This Morning's Breakfast, Last Night's Game: Detecting Extraneous Influences on Judging

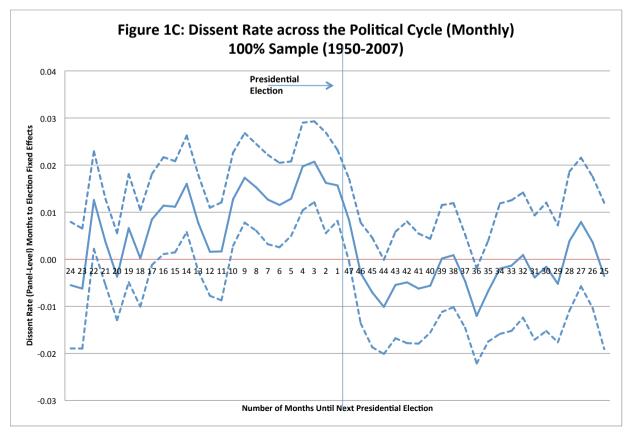
Daniel L. Chen

Trilogy

- Trilogy
  - Priming

### Trilogy

 Priming Ideology? Electoral Cycles Without Electoral Incentives Among U.S. Judges



- Trilogy
  - Judgment under the Gambler's Fallacy

### Trilogy

Judgment under the Gambler's Fallacy

How people often imagine a sequence of coin flips:

010100101100101010110100

A real sequence of coin flips:

0101011111011000001001101

### Trilogy

Judgment under the Gambler's Fallacy: Evidence From Asylum Courts,
 Loan Officers, and Baseball Umpires

Dependent Variable	Grant		
	(1)	(2)	(3)
Lagged Grant	-0.0159***	-0.0116***	-0.0156***
	(0.00422)	(0.00401)	(0.00422)
Applicant Controls	Yes	Yes	Yes
Num prev asylums granted by judge	Yes	Yes	Yes
Num prev asylums granted in city	Yes	Yes	Yes
Judge-specific time trends	No	Yes	No
Time of day	No	No	Yes
N	106071	106071	106071
$R^2$	0.125	0.167	0.126

- Trilogy
  - Priming
  - Gambler's Fallacy
  - Extraneous Factors
    - Mood

- Trilogy
  - Priming
  - Gambler's Fallacy
  - Extraneous Factors
    - Mood
      - NFL
      - Weather

## Highlights

- Detect intra-judge variation unrelated to case facts
- After city's NFL team wins or when weather good
  - Federal district judges: more lenient sentencing
    - E.g., 1 month shorter sentences after win
  - Immigration judges: more asylum grants
- NFL wins reflected in Twitter mood
  - Weather factors that predict mood also affect decisions
    - Video-teleconference cases: judge is the affected agent
- Implications for legal system design: should accept intentional randomness as well

# 1. Background Inter- vs. Intra-Judicial Variation

- Inter-judicial variation (for same case, or large randomly drawn samples)
  - Widely documented: e.g., judicial panels; IJs
  - Rejects naïve theory that "the law" decides case
  - But: consistent with other "rational" theories (e.g., Dworkin)
- Intra-judicial variation rejects "rational" theories
  - Same judge, (statistically) identical case, different result
  - Cf. caricature of Frank (1930): "What the judge had for breakfast"

# 1. Background Literature on intra-judicial variation

- Experiments (e.g., Rachlinski et al.): race, ...
- Field evidence: exists, but: clean?
  - Meals → Israeli parole decisions (Danziger et al.)
    - But: is case order random?
  - Elections → US appellate judge politicization (Berdejo & Chen)
    - But: is it extrajudicial?
  - Workload → fewer opinions etc. (Huang)
    - But: adjusting to workload may be "legally correct"

**—** ...

# 2. Research Design Basics

To identify intra-judge variation, use:

- Large sample of relatively homogenous cases so we can "average out" confounding factors
  - Federal sentencing; Immigration courts (asylum)
- Extraneous factors that are
  - 1. Plausibly exogenous to cases
    - True for sports outcomes and weather at least for given judge, year, week of the year, day of the week
  - 2. Plausible influences on decision (following slide)

## Judge Reid

"Judge Reid is best avoided on a Monday following a weekend in which the USC football team loses."

