Do Judges Flip A Coin

Judicial Inattention in the US Asylum Courts

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November 28, 2022

Outline

Introduction

Inspiration

Immigration court ruling

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- High stake: granted asylum or deported

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Are judges doing their job **careful** enough?

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Prediction	Impact

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Impact

- The heterogeneity in judicial inattention
- Can we nudge judges to pay more atention?

A Preview

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- **There is evdience of behavioral anomalies**: judges show different level of early predictability
- **Attentiveness can be proxied**: leveraging appeal court decisions, I create a proxy for attentiveness of lower court judges
- **Judicial inattention can be improved**: observational evidence suggests several channels for further nudging RCTs

Data

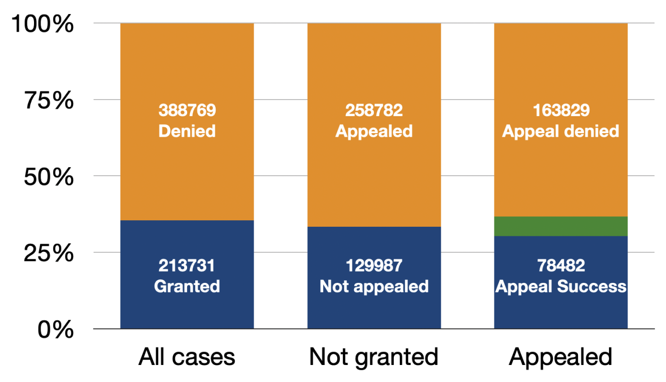


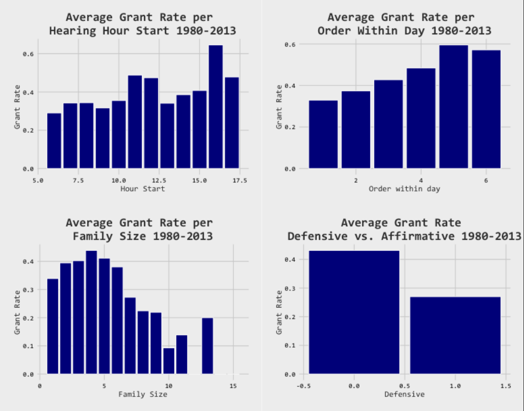
Figure 1: Data Structure

- **Total cases**: 602500 cases (35% granted)
- **Appeal cases**: 242466 appeals (32.4% successful) after removing recent appeals and appeal by the government

From Chen, Moskowitz, and Shue (2016) and Dunn, Sagun, Şirin, and Chen (2017)

Prediction: Lower Court

Descriptive Evidence: Case Informaion Matters



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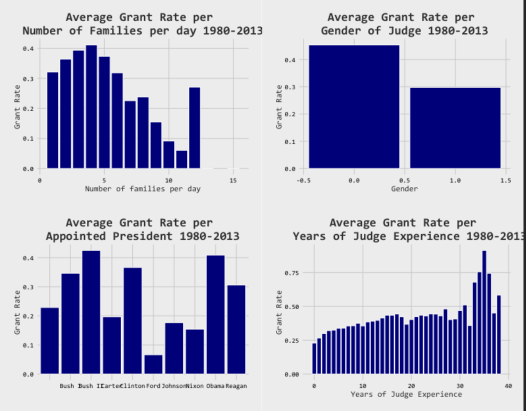
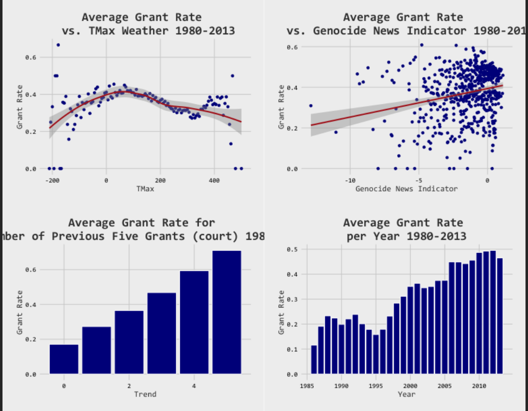


