

# Are Judges Like Umpires?

## Political Affiliation and Corporate Prosecutions

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# Motivation

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- 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...

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- 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

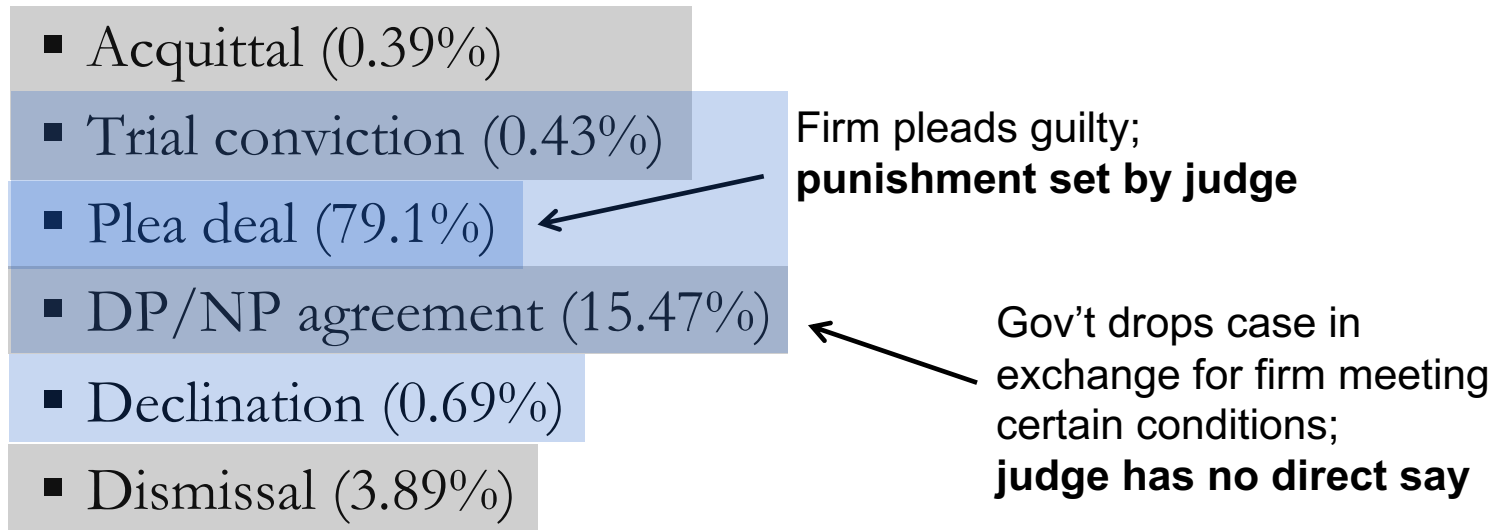
# Data on corporate prosecutions

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- **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.**

# Types of crimes

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- 24 possible crime types; e.g.,

- Fraud – General (18.32%)

- Environmental (15.78%)

← 2<sup>nd</sup> most  
common crime

- False statements (4.54%)

- Immigration (4.47%)

← 9<sup>th</sup> most  
common crime

- Money laundering (2.50%)

- OSHA / Workplace Safety / Mine Safety (0.86%)

↑  
20<sup>th</sup> most common crime

# Data on judge names & affiliations

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

# Identification strategy

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- 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 =

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- 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

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$$Y_{ijklt} = \beta Democrat_j \times DemTilt_k + \alpha_j + \gamma_k + \delta_t + \varepsilon_{ijklt}$$

- $Y_{ijklt}$  = 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

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

# No shift in proportion of outcomes

Point estimates all economically small at < 1.6 percentage points



	<i>Plea</i>	<i>NP/DP</i>	<i>Dismissal</i>	<i>Declination</i>	<i>Conviction</i>	<i>Acquittal</i>
<i>DemocratxDemTilt</i>	-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	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Crime FE	Y	Y	Y	Y	Y	Y

# But big shift in monetary penalty

Dep. Var =  $\ln(\text{Fine})$

188% increase in avg. fine when *DemTilt* increases by one unit and have Democrat judge



<i>Democrat</i> × <i>DemTilt</i>	1.060*** [0.313]	1.047*** [0.303]
<i>Public Firm</i>		2.269*** [0.503]
<i>Criminal History</i>		-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

Dep. Var =  $\ln(\text{Fine})$

<i>Democrat</i> × <i>Labor&amp;Environmental</i>	0.859*** [0.297]	0.866*** [0.291]
<i>Democrat</i> × <i>Immigration</i>	-2.495** [1.050]	-2.340** [1.059]
<i>Public Firm</i>		2.263*** [0.505]
<i>Criminal History</i>		-0.025 [0.231]
Obs.	1,404	1,404
R-squared	0.539	0.572
Judge FE	Y	Y
Case Year FE	Y	Y
Crime Type FE	Y	Y

**Labor & environmental** fines are 137% larger when assigned to Democrat judge

**Immigration** fines are 90% smaller when assigned to Democrat judge

# Larger when more partisanship

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- If findings driven by partisanship, might expect amplification during time periods of greater political polarization
  - **Results only exist in periods of high polarization**

# Larger prior to elections

Dep. Var = Ln(Fine)

<i>Democrat</i> × <i>DemTilt</i> × <i>Election</i>	1.918** [0.832]
<i>Democrat</i> × <i>DemTilt</i>	1.090*** [0.305]
<i>DemTilt</i> × <i>Election</i>	0.274 [0.344]
<i>Democrat</i> × <i>Election</i>	-0.429 [0.290]
Obs.	1,365
R-squared	0.603
Judge FE	Y
Case Year-Month FE	Y
Crime Type FE	Y
Firm-level controls	Y

Indicator for July, Aug., Sept., and Oct. in year with Congressional election

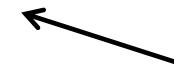
Avg. penalty is 483% larger in months prior to an election if assigned to a Democrat

Within-judge estimates indicate findings are not driven by fixed ideological differences

# Larger during high-court vacancies

Dep. Var = Ln(Fine)

<i>Vacancy</i>	-0.035 [0.484]
<i>Democrat</i>	-0.136 [0.113]
<i>Democrat x Vacancy</i>	-0.385 [0.644]
<i>DemocratTilt x Vacancy</i>	-0.332 [0.551]
<i>Democrat x DemocratTilt</i>	0.490*** [0.169]
<i>Democrat x DemocratTilt x Vacancy</i>	1.373* [0.769]
Observations	1,880
R-squared	0.541
Jurisdiction FE	Y
Year-Month FE	Y
Crime Type FE	Y



Fines are 293%  
higher during vacancy  
periods



# Additional findings & robustness

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- **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

# Concluding remarks

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- 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**