true Manne impact may be larger.

◀ Highlights

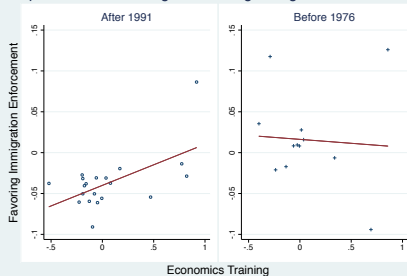
Ideological Shifts

Impact of Econ Training on Favoring Environment Enforcement



After attendance, Economics Trained Judges reject environmental enforcement (normalized)

Impact of Econ Training on Favoring Immigration Enforcement



but support immigration enforcement (normalized).

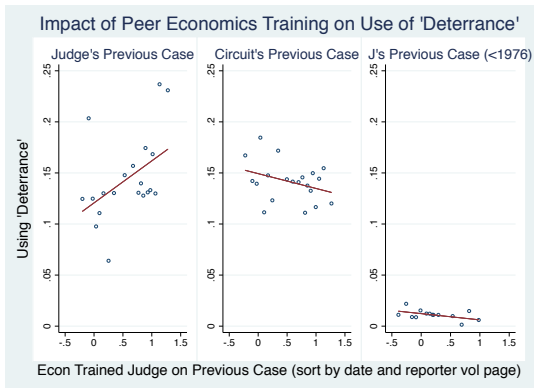
Note: both **switch in direction**. [◀ Highlights](#)

Impact of Economics Judges on Regulation Cases

| | <u># Uses of "Efficient"</u> | | |
|------------------------|------------------------------|-----------------------|-----------------|
| | (1) | (2) | (3) |
| Econ Training | -0.00407 | 0.0494*** | |
| | (0.00455) | (0.0188) | |
| Econ Training * | | | 0.0495* |
| Post 1991 | | | (0.0272) |
| N | 45752 | 11372 | 72005 |
| adj. R-sq | 0.125 | 0.148 | 0.261 |
| Circuit-Year FE | Y | Y | Y |
| Control | N | N | N |
| Judge FE | N | N | Y |
| Sample | Year < 1976 | Year > 1991 | All |

Similar with Republican control.

Impact of Peer Econ Judges on Criminal Case Reasoning



Previous judge case (median) 9 days ago; previous circuit case (median) 2 days ago. Exclude same day cases.

◀ Impacts on Criminal Cases

Immigration Charges

| Lead Charge | Count | Rank | 1 yr ago | 5 yrs ago | 10 yrs ago | 20 yrs ago |
|---|--------|------|----------|-----------|------------|------------|
| 08 USC 1325 - Entry of alien at improper time or place; etc. | 35,367 | 1 | 1 | 1 | 2 | 3 |
| 08 USC 1326 - Reentry of deported alien | 28,930 | 2 | 2 | 2 | 1 | 1 |
| 08 USC 1324 - Bringing in and harboring certain aliens | 3,794 | 3 | 3 | 3 | 3 | 2 |
| 18 USC 1546 - Fraud and misuse of visas, permits, and other documents | 502 | 4 | 4 | 4 | 4 | 4 |
| 18 USC 1544 - Misuse of passport | 333 | 5 | 5 | 8 | 15 | 16 |
| 18 USC 1028 - Fraud and related activity - id documents | 165 | 6 | 6 | 5 | 6 | 7 |
| 18 USC 1542 - False statement in application and use of passport | 72 | 7 | 7 | 9 | 10 | 8 |
| 18 USC 922 - Firearms; Unlawful acts | 50 | 8 | 11 | 12 | 13 | 22 |
| 21 USC 841 - Drug Abuse Prevention & Control-Prohibited acts A | 45 | 9 | 10 | 14 | 14 | 11 |
| 18 USC 371 - Conspiracy to commit offense or to defraud US | 40 | 10 | 16 | 10 | 11 | 5 |

Impact of Economics Judges, by Crime Type

| | <u>Log of Total Sentence</u> | | | | |
|--|------------------------------|----------------------|---------------------|---------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Econ Training | -0.0695 (0.0839) | -0.00621 (0.0347) | -0.0369 (0.0559) | -0.0213 (0.0619) | -0.0226 (0.0599) |
| Econ Training * | 0.245** | 0.0467 | 0.200** | 0.184** | 0.219** |
| Booker (≥ 2005) | (0.100) | (0.0411) | (0.0856) | (0.0903) | (0.0900) |
| N | 600010 | 697844 | 798823 | 838643 | 786472 |
| adj. R-sq | 0.043 | 0.044 | 0.051 | 0.037 | 0.043 |
| Courthouse and Calendar FE | Y | Y | Y | Y | Y |
| Drop Crime | Drug | Immigration | Fraud | Weapon | Other |

Milton Friedman for legalizing drugs (against victimless crimes). Immigration severity consistent with Circuit results.

◀ Impacts on Criminal Cases

Judge Randomization Check

| | <u>Econ Training</u> | | | | |
|----------------------------|----------------------|-------------|----------|-----------|-----------|
| | (1) | (2) | (3) | (4) | (5) |
| Crime Type | -0.00545 | 0.0148 | -0.00362 | 0.00319 | -0.000646 |
| | (0.0157) | (0.0441) | (0.0107) | (0.00898) | (0.00939) |
| Crime Type * | 0.0127 | -0.0132 | -0.00621 | -0.00825 | -0.00691 |
| Booker (≥ 2005) | (0.0127) | (0.0445) | (0.0160) | (0.0147) | (0.0142) |
| N | 930448 | 930448 | 930448 | 930448 | 930448 |
| adj. R-sq | 0.245 | 0.245 | 0.245 | 0.245 | 0.245 |
| Courthouse and Calendar FE | Y | Y | Y | Y | Y |
| Crime Type | Drug | Immigration | Fraud | Weapon | Other |

Omnibus check: No endogenous settlement or selection of cases.