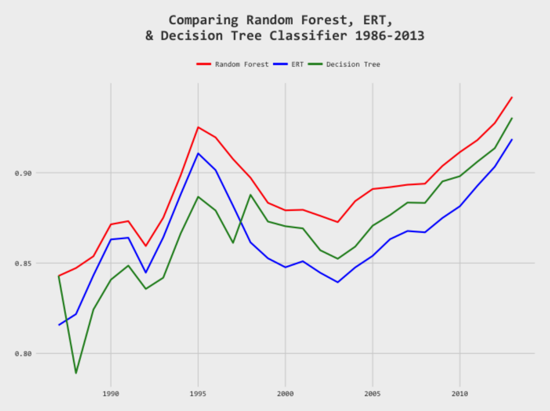
Descriptive Evidence: Other Predictors



Top 7 Countries by Applicants

Country	Count	Percentage	Grant Rate
China	107964	19%	53%
Haiti	42013	7.4%	16%
El Salvador	41626	7.4%	8.7%
Guatemala	34705	6.1%	11%
Colombia	27713	4.9%	35%
India	19161	3.4%	37%
Mexico	19031	3.4%	7.3%
Nicaragua	15987	2.8%	20%
Albania	12036	2.1%	52%
Indonesia	11399	2%	32%

Prediction: A Random Forest Model

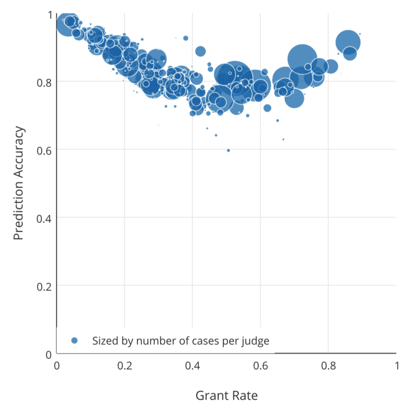


Category	Weight
Case Information	20%
Court Information	7%
Judge Information	10%
News Trend	7%
Ruling Trend	49%
Weather	2%

Early Predictability of Judges

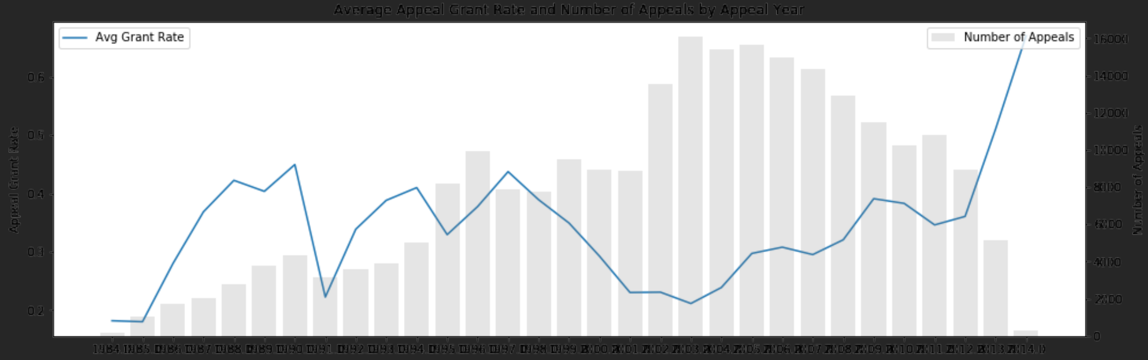
Model	Accuracy	ROC AUC
Judge ID	71%	0.74
Judge ID & Nationality	76%	0.82
Judge ID & Opening Date	73%	0.77
Judge ID & Nationality & Opening Date	78%	0.84
Full model at case completion	82%	0.88

