Are Judges Like Umpires? Political Affiliation and Corporate Prosecutions

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Motivation

- Outcomes of corporate criminal prosecutions can be quite important
 - Ex. #1 *Hudson River v. US* in 1909
 - Ex. #2 Arthur Andersen in 2002
- And sentencing fines, which increased 9-fold in recent years, can shift firms' priorities

Question = Does political affiliation of appointing president influence case outcomes?

Idea is widely discussed, but...

Judges [e.g., Chief Justice Roberts] push back

- "[Judges] don't work as Democrats or Republicans" 2016
- "[W]e do not have Obama judges or Trump judges..." 2018
- And current discussion ignores potential impact on corporate prosecutions, which could matter
 - E.g., if expected punishment for violating environmental regulations goes up, firms might adjust their investments

Finding = Affiliation seems to matter

If case assigned to a Democrat judge...

- 138% <u>larger</u> fine for labor or environmental crimes
- 90% <u>smaller</u> fine for immigration crimes
- But, <u>no</u> association with decisions of guilt or in cases where judge doesn't directly approve fine

Evidence of partisanship and career motives

 E.g., larger differences when (1) political polarization is higher, (2) in months prior to national elections, and (3) when vacancy on appellate court

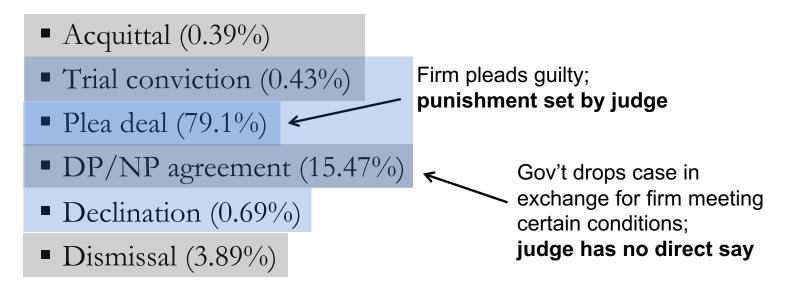
Data on corporate prosecutions

Corporate Prosecutions Registry

- Includes list of prosecutions from 2000 to 2018, resulting in a total of 3,372 cases
- For each case, provides the following:
 - Company name and docket number
 - Crime code (i.e., type of crime)
 - Outcome (e.g., plea, trial conviction, acquittal, etc.) and amount of monetary damages (if any)

Types of prosecution outcomes

Six possible prosecution outcomes



• **Avg. fine** = \$20mm.; **std. dev.** = \$103mm.

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Types of crimes

24 possible crime types; e.g.,

• Immigration
$$(4.47\%)$$
 \leftarrow 9th most

OSHA / Workplace Safety / Mine Safety (0.86%)

20th most common crime

Data on judge names & affiliations

- Extract judge name from official case dockets [available at www.pacer.gov] using Python
- Identify political party of appointing president using biographies on US Courts' website

Identification strategy

- Exploit random assignment of federal judges to cases originating in their jurisdiction
 - 94 US District Court jurisdictions; 700+ judges
 - Evidence supports randomization [see paper]
- Estimate a diff-in-diffs-type regression
 - **Diff #1** Democrat *vs*. Republican judge
 - **Diff #2** Partisan tilt of underlying crime

I.e., does crime involve political issue where Democrats and Republicans exhibit sharply different views?

Define partisan tilt *[DemTilt]* as =

- 1 if crime involved violating environment or labor regulations
- 0 if crime has no clear association to partisan issue [e.g., fraud, money laundering, etc.]
- -1 if crime involved immigration violations and hiring illegal workers

Our main specification

$Y_{ijklt} = \beta Democrat_{j} \times DemTilt_{k} + \alpha_{j} + \gamma_{k} + \delta_{t} + \varepsilon_{ijklt}$

- Y_{ijklt} = outcome for case *i* assigned to judge *j* involving crime type *k* in jurisdiction *l* and year *t*
- *Democrat_j* = indicator that judge was nominated by Democrat president
- $DemTilt_k$ = political tilt of crime type k
- Judge, crime, and year fixed effects

 β captures average change in case outcome for one-unit increase in *DemTilt* of crime when the judge is a *Democrat*

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No shift in proportion of outcomes