◀ Impacts on Criminal Cases

Impact of Economics Judges on Racial Gaps, Pre *Booker*

| | <u>Life</u> | <u>Months</u> | <u>Life</u> | <u>Months</u> |
|---------------------|------------------|-----------------|------------------|-----------------|
| | (1) | (2) | (3) | (4) |
| <i>Minority</i> | 0.00395*** | 20.84*** | 0.00388*** | 20.34*** |
| | (0.000770) | (1.979) | (0.00102) | (2.170) |
| * Economics | 0.00401** | 5.413*** | 0.00379** | 3.180* |
| | (0.00157) | (2.044) | (0.00170) | (1.910) |
| * Republican | | | 0.000641 | 4.096** |
| | | | (0.00103) | (1.723) |
| * Minority J | | | -0.00119 | -7.451** |
| | | | (0.00135) | (3.167) |
| N | 156650 | 155977 | 154920 | 154253 |
| adj. R-sq | 0.015 | 0.102 | 0.015 | 0.102 |
| Judge FE | Y | Y | Y | Y |
| Sample | All | All | All | All |

Economics Trained Judges harsher to minorities (1992-2003 30% merge to USSC)

Cohen and Yang (AEJ 2017): Republican J sentence 3 more months for blacks

Impact of Economics Judges on Gender Gaps, Pre Booker

| | <u>Life</u> | <u>Months</u> | <u>Life</u> | <u>Months</u> |
|---------------------|-------------------|------------------|------------------|-----------------|
| | (1) | (2) | (3) | (4) |
| <i>Female</i> | -0.00397*** | -31.01*** | -0.00395*** | -29.84*** |
| | (0.000562) | (1.676) | (0.000718) | (2.127) |
| * Economics | -0.00247** | -5.083*** | -0.00227* | -4.120** |
| | (0.00113) | (1.717) | (0.00116) | (1.617) |
| * Republican | | | -0.000372 | -2.549* |
| | | | (0.000678) | (1.456) |
| * Female J | | | 0.000697 | 0.145 |
| | | | (0.000750) | (1.218) |
| N | 160402 | 159713 | 158634 | 157951 |
| adj. R-sq | 0.014 | 0.109 | 0.015 | 0.109 |
| Judge FE | Y | Y | Y | Y |
| Sample | All | All | All | All |

Economics Trained Judges more lenient to females (1992-2003 30% merge to USSC)

Cohen and Yang (AEJ 2017): Female J sentence 2 fewer months for females

Coarse Communication

- Communication constraint works as a magnifier of correlation (Kweik 2013)

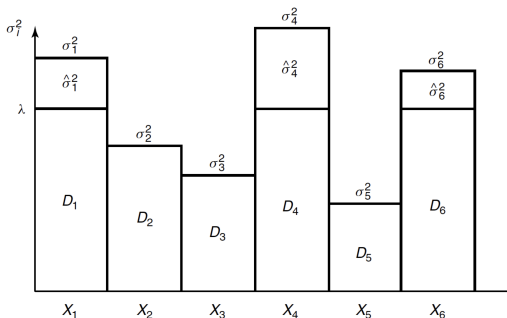


FIGURE 10.7. Reverse water-filling for independent Gaussian random variables.

Elements of Information Theory (Cover and Thomas 1991)

- No bits used to describe information with variance less than a constant
- Results in exaggerating pre-existing correlations
- Use of stereotypes under information constraints (Bordalo et al. 2016)
 - Representative heuristic will “overweight” and distort beliefs

- Economics judges
 - **vote** for and **author** conservative verdicts, especially for economics cases
 - more **opposed** to government regulation and criminal appeals
 - Against environmental and labor, but **for** immigration enforcement
 - Friedman trainees more lenient on criminal appeals
 - **impact** their panelists and peers on subsequent cases
 - Increase use of “deterrence” in panelists’ subsequent opinion
 - Transmission from regulatory to criminal cases
 - **render** harsher criminal sentences
 - Especially for immigration crimes (but not drug crimes)
 - Also predictive of Pre-*Booker* disparities along race and gender

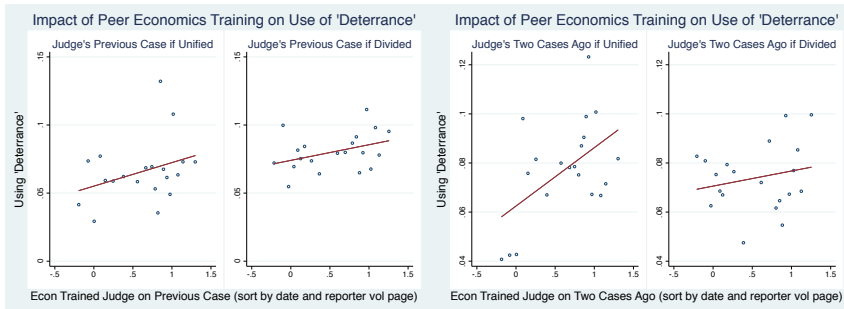
Despite significant negative impacts of incarceration on families, communities, and **limited** deterrence effects. (e.g. Mueller-Smith 2014; Chalfin et al. 2014; Morsy et al. 2016)

- Economics judges
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Despite significant negative impacts of incarceration on families, communities, and **limited** deterrence effects. (e.g. Mueller-Smith 2014; Chalfin et al. 2014; Morsy et al. 2016)

Active or Passive Persuasion?

Uniform panel (DDD or RRR) as proxy for passive persuasion



Transmission seems generalized, somewhat greater when panel is unified.

Leeper et al (1979) reports evidence that people are **more likely to be influenced by someone whose opinion is close to theirs**, and they often reject opinions which are very far from their own.