Early Prediction and Inattention

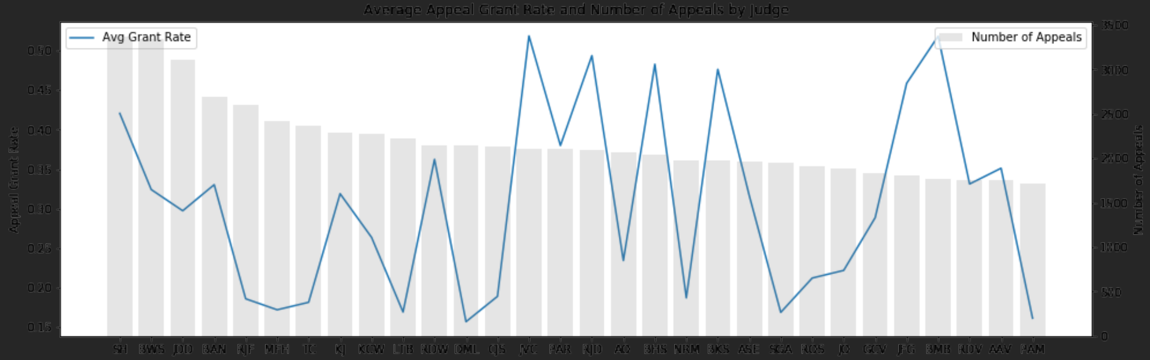


Prediction: Appeal Court

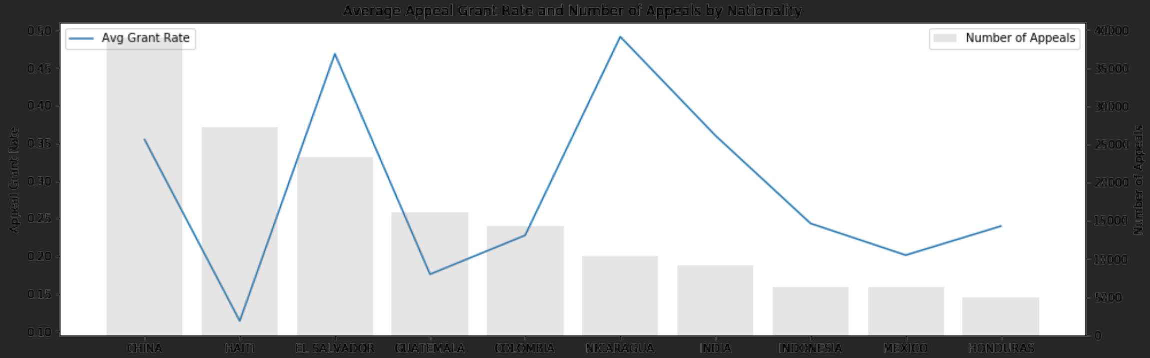
Appeal Grant Rate: By Appeal Year



Appeal Grant Rate: By Appeal Judge



Appeal Grant Rate: By Nationality



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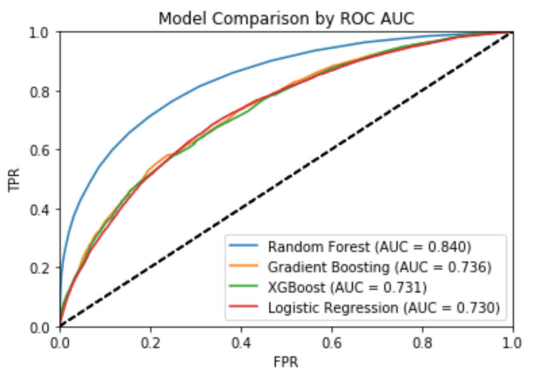

Category	Weight
Time Information	37.78%
Judge Information	27.71%
Respondent	17.79%
Trend Features	7.45%
Proceeding Features	6.05%
Location Features	4.26%

Prediction Accuracy Driven by Lower Court Judges

Model	Accuracy	ROC AUC
Judge ID	67.5%	0.625
Judge ID & Nationality	70.4%	0.701
Judge ID & Nationality & Year	74.1%	0.765
Full model	79.2%	0.840

	Predicted denial	Predicted success
Actual denial	195223	65798
Actual success	73269	104406

Accuracy = 68.3%

F1 = 0.6

Impact Evaluation

Shock of Surprising Reverses

	Predicted denial	Predicted success
Actual denial		
Actual success		

Shock of Surprising Reverses

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Shock of Surprising Reverses

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- reverse: denial asylum in the lower court, but grant asylum in the appeal court
- **surprising reverse**: predicted affirm, but actually reversed