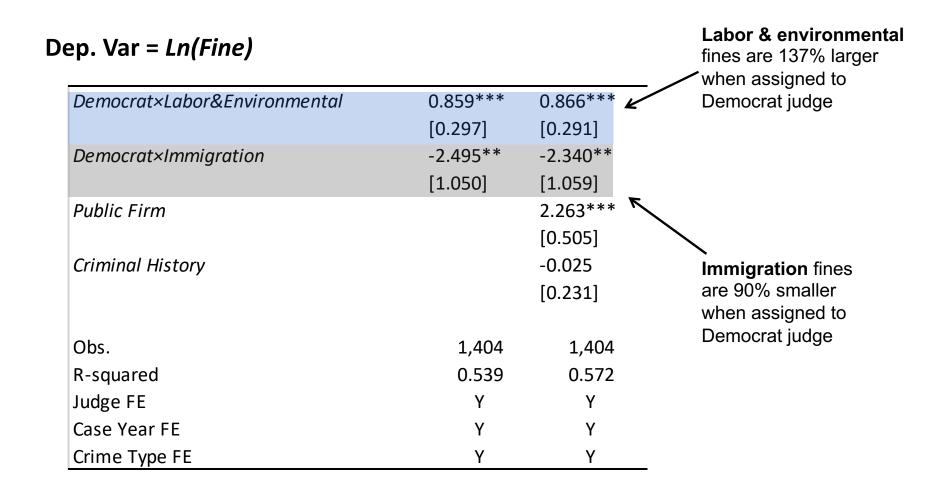
Point estimates all economically , small at < 1.6 percentage points

	Plea	NP/DP	Dismissal	Declination	Conviction	Acquittal
Democrat×DemTilt	-0.016 [0.035]	0.00 [0.028]	0.00 [0.013]	0.012 [0.011]	-0.001 [0.010]	0.004 [0.004]
Obs.	2,560	2,560	2,560	2,560	2,560	2,560
R-squared	0.377	0.361	0.268	0.11	0.058	0.173
Judge FE	Y	Y	Y	γ	Y	Y
Year FE	Y	Y	Y	γ	Y	Y
Crime FE	Y	Y	Y	Y	Y	Y

But big shift in monetary penalty

Dep. Var = <i>Ln(Fine)</i>		188% increase in avg. fine when <i>DemTilt</i> increases by one unit <u>and</u> have Democrat judge		
	Democrat×DemTilt	1.060***	1.047***	
		[0.313]	[0.303]	
	Public Firm		2.269***	
			[0.503]	
	Criminal History		-0.024	
			[0.230]	
	Obs.	1,404	1,404	
	R-squared	0.538	0.572	
	Judge FE	Y	Y	
	Case Year FE	Y	Y	
	Crime Type FE	Y	Y	

Driven by **both** types of crimes



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Larger when more partisanship

If findings driven by <u>partisanship</u>, might expect amplification during time periods of greater political polarization

Periods of high polarization

Dep. Var = Ln(Fine)

	Partisan Diff. in President Appr. Rating		
	Low	High	
Democrat * DemocratTilt	-0.278	1.298**	
	[0.548]	[0.486]	
Public Firm	2.586***	2.297***	
	[0.698]	[0.423]	
Firm With Criminal History	-0.242	0.03	
	[0.308]	[0.373]	
Observations	668	784	
R-squared	0.628	0.568	
Judge FE	Y	Y	
Case Year FE	Y	Y	
Crime Type FE	Y	Y	

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Larger prior to elections

Dep. Var = Ln(Fine)		Indicator for July, Aug., Sept., and Oct. in year with Congressional election
Democrat×DemTilt×Election	← 1.918**	Congressional election
	[0.832]	$\bigwedge \text{Ave populty is } 483\% \text{ larger in}$
Democrat×DemTilt	1.090***	Avg. penalty is 483% larger in months prior to an election if
	[0.305]	assigned to a Democrat
DemTilt×Election	0.274	
	[0.344]	
Democrat×Election	-0.429	
	[0.290]	
Obs.	1,365	
R-squared	0.603	Within-judge estimates indicate findings are <u>not</u> driven by fixed
Judge FE	Y	ideological differences
Case Year-Month FE	Y	
Crime Type FE	Y	
Firm-level controls	Y	

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Larger during high-court vacancies

Dep. Var = Ln(Fine)

Vacancy	-0.035	-
	[0.484]	
Democrat	-0.136	
	[0.113]	
Democrat x Vacancy	-0.385	
	[0.644]	
DemocratTilt x Vacancy	-0.332	
	[0.551]	
Democrat x DemocratTilt	0.490***	
	[0.169]	
Democrat x DemocratTilt x Vacancy	1.373*	
	[0.769]	K
Observations	1,880	Fines are 293%
R-squared	0.541	higher during vacancy
Jurisdiction FE	Y	periods
Year-Month FE	Y	
Crime Type FE	Y	_

Additional findings & robustness

Results are robust to:

- Controlling for interactions of *DemTilt* and other judge characteristics (age, experience, etc.)
- Dropping the largest 5% of fines each year
- Dropping jurisdictions with greater than 75% judges from the same party
- Our results become stronger when we exclude NP/ DP cases

Concluding remarks

Findings suggest novel channel by which partisanship might influence economic behavior

Many potential implications for firms...

 E.g., shifts in expected penalties [e.g., surge in 'Trump' judges] might shift companies' priorities
E.g., our estimates suggest Trump's 2016 election will result in average immigration fine being 31% higher by

end of 2020 than if Clinton had won