Morris Wolf, California Courts and Judges (1996)

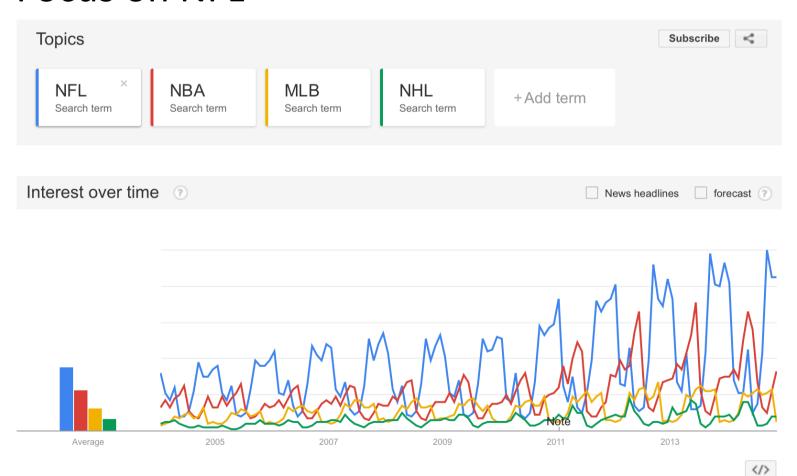
## 2. Research Design

Plausibility: Sports & Weather

- Sports found to predict
  - stock returns (Edmans et al. 2007),
  - elections (Healy et al. 2010),
  - domestic violence (Card/Dahl 2011),
  - •
- Weather found to predict
  - College enrollment (Simonsohn 2009)
  - Financial decisions via risk attitudes (Bassi et al 2013)
  - •

# 3. Data Sports

### Focus on NFL



# 3. Data Sports

- Focus on NFL
  - Few games, so each one matters
  - Season is short, so little seasonal heterogeneity
  - Almost all games played on Sundays, so little dayof-week heterogeneity
  - Cf. college football: Saturday games (2-day lag),
     few judge-college matches (3k)
- Other pro sports same sign, mixed significance

### 3. Data

#### **Decision data**

- Federal sentencing: 900k district court decisions (TRAC)
  - 63k (58k) on (Mon)days after NFL games
  - Case covariates: trial yes/no, charge type (felony etc.), department (drug crimes etc.)
- Asylum: 434k immigration judge decisions (FOIA)
  - 24k (22k) on (Mon)days after NFL games
  - Case covariates: lawyer yes/no, defensive/affirmative, origin
    - According to one estimate: 7 minutes per case (Saslow 2014)

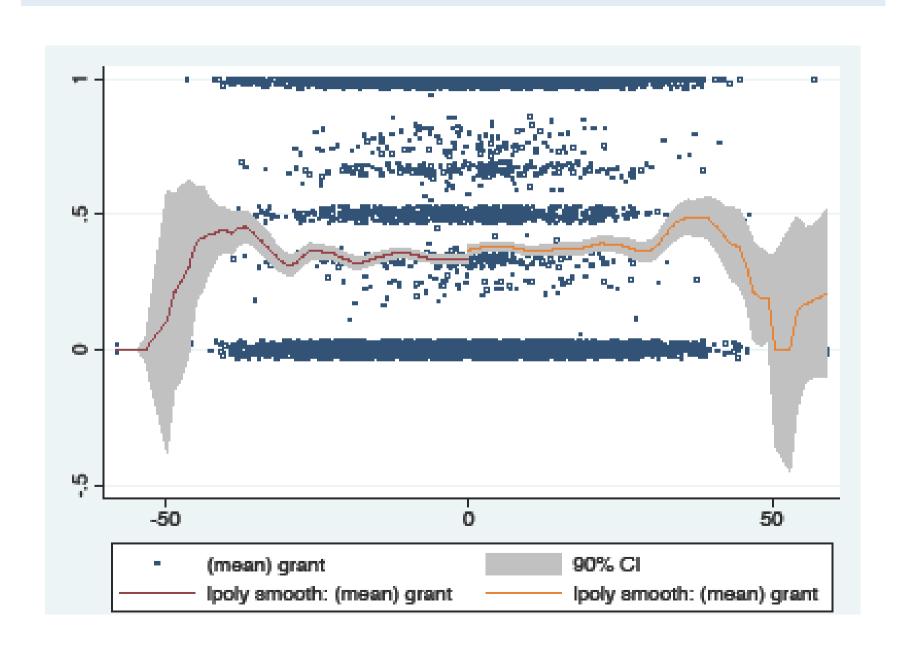
### 3. Data

### Sports-decision match

### Match teams to decisions by city

- Noisy: cities divided (e.g., Giants vs. Jets)
  - Measurement error bias results to 0
- Not specific to judge
  - Agnostic about channels: judge may care about
    - Sports
    - Lawyers' arguments, and lawyers care about sports
    - ...
  - In either case, it is an extraneous influence
- Video-teleconferencing for asylum applicants without lawyers

### NFL & Asylum: grant rates by point difference



# 4. Results Estimating equation (OLS)

Outcome<sub>ijcts</sub> =

$$\delta T_{cts} + FE_{JudgeXCityXSeason} + \beta X_{ijcts} + DOW_t + WEEK_t + \epsilon_{ijcts}$$

4. Results
NFL & sentencing

Dependent variable	Any Prison	Prison Months	Death Sentence	Life Sentence	Fine, \$	Probation Months
(1) Yesterday's Win	-0.003	-0.44	0.00003	-0.0003	-17320	0.27
	(0.002)	(0.53)	(0.00006)	(0.0003)	(40493)	(0.12)
(2) Yesterday's Loss	0.0008	0.50	-0.00005	0.00002	15589	-0.12
	(0.0018)	(0.60)	(0.00005)	(0.0004)	(44033)	(0.11)
P-value of (2)-(1)>0	0.05	0.09	0.87	0.27	0.13	0.04
N	900,490	900,490	900,490	900,490	163,223	900,490

Fixed effects: JudgeXCityXSeason; Week (1-52); DOW (Mon-Fri).