Event Study: around Surprising Reverses

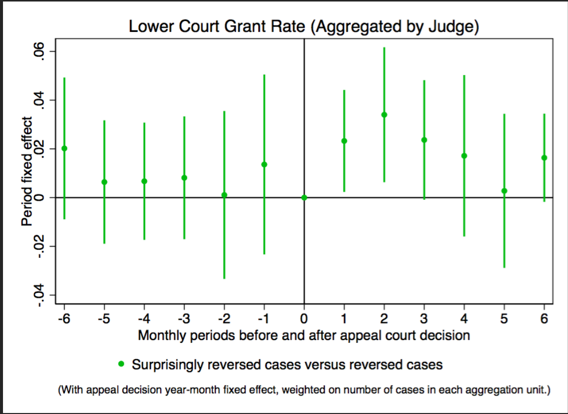
An event study design around the surprising reverse shock:

$$\bar{y}_{i,s,t} = \alpha D_{s,k} + \beta \mathbf{1}\left(\text{Surprising Reverse}\right)_s + \boxed{\gamma} D_{s,k} \times \mathbf{1}\left(\text{Surprising Reverse}\right)_s + \mu_t + \nu_c + \varepsilon_{i,s,t}$$

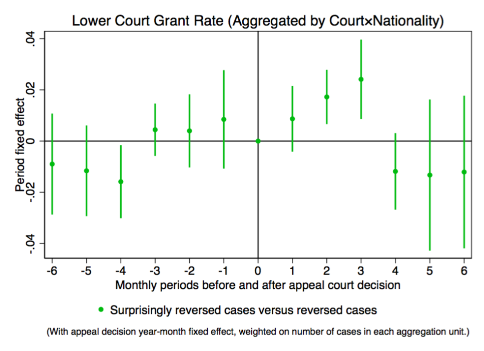
where:

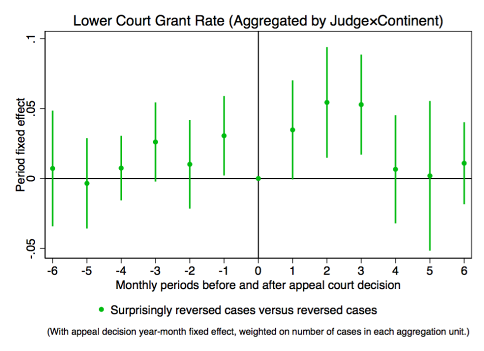
- $\bar{y}_{i,s,t}$: the leave-out average grant rate of judge i, for case s
- μ_t: appeal decision year and month fixed effects
- ν_c: court fixed effects
- $k \in \{T-6, T-5, T-4, T-3, T-2, T-1, T, T+1, T+2, T+3, T+4, T+5, T+6\}$, where T is the time when the appeal decision is made.

Event Study: Results

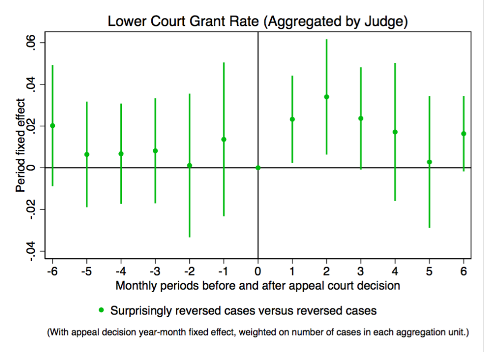


Event Study: Robustness to Granular Dependent Variable Construction





Event Study: Construct A Measure of Attentiveness



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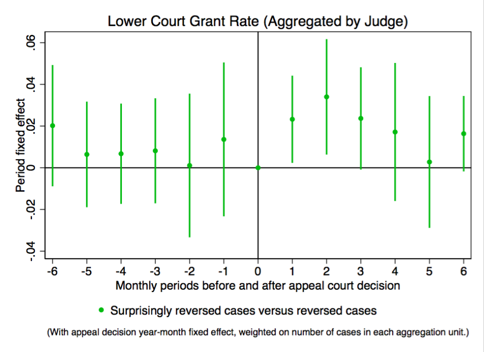

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Now, limit to a smaller window and re-pool data: $k \in \{T' - 1, T', T' + 1\}$, and extract γ as attentiveness of judges

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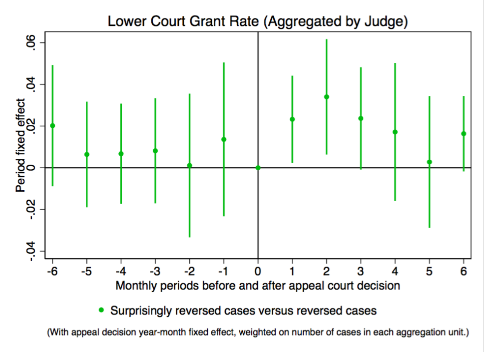