◀ General Equilibrium Effects

- The text of the opinions provide a window into rich representations of legal/political institutions, as we well as **human social psychology**.
- Caliskan, Bryson, and Narayanan (Science 2017) show that implicit gender and racial biases are embedded in human language.
 - We ask whether this implicit language bias varies across judges.

Word Embedding Association Test

| Sentiment Attribute Words | |
|-----------------------------------|-----------------------------------|
| joy, love, peace, wonderful, | agony, terrible, horrible, nasty, |
| pleasure, friend, laughter, happy | evil, war, awful, failure |

| Implicit Sexism Target Words | |
|------------------------------|------------------------------|
| male, man, boy, brother, | female, woman, girl, sister, |
| he, him, his, son | she, her, hers, daughter |

| Implicit Racism Target Words | |
|------------------------------|-----------------------|
| european, white, caucasian | black, african, negro |

- Compute “Association” as the average word-vector similarities between a group of target words and a group of attribute words.

$$\text{Implicit Sexism} = \frac{\text{Male-Pleasant Association}}{\text{Male-Unpleasant Association}} - \frac{\text{Female-Pleasant Association}}{\text{Female-Unpleasant Association}}$$

$$\text{Implicit Racism} = \frac{\text{White-Pleasant Association}}{\text{White-Unpleasant Association}} - \frac{\text{Black-Pleasant Association}}{\text{Black-Unpleasant Association}}$$

- We train Word2Vec separately by judge, using Caliskan et. al (2017) windows

Word Embedding Association Test

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$$\text{Implicit Racism} = \frac{\text{White-Pleasant Association}}{\text{White-Unpleasant Association}} - \frac{\text{Black-Pleasant Association}}{\text{Black-Unpleasant Association}}$$

- We train Word2Vec separately by judge, using Caliskan et. al (2017) windows

Word Embedding Association Test

| Sentiment Attribute Words | |
|-----------------------------------|-----------------------------------|
| joy, love, peace, wonderful, | agony, terrible, horrible, nasty, |
| pleasure, friend, laughter, happy | evil, war, awful, failure |

| Implicit Sexism Target Words | |
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| male, man, boy, brother, | female, woman, girl, sister, |
| he, him, his, son | she, her, hers, daughter |

| Implicit Racism Target Words | |
|------------------------------|-----------------------|
| european, white, caucasian | black, african, negro |

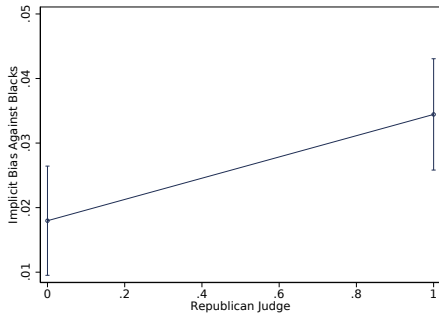
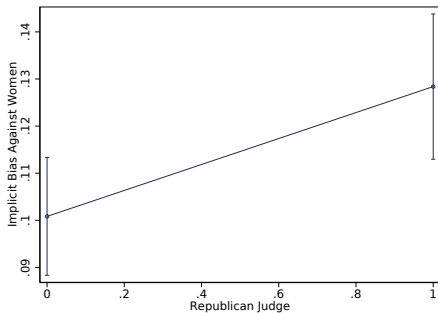
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$$\text{Implicit Sexism} = \frac{\text{Male-Pleasant Association}}{\text{Male-Unpleasant Association}} - \frac{\text{Female-Pleasant Association}}{\text{Female-Unpleasant Association}}$$

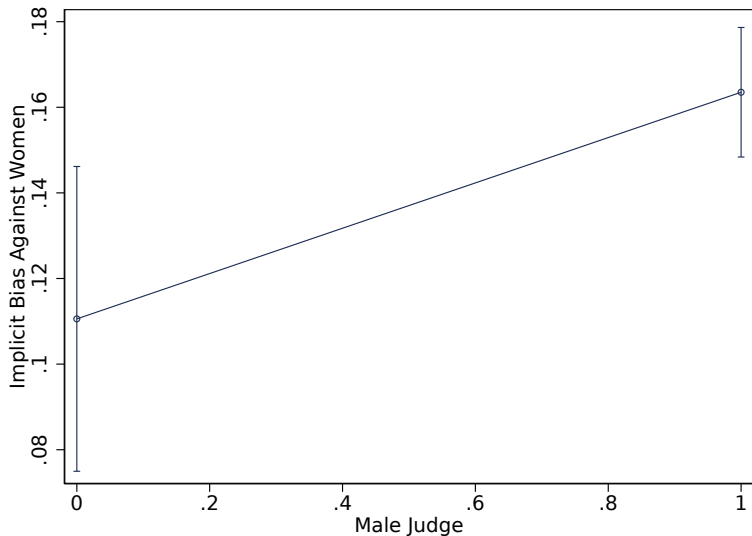
$$\text{Implicit Racism} = \frac{\text{White-Pleasant Association}}{\text{White-Unpleasant Association}} - \frac{\text{Black-Pleasant Association}}{\text{Black-Unpleasant Association}}$$

- We train Word2Vec separately by judge, using Caliskan et. al (2017) windows

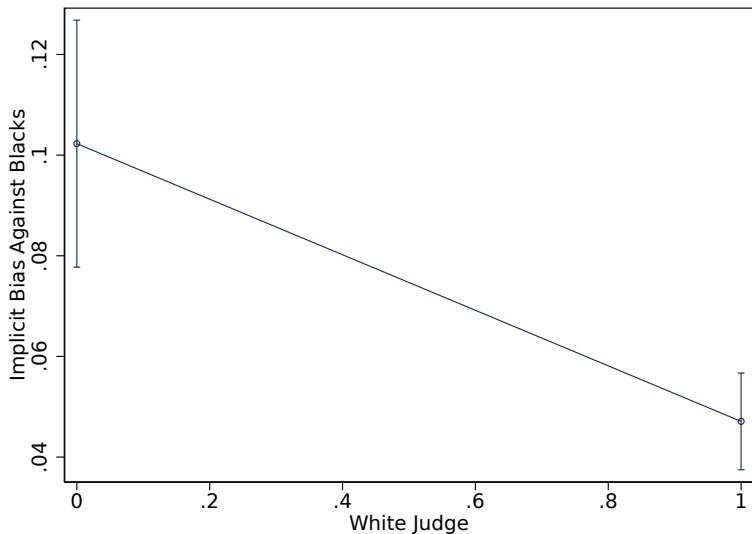
Republican judges have higher gender bias and race bias



Male judges have higher gender bias than female judges



White judges have *lower* race bias than black judges



Both the words and the IAT work at an unconscious level, in contrast to the decisions which are more conscious.