Case controls: department, charge type, trial yes/no.

OLS. Clustering by city.

# 4. Results NFL & asylum

	(1)	(2)	(3)	(4)
Dependent variable	Grant	Rate <sub>ijco</sub>	Grant	Ratio <sub>ijc</sub>
Yesterday's NFL Win	0.011	0.008	0.013	0.013*
	(0.009)	(0.008)	(0.009)	(0.007)
JudgeXCityXSeason FE	Ye	es	Ye	es
Week FE	Ye	es	Ye	es
Application controls	No	Yes	No	Yes
N	16,502	16,496	13,508	13,504
Clustering		City an	d judge	

More precise at higher levels of aggregation (city-day and judge-day)

# 4. Results NFL & asylum

Grant vs. Grant Ratio (lower variance vs. lower N)

Y
X
Y
X
1
0
1
0
1
0
0
0
0
0

4. Results
Weather & asylum

Dep. var.: grant rate (judgeXday)	(1)	(2)	(3)	(4)
Rain present	-0.006*	-0.006*	-0.004	-0.003
Nam present	(0.003)	(0.003)	(0.003)	(0.003)
Highwinds procent	-0.018	-0.013	-0.017	-0.028
Highwinds present	(0.013)	(0.014)	(0.015)	(0.019)
	-0.007	-0.012	-0.012*	-0.012**
Snow present	(0.007)	(0.007)	(0.007)	(0.006)
Rain/Wind/Snow continuous	Yes	Yes	Yes	Yes
p-value from joint F-Test	0.02	0.06	0.03	0.01
Other controls	Judge FE	+ App. controls	+ Time FE	+ Origin FE
A.I.	424720	427427	427427	427427
N	131720	127437	127437	127437
$R^2$	0.12	0.16	0.17	0.26

## 5. Additional tests

- Sports-city match: continuous measure of % following team from Facebook
- Weather: hedonic measure sensitive to seasonal expectations etc.
- Case covariates: sentencing commission recommendation
- Game covariates: importance of game for playoffs
- Discretion: great effect post mandatory sentencing guidelines?

## 5. Additional tests

- Sports-city match: continuous measure of % following team from Facebook (similar results)
- Weather: hedonic measure sensitive to seasonal expectations etc.
  - Twitter data
    - "Pulse of the nation: US mood throughout the day inferred from twitter" (Mislove et al 2010)
    - Daily for 1 year in 8 cities
- Case covariates: sentencing commission recommendation
- Game covariates: importance of game for playoffs
- Discretion: great effect post mandatory sentencing guidelines?

### 6. Sentiment

• Step 1: LASSO weather variables using Tweet outcome, 8 cities, one year.

 Step 2: Regress outcome directly on selected weather variables across all cities, all years.

# 6. Sentiment NFL & twitter

	I weet Mood
Yesterday's NFL Win	0.239***
	(0.0512)

N	1217
R-sq	0.414
P-value of (1)>0	0.00

Tweet Mood: 9 point scale

Standard errors in parentheses
= "\* p<0.10 \*\* p<0.05 \*\*\* p<0.01"

<u>Fixed effects: CityxSeason</u>; Week (1-52); DOW (Mon-Fri).

Case controls: department, charge type OLS. (Clustering by city or none). Weights to account for the twitterer being sampled from city population.

## 6. Sentiment Weather & twitter

	Tweet Mood	21 Lasso-selected weat characteristics also inc
Ground Fog * Hail	-0.113***	
	(0.0192)	<ul><li>Freezing Rain</li><li>Drizzle * Heavy Fog</li></ul>
Snow * Thunder	-0.0879***	<ul><li>Ground Fog * Minu</li><li>Hail * Ground Fog</li></ul>
	(0.0263)	<ul><li>Hail * Mist</li><li>Hail * Torando</li></ul>
Max Temperature^2	0.00185**	<ul><li>Heavy Fog * Drizzle</li><li>Ice * Smoke</li></ul>
	(0.000685)	<ul><li>Mist * Hail</li><li>Freezing Rain * Gro</li></ul>
Precipitation (mm) * High Winds	-0.000594***	<ul><li>Freezing Rain * Free</li><li>Smoke * Ice</li></ul>
	(0.0000982)	<ul><li>Thunder * Snow</li></ul>
N R-sa	25182 0.414	<ul><li>Tornado * Hail</li><li>Minutes of Sun * G</li><li>Sun * Min Tempera</li></ul>
N R-sq	25182 0.414	<ul> <li>Minutes</li> </ul>

Standard errors in parentheses = "\* p<0.10 \*\* p<0.05 \*\*\* p<0.01"

Fixed effects: CityXSeason; Week (1-52); DOW (Mon-Fri).