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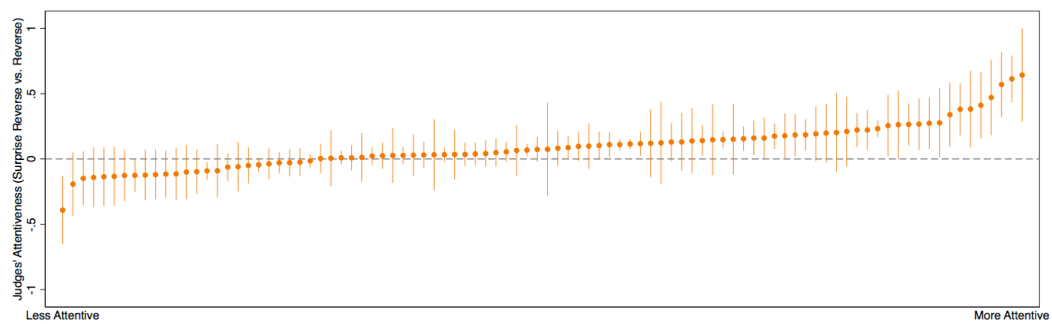
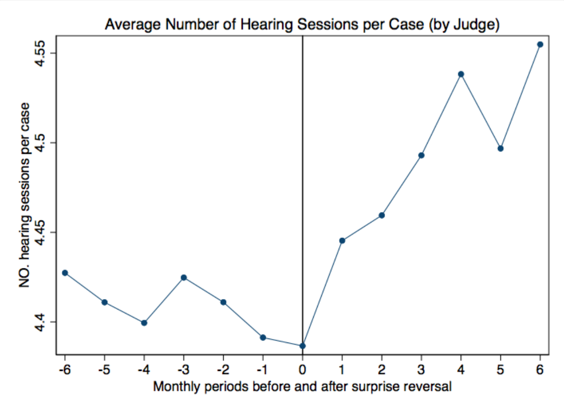
Variation in Attentiveness of Judges

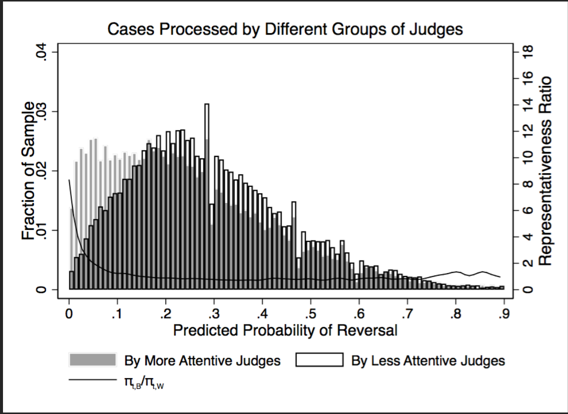


Notes: Time window: 3 monthly periods pooled together before/after a shock.

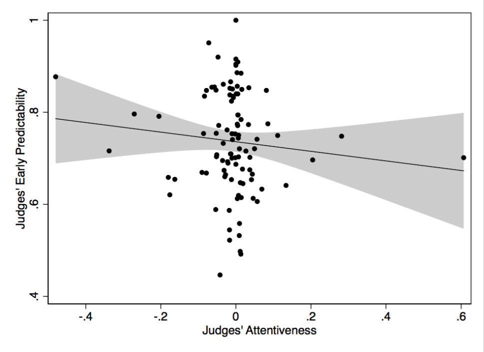
Validity of the Attentiveness Measure: Judges' Effort

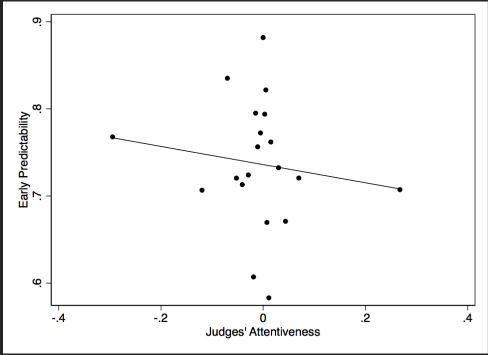


Validity of the Attentiveness Measure: Judges' Errors



Validity of the Attentiveness Measure: Early Predictability





The Impact of Judicial Inattention: Implicit Risk Ranking

Generate a residualized, leave-out judge leniency measure following Dobbie et al. (2018):

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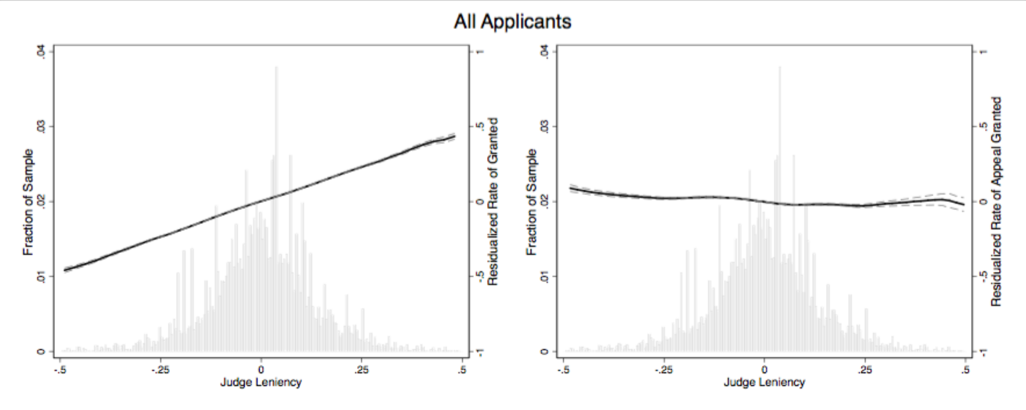
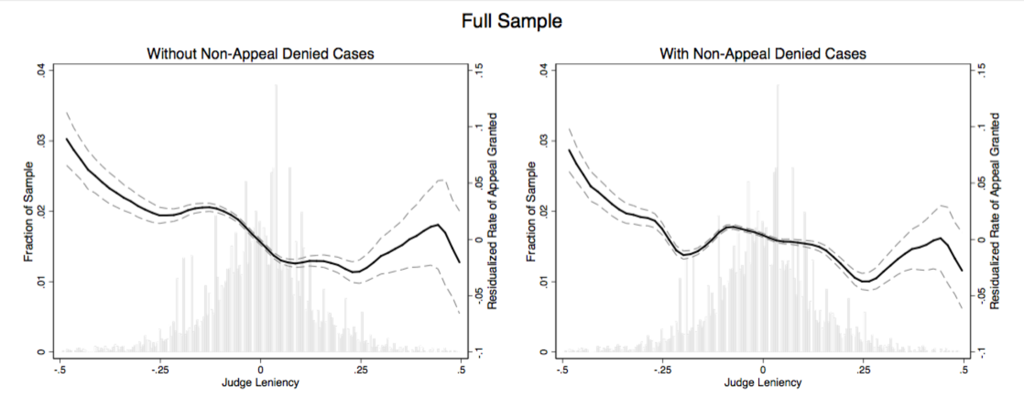
This will give us a leniency measure