Trump nominees have high race and gender bias

President Donald J. Trump's Supreme Court List

Amy Coney Barrett of Indiana, U.S. Court of Appeals for the Seventh Circuit

Keith Blackwell of Georgia, Supreme Court of Georgia

Charles Canady of Florida, Supreme Court of Florida

Steven Colloton of Iowa, U.S. Court of Appeals for the Eighth Circuit

Allison Eid of Colorado, U.S. Court of Appeals for the Tenth Circuit

Britt Grant of Georgia, Supreme Court of Georgia

Raymond Gruender of Missouri, U.S. Court of Appeals for the Eighth Circuit

Thomas Hardiman of Pennsylvania, U.S. Court of Appeals for the Third Circuit

Brett Kavanaugh of Maryland, U.S. Court of Appeals for the District of Columbia Circuit

Raymond Kethledge of Michigan, U.S. Court of Appeals for the Sixth Circuit

Joan Larsen of Michigan, U.S. Court of Appeals for the Sixth Circuit

Mike Lee of Utah, United States Senator

Thomas Lee of Utah, Supreme Court of Utah

Edward Mansfield of Iowa, Supreme Court of Iowa

Federico Moreno of Florida, U.S. District Court for the Southern District of Florida

Kevin Newsom of Alabama, U.S. Court of Appeals for the Eleventh Circuit

William Pryor of Alabama, U.S. Court of Appeals for the Eleventh Circuit

Margaret Ryan of Virginia, U.S. Court of Appeals for the Armed Forces

David Stras of Minnesota, U.S. Court of Appeals for the Eighth Circuit

Diane Sykes of Wisconsin, U.S. Court of Appeals for the Seventh Circuit

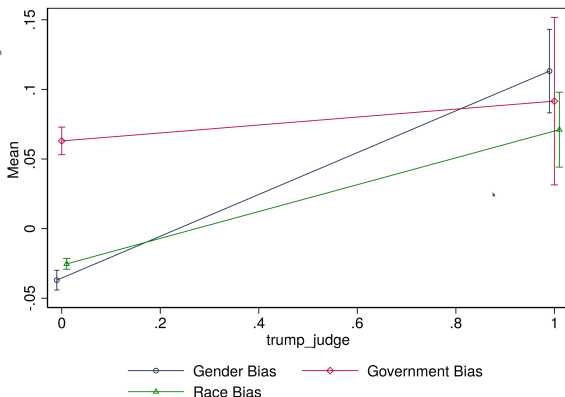
Amul Thapar of Kentucky, U.S. Court of Appeals for the Sixth Circuit

Timothy Tymkovich of Colorado, U.S. Court of Appeals for the Tenth Circuit

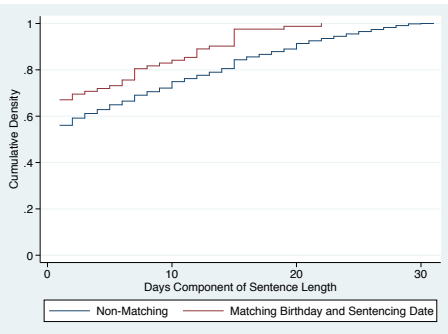
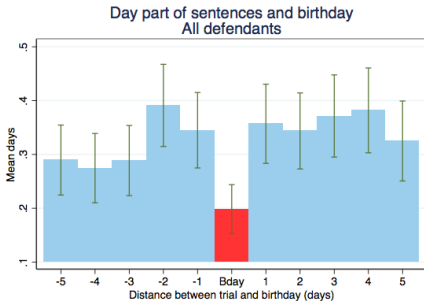
Robert Young of Michigan, Supreme Court of Michigan (Ret.)

Don Willett of Texas, Supreme Court of Texas

Patrick Wyrick of Oklahoma, Supreme Court of Oklahoma



Judicial leniency on defendant birthdays



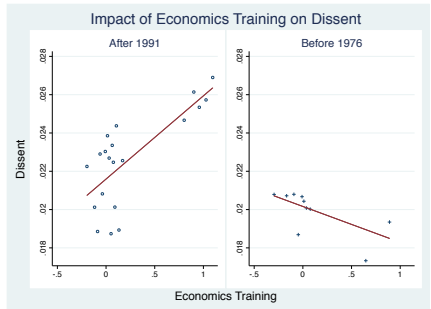
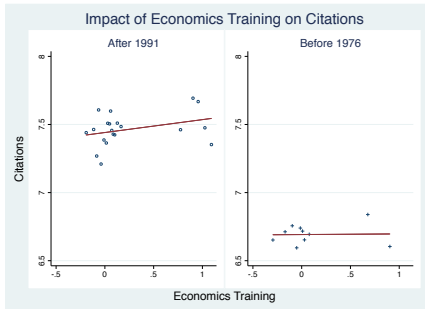
“Perceptibility the policy pendulum is swinging **toward rationality** and intellect and **away from magic and emotion.**” (Manne 1980, LEC annual report)