Case controls: department, charge type OLS. Clustering by city.

#### ather clude:

- nutes of Sun
- le
- round Fog
- eezing Rain
- Ground Fog
- rature
- Min Temperature \* Minutes of Sun

# 6. Sentiment Weather & sentencing

	Any Prison	Prison Months	Death Sentence	Life Sentence	Fine, \$	Probation Months	Deviate Above	Deviate Below	(Falsificati on)
Ground Fog * Hail	0.00280	4.239	-0.000107	0.00319	-96839.9	-0.529	-0.00208	0.0722*	-0.00340
	(0.0233)	(6.251)	(0.000195)	(0.00438)	(66031.6)	(0.657)	(0.0524)	(0.0383)	(0.0156)
Snow * Thunder	0.00660 (0.0143)	-3.352 (2.902)	-0.0000668 (0.0000462)	-0.00308** (0.00146)	-38422.3 (40598.1)	-0.448 (0.570)	-0.0114 (0.0143)	-0.0110 (0.0328)	-0.00398 (0.00896)
Max Temperature^2	-0.0000920	-0.00395	0.000000805	-0.00000431	-1262.8	0.00450	-0.0000930	0.000150	-0.000134*
	(0.000103)	(0.0371)	(0.00000256)	(0.0000262)	(2218.6)	(0.00421)	(0.000196)	(0.000258)	(0.0000741)
Precipitation (mm) * High Winds	0.0000202	-0.0000593	-0.000000201*	-0.000000956	-59.87	-0.000405	-0.0000322	-0.000130	-0.00000189
N	(0.0000291) 916170	(0.0119) 916004	(0.000000113) 916170	(0.00000912) 916170	(86.73) 314582	(0.00158) $916161$	(0.0000751) $194022$	(0.000152) $194021$	(0.0000264) 916138
R-sq	0.141	0.117	0.005	0.015	0.085	0.090	0.051	0.103	0.041
P-value from joint F- Test	0.05	0.43	0.05	0.03	0.73	0.24	0.00	0.20	0.63

Standard errors in parentheses
= "\* p<0.10 \*\* p<0.05 \*\*\* p<0.01"

<u>Fixed effects: CityXSeason</u>; Week (1-52); DOW (Mon-Fri).

Trial

Case controls: department, charge type

OLS. Clustering by city and year.

# 6. Sentiment Weather & asylum

		Defensive Ratio	
	Grant Ratio	(Falsification)	Lawyer Ratio (Falsification)
Blowing Snow * Ground Fog	-0.163***	-0.0415	-0.00904
	(0.0458)	(0.104)	(0.0515)
Dust * Ground Fog	0.138*	-0.0894	-0.0115
	(0.0791)	(0.100)	(0.0539)
Snow * Thunder	-0.00174	0.00660	-0.0182
	(0.0230)	(0.0315)	(0.0158)
Snow * Minimum Temperature	-0.00620	0.00666*	0.00182
	(0.00384)	(0.00358)	(0.00338)
N	388131	461000	461000
R-sq	0.187	0.325	0.150
P-value from joint F-Test	0.00	0.21	0.90

Standard errors in parentheses
= "\* p<0.10 \*\* p<0.05 \*\*\* p<0.01"

Fixed effects: CityXSeason; Week (1-52); DOW (Mon-Fri).

Case controls

OLS. Clustering by city and year.

# 6. Sentiment Weather & asylum

	Grant Ratio	Grant Ratio
Restriction	Video-teleconference without Lawyers	Video-teleconference without Lawyers
Fixed Effects	JudgeXCityXSeason	CityXSeason
N	2350	2506
R-sq	0.434	0.203
P-value from joint F-Test	0.00	0.00

Standard errors in parentheses
= "\* p<0.10 \*\* p<0.05 \*\*\* p<0.01"

<u>Fixed effects:</u> Week (1-52); DOW (Mon-Fri). Case controls

OLS. Clustering by city and year.

### Trilogy

- Priming
- Gambler's Fallacy
- Extraneous Factors
  - Mood
    - NFL wins increase mood, asylum grants, and sentencing leniency
    - Weather factors that predict daily mood also affect asylum grants and sentencing leniency but not pre-determined controls
  - Judge or litigant?
    - Video/teleconference (detainee is remote from the judge)