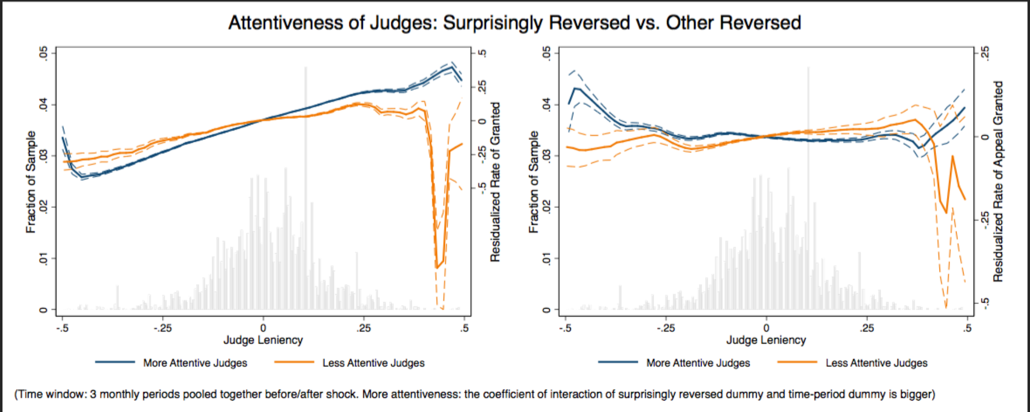
Risk Ranking of Judges



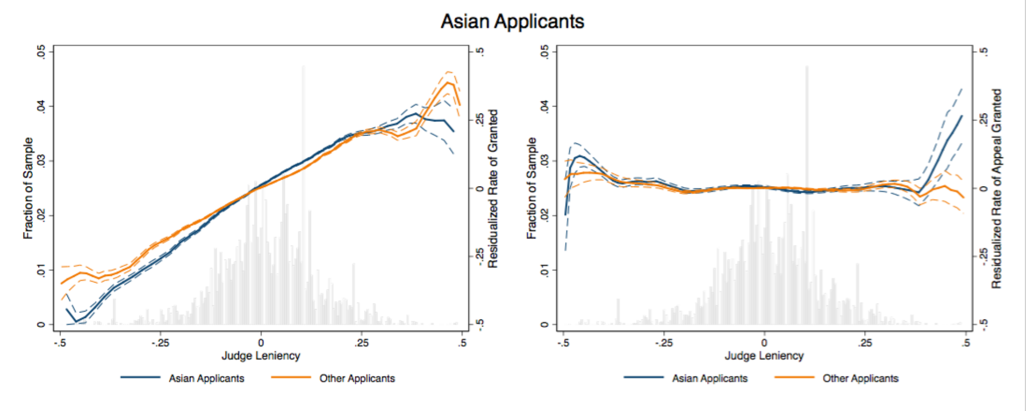
Risk Ranking of Judges: Appeal Courts



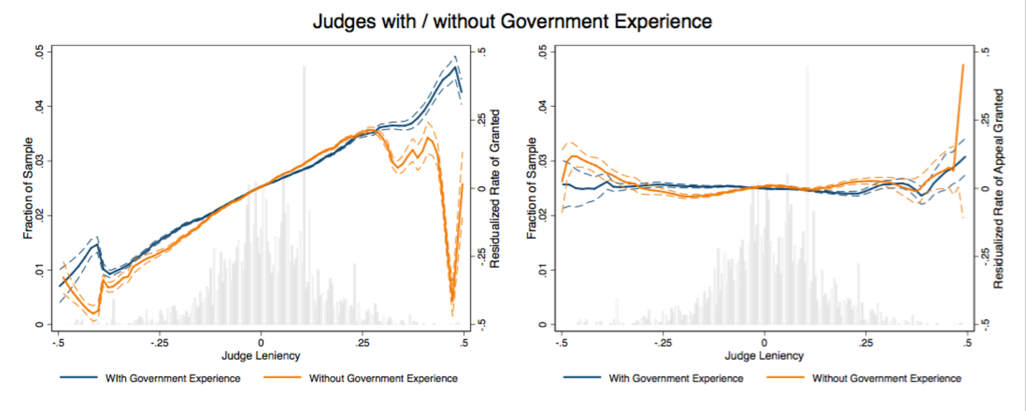
Implicit Risk Ranking and Inattention



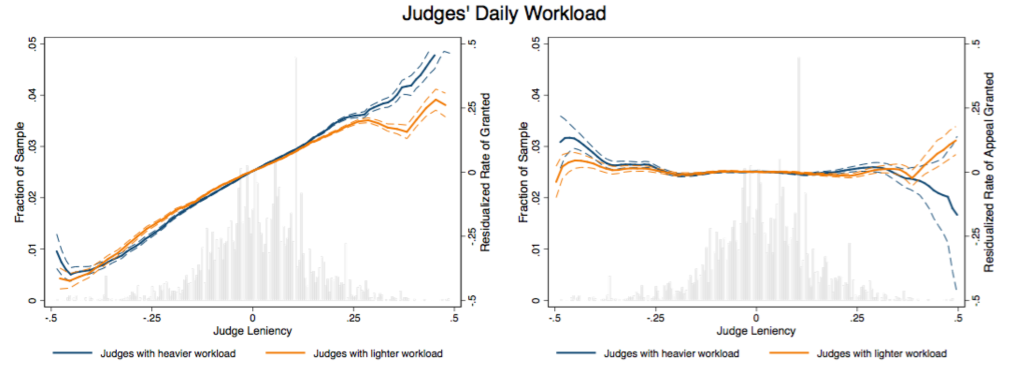
Risk Ranking of Judges: Asian Applicants



Risk Ranking of Judges: Government Experience

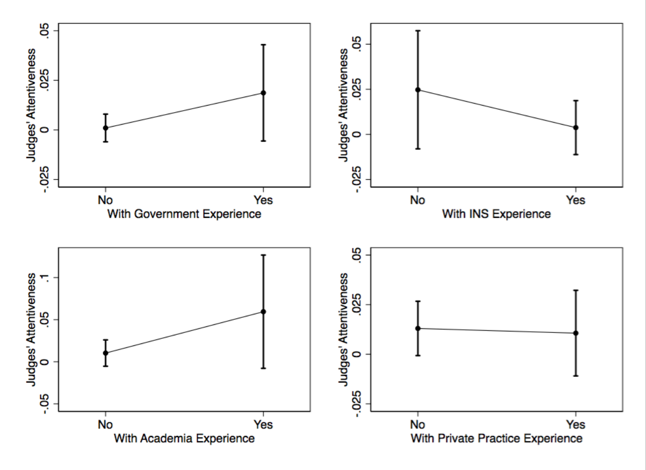


Risk Ranking of Judges: Workload



Judges with heavier workload: Judges whose daily workload is no less than the median

Judges' Inattention: Experience Heterogeneity



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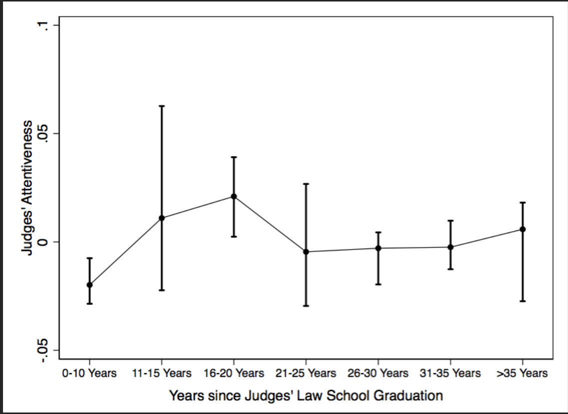
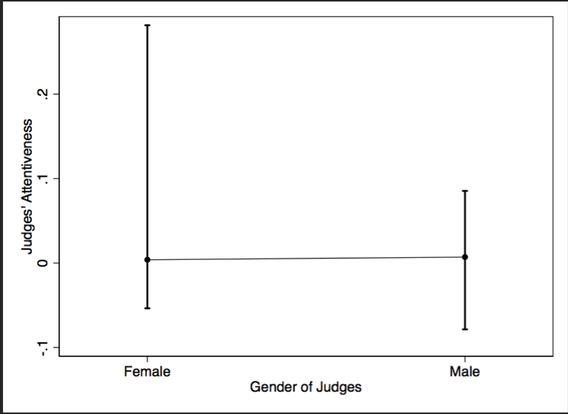
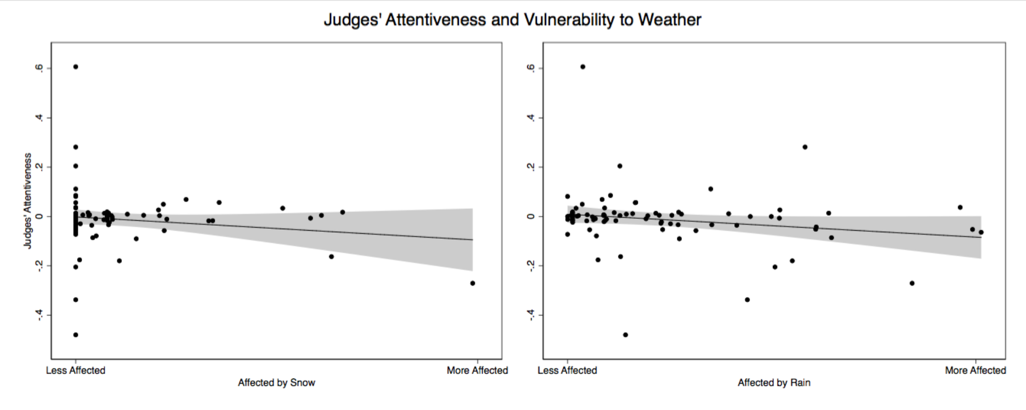


Judges' Inattention: Gender Heterogeneity



Judges' Inattention: The Influence of Weather



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