Judges' experience and training

- Is the leniency on birthday dependent on judges' characteristics?
 - Judicial experience does not mute the birthday norm...
 - but economics does (measured in their writing in civil cases).

| | Day component, excluding 12 months sentences | | | |
|---|--|-------------------|------------------------|------------------------------|
| | Tenure > median | Tenure < median | Use econ related words | Don't use econ related words |
| Panel A : control placebo and week | | | | |
| Bday | -0.16 (0.098) | -0.030 (0.073) | -0.042 (0.091) | -0.15* (0.084) |
| Panel B : control week | | | | |
| Bday | -0.24*** (0.065) | -0.063 (0.065) | -0.067 (0.076) | -0.22*** (0.054) |
| Panel C : control placebo | | | | |
| Bday | -0.13*** (0.025) | -0.11* (0.057) | -0.043 (0.065) | -0.19*** (0.0086) |
| Cst | 0.18*** | 0.17*** | 0.14*** | 0.20*** |
| Obs | 82,194 | 88,578 | 84,089 | 83,315 |

Citations and Dissent (Legal and Normative Innovation)



After attendance, Economics Trained Judges cited more

and increase dissents (normalized)

Dissents as contribution to legal innovation and self-expression

◀ General Equilibrium Effects

Appeals to (but not Reversals at) Supreme Court

| | Supreme Court Takes Case | | Supreme Court Reverses | |
|-----------------------|--------------------------|-----------|------------------------|----------|
| Mean of dep var. | 0.011 | | 0.677 | |
| | (1) | (2) | (3) | (4) |
| Manne Training | 0.00263* | 0.00129 | 0.0185 | 0.0239 |
| | (0.00139) | (0.00318) | (0.0305) | (0.0444) |
| N | 372244 | 493728 | 3348 | 5653 |
| adj. R-sq | 0.007 | 0.024 | 0.350 | 0.300 |
| Circuit-Year FE | Y | Y | Y | Y |
| Sample | Post 1991 | Pre 1976 | Post 1991 | Pre 1976 |

Appeals to (but not Reversals at) Supreme Court increase after economics training.

Supreme Court increases 25% attention to economics-trained cases.

◀ General Equilibrium Effects

Consequentialist vs. deontological reasoning

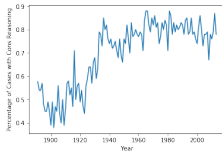
- Train classifier on applied ethics articles
- Extract phrases that are most distinctive of consequentialist reasoning
 - “the optimal number”, “of likelihood of”, “cost of not”, “minimize expected impermissibility”, “benefit someone”

Consequentialist reasoning

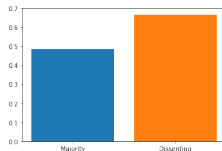
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higher over time

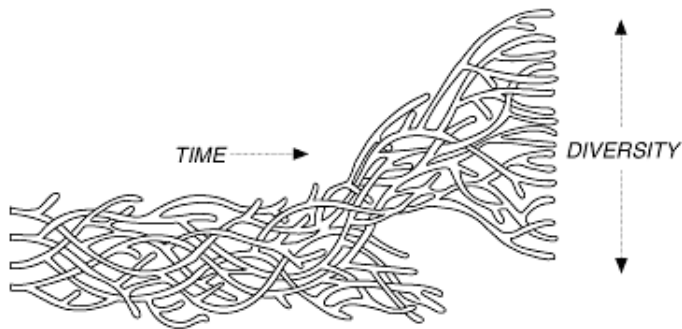


and in dissents



◀ General Equilibrium Effects

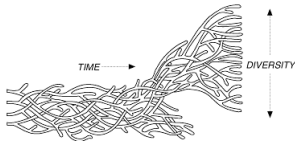
How to Examine General Equilibrium Effects?



- Precedent?
- Paradigm shifts?

- Legal terminology
 - A: Adjective, N: Noun, V: Verb, P: Preposition, D: Determinant, C: Conjunction.
 - 2-grams: AN, NN, VN, VV, NV, VP.
 - 3-grams: NNN, AAN, ANN, NAN, NPN, VAN, VNN, AVN, VVN, VPN, ANV, NVV, VDN, VVV, NNV, VVP, VAV, VVN, NCN, VCV, ACA, PAN.
 - 4-grams: NCVN, ANNN, NNNN, NPNN, AANN, ANNN, ANPN, NNPN, NPAN, ACAN, NCNN, NNCN, ANCN, NCAN, PDAN, PNPV, VDNN, VDAN, VVDN.
 - 350,000 N-grams
- Phrase that propagates along the citation/seating graph
 - Citation meme that propagates along the citation/seating graph

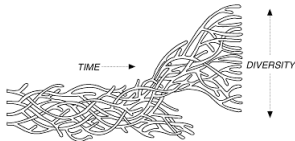
Scoring Memetic Phrases



$$P_m = \frac{d_{m \rightarrow m}}{d_{\rightarrow m} + \delta} / \frac{d_{m \rightarrow \cancel{m}} + \delta}{d_{\rightarrow \cancel{m}} + \delta}$$

- $d_{m \rightarrow m}$ = # of cases with m , and cite ≥ 1 case with m
- $d_{\rightarrow m}$ = # of cases which cite ≥ 1 case with m
- $d_{m \rightarrow \cancel{m}}$ = # of cases with m , and do not cite any other case with m
- $d_{\rightarrow \cancel{m}}$ = # of cases which do not cite any other case with m
- δ is a noise factor to account for non-citing cases
- The overall meme score of a phrase is: $S_m = \frac{N_{has\ meme}}{N_{total}} \times P_m$

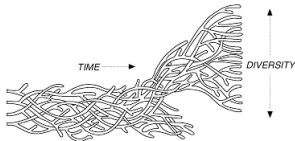
Scoring Memetic Phrases



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Memetic Phrases

| Phrase | Normalized Meme Score |
|------------------------------|-----------------------|
| red heat | 0.138 |
| salvage services | 0.0039 |
| said cars | 0.0029 |
| Atlantic coast | 0.00216 |
| citizens of different states | 0.00212 |
| insurance effected | 0.0020 |
| separable controversy | 0.0018 |
| taken in tow | 0.0017 |
| schooner was | 0.00126 |
| fourteenth amendment | 0.00125 |
| contract of affreightment | 0.00119 |
| patented design | 0.0011 |
| constitution or laws | 0.0009 |
| mere transient or sojourner | 0.0008 |

Maritime Law: salvage services, Atlantic coast, citizens of different states, insurance effected, taken in tow, schooner was, contract of affreightment, mere transient or sojourner; **Fourteenth Amendment** one of the most litigated parts of Constitution, basis for *Brown v. Board of Education* (1954) [racial segregation], *Roe v. Wade* (1973) [abortion], *Bush v. Gore* (2000) [2000 election], and *Obergefell v. Hodges* (2015) [same-sex marriage].

Mitosis of Ideology

Integration and Assimilation? or Dis-integration, Radicalization, Other-ing, and Egotism?

◀ The Effect of Being Minority (DRR or RDD): Instead of assimilation, we see **dis-assimilation**

◀ The Effect of Being Majority (DDR or RRD): Instead of integration, we see **radicalization**

◀ The Effect of Uniformity (DDD or RRR): Instead of conformity, we see **egotism**

| Minority: <u>D</u> RR | Majority: <u>D</u> DR | Uniformity: <u>D</u> DD |
|----------------------------------|--------------------------------|-----------------------------|
| Assimilation: --> <u>D</u> RR | Integration: --> <u>D</u> DR | Conformity: --> <u>D</u> DD |
| Dis-assimilation: <u>D</u> ←--RR | Radicalization: <u>D</u> ←--DR | Egotism: <u>D</u> ←--DD |
| Persuasion: <u>D</u> R←--R | Other-ing: <u>D</u> D←--R | Sectism: <u>D</u> D←--D |

◀ Identification : Circuit x YearQuarter x Party Fixed Effects (stability w/ Judge FE, Topic FE)

◀ General Equilibrium Effects

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|----------------------------------|--------------------------------|-----------------------------|
| Assimilation: --> <u>D</u> RR | Integration: --> <u>D</u> DR | Conformity: --> <u>D</u> DD |
| Dis-assimilation: <u>D</u> ←--RR | Radicalization: <u>D</u> ←--DR | Egotism: <u>D</u> ←--DD |
| Persuasion: <u>D</u> R←--R | Other-ing: <u>D</u> D←--R | Sectism: <u>D</u> D←--D |

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|----------------------------------|--------------------------------|-----------------------------|
| Assimilation: --> <u>D</u> RR | Integration: --> <u>D</u> DR | Conformity: --> <u>D</u> DD |
| Dis-assimilation: <u>D</u> ←--RR | Radicalization: <u>D</u> ←--DR | Egotism: <u>D</u> ←--DD |
| Persuasion: <u>D</u> R←--R | Other-ing: <u>D</u> D←--R | Sectism: <u>D</u> D←--D |

◀ Identification : Circuit x YearQuarter x Party Fixed Effects (stability w/ Judge FE, Topic FE)

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| Minority: <u>D</u> RR | Majority: <u>D</u> DR | Uniformity: <u>D</u> DD |
|----------------------------------|--------------------------------|-----------------------------|
| Assimilation: --> <u>D</u> RR | Integration: --> <u>D</u> DR | Conformity: --> <u>D</u> DD |
| Dis-assimilation: <u>D</u> ←--RR | Radicalization: <u>D</u> ←--DR | Egotism: <u>D</u> ←--DD |
| Persuasion: <u>D</u> R←--R | Other-ing: <u>D</u> D←--R | Sectism: <u>D</u> D←--D |

◀ Identification : Circuit x YearQuarter x Party Fixed Effects (stability w/ Judge FE, Topic FE)

◀ General Equilibrium Effects

Mitosis of Ideology

Integration and Assimilation? or Dis-integration, Radicalization, Other-ing, and Egotism?

◀ The Effect of Being Minority (DRR or RDD): Instead of assimilation, we see **dis-assimilation**

◀ The Effect of Being Majority (DDR or RRD): Instead of integration, we see **radicalization**

◀ The Effect of Uniformity (DDD or RRR): Instead of conformity, we see **egotism**

| Minority: <u>D</u> RR | Majority: <u>D</u> DR | Uniformity: <u>D</u> DD |
|----------------------------------|--------------------------------|-----------------------------|
| Assimilation: --→ <u>D</u> RR | Integration: --→ <u>D</u> DR | Conformity: --→ <u>D</u> DD |
| Dis-assimilation: <u>D</u> ←--RR | Radicalization: <u>D</u> ←--DR | Egotism: <u>D</u> ←--DD |
| Persuasion: <u>D</u> R←--R | Other-ing: <u>D</u> D←--R | Sectism: <u>D</u> D←--D |

◀ Identification : Circuit x YearQuarter x Party Fixed Effects (stability w/ Judge FE, Topic FE)

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| Minority: <u>D</u> RR | Majority: <u>D</u> DR | Uniformity: <u>D</u> DD |
|----------------------------------|--------------------------------|-----------------------------|
| Assimilation: --→ <u>D</u> RR | Integration: --→ <u>D</u> DR | Conformity: --→ <u>D</u> DD |
| Dis-assimilation: <u>D</u> ←--RR | Radicalization: <u>D</u> ←--DR | Egotism: <u>D</u> ←--DD |
| Persuasion: <u>D</u> R←--R | Other-ing: <u>D</u> D←--R | Sectism: <u>D</u> D←--D |

◀ Identification : Circuit x YearQuarter x Party Fixed Effects (stability w/ Judge FE, Topic FE)

◀ General Equilibrium Effects

Mitosis of Ideology

Unique setting of DDD, DDR, DRR, RRR (uniformity, majority, minority)

- Repeated random assignment to teams
 - New evidence of
 - Integration: $\rightarrow \text{DDR}$
 - Assimilation: $\rightarrow \text{DRR}$
 - Dis-assimilation: $\underline{\text{D}} \leftarrow \text{--RR}$
 - Radicalization: $\underline{\text{D}} \leftarrow \text{--DR}$
 - Other-ing: $\underline{\text{D}} \text{D} \leftarrow \text{--R}$
 - Egotism: $\underline{\text{D}} \leftarrow \text{--DD}$
 - D is the treated individual

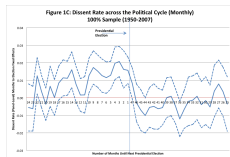
Sources of Normativity

Did seeing small differences lead to adoption of legal innovation?

“as a result of what I have learned at these seminars, **I have become a much better judge**” (Judge Alaimo, U.S.D.C. Southern Georgia)

- concavity in self-image renders superstar effect (Benabou and Tirole 2011)
- small deviations from moral ideal are costly; “What the hell” (Ariely 2012)
- ego rents and judicial fact discretion (Gennaioli and Shleifer 2008)
- narcissism of small differences (Freud 1917)
- preferences for belief consonance (Golman et al 2016)
- social identity lies in difference; difference is asserted against what is closest (Bourdieu 1979)

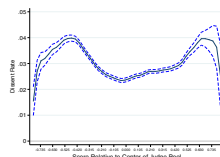
Dissents as Self-Expression



Identity



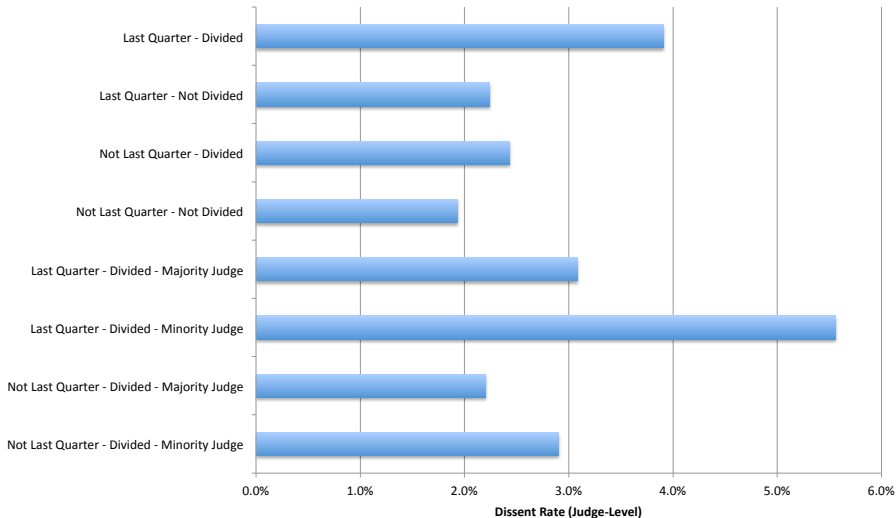
and Peer Pressure



Dissent as Self-Expression

average dissent rate is 2.1%

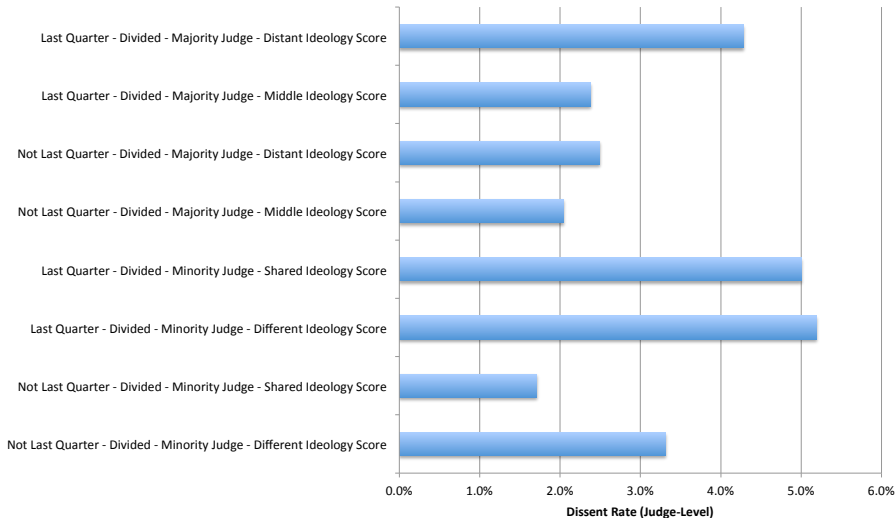
Figure 7A: The Role of Judicial Panel Characteristics in Electoral Cycles in Dissents



Dissent as Self-Expression

average dissent rate is 2.1%

Figure 7B: The Role of Judicial Ideology Score in Electoral Cycles in Dissents



The Effect of Being Minority

- **(1) Dis-assimilation from majority ($\underline{D} \leftarrow -RR$); conformity to own group ($-- \rightarrow \underline{D}DD$)**
- No significant effect of being minority in other situations of group diversity

| | <u>Dissent Vote</u> | | | | |
|-------------------------------------|-------------------------|-------------------------|-------------------------|-------------------------|-------------------------|
| | (1) | (2) | (3) | Xp ≤ 10 y | Xp > 10 y |
| <i>Majority (e.g., DDR)</i> | -0.0146*** (0.00125) | -0.0147*** (0.00116) | -0.0149*** (0.00128) | -0.0158*** (0.00157) | -0.0143*** (0.00195) |
| <i>Unified (e.g., DDD)</i> | -0.0145*** (0.00130) | -0.0153*** (0.00120) | -0.0148*** (0.00134) | -0.0168*** (0.00164) | -0.0130*** (0.00200) |
| Majority (e.g., DDR) | -0.000417 | -0.000797 | -0.000401 | 0.00126 | -0.000476 |
| * % Minority in Last Quarter | (0.00155) | (0.00117) | (0.00160) | (0.00256) | (0.00230) |
| Minority (e.g., DRR) | 0.00156 | -0.00152 | 0.00158 | -0.000250 | 0.00487 |
| * % Minority in Last Quarter | (0.00221) | (0.00167) | (0.00227) | (0.00320) | (0.00343) |
| (1) Unified (e.g., DDD) | -0.00843*** | -0.00807*** | -0.00830*** | -0.00530 | -0.0101*** |
| * % Minority in Last Quarter | (0.00216) | (0.00195) | (0.00223) | (0.00348) | (0.00330) |
| N | 1109611 | 1109611 | 1060203 | 588120 | 438050 |
| adj. R-sq | 0.020 | 0.020 | 0.021 | 0.025 | 0.034 |
| Circuit-Year Quarter-Party FE | Yes | No | Yes | Yes | Yes |
| Judge FE | No | Yes | No | No | No |

The Effect of Being Majority

- (2) Radicalization to dissent ($\underline{D} \leftarrow --DR$)
- (3) Conformity to own group ($-- \rightarrow \underline{D}DD$)
- No significant effect of being majority in next experience as minority

| | <u>Dissent Vote</u> | | | | |
|-------------------------------------|---------------------|-------------------|--------------------|------------------|--------------------|
| | (1) | (2) | (3) | Xp ≤ 10 y | Xp > 10 y |
| <i>Majority (e.g., DDR)</i> | -0.0202*** | -0.0169*** | -0.0205*** | -0.0177*** | -0.0230*** |
| | (0.00177) | (0.00147) | (0.00182) | (0.00238) | (0.00271) |
| <i>Unified (e.g., DDD)</i> | -0.0160*** | -0.0148*** | -0.0163*** | -0.0167*** | -0.0161*** |
| | (0.00182) | (0.00141) | (0.00186) | (0.00251) | (0.00308) |
| (2) Majority (e.g., DDR) | 0.00512*** | 0.00426*** | 0.00508*** | 0.00363* | 0.00533** |
| * % Majority in Last Quarter | (0.00146) | (0.00110) | (0.00151) | (0.00212) | (0.00264) |
| Minority (e.g., DRR) | -0.00327 | 0.000565 | -0.00329 | -0.000364 | -0.00517 |
| * % Majority in Last Quarter | (0.00288) | (0.00223) | (0.00295) | (0.00409) | (0.00487) |
| (3) Unified (e.g., DDD) | -0.00606*** | -0.00339** | -0.00639*** | -0.00281 | -0.00951*** |
| * % Majority in Last Quarter | (0.00176) | (0.00138) | (0.00184) | (0.00238) | (0.00329) |
| N | 1109611 | 1109611 | 1060203 | 588120 | 438050 |
| adj. R-sq | 0.020 | 0.020 | 0.021 | 0.025 | 0.034 |
| Circuit-Year Quarter-Party FE | Yes | No | Yes | Yes | Yes |

The Effect of Uniformity

- (4) Other-ing a minority ($\underline{D}D\leftarrow--R$)
- (5) Egotism amid uniformity ($\underline{D}\leftarrow--DD$)
- No significant effect of uniformity in next experience as minority

| | Dissent Vote | | | | |
|------------------------------------|--------------------------|--------------------------|-------------------------|-------------------------|-------------------------|
| | (1) | (2) | (3) | $X_p \leq 10\ y$ | $X_p > 10\ y$ |
| <i>Majority (e.g., DDR)</i> | -0.0141*** (0.000989) | -0.0128*** (0.000870) | -0.0144*** (0.00102) | -0.0138*** (0.00132) | -0.0157*** (0.00142) |
| <i>Unified (e.g., DDD)</i> | -0.0194*** (0.00120) | -0.0177*** (0.00108) | -0.0197*** (0.00124) | -0.0180*** (0.00159) | -0.0220*** (0.00183) |
| (4) Majority (e.g., DDR) | -0.00473*** | -0.00399*** | -0.00466*** | -0.00384* | -0.00645*** |
| * % Unified in Last Quarter | (0.00144) | (0.00110) | (0.00149) | (0.00213) | (0.00241) |
| Minority (e.g., DRR) | 0.000983 (0.00285) | 0.00393 (0.00260) | 0.00112 (0.00293) | 0.00427 (0.00439) | -0.00397 (0.00431) |
| * % Unified in Last Quarter | | | | | |
| (5) Unified (e.g., DDD) | 0.00675*** | 0.00519*** | 0.00690*** | 0.00281 | 0.0103*** |
| * % Unified in Last Quarter | (0.00141) | (0.00112) | (0.00145) | (0.00195) | (0.00244) |
| N | 1109611 | 1109611 | 1060203 | 588120 | 438050 |
| adj. R-sq | 0.020 | 0.020 | 0.021 | 0.025 | 0.034 |
| Circuit-Year Quarter-Party FE | Yes | No | Yes | Yes | Yes |

Implicit Egotism and Manne Attendance

| | <u>Manne Attendance</u> |
|-----------------------|-------------------------|
| | (1) |
| Unified on Last Panel | 0.0378*** |
| | (0.0124) |
| Unified on Last Panel | -0.0029 |
| in Circuit | (0.0047) |
| N | 354,651 |
| adj. R-sq | 0.060 |
| Circuit-Year FE | Y |
| Cluster | Judge |
| Sample | 1991- |

Did seeing small differences lead to adoption of legal innovation?

◀ General Equilibrium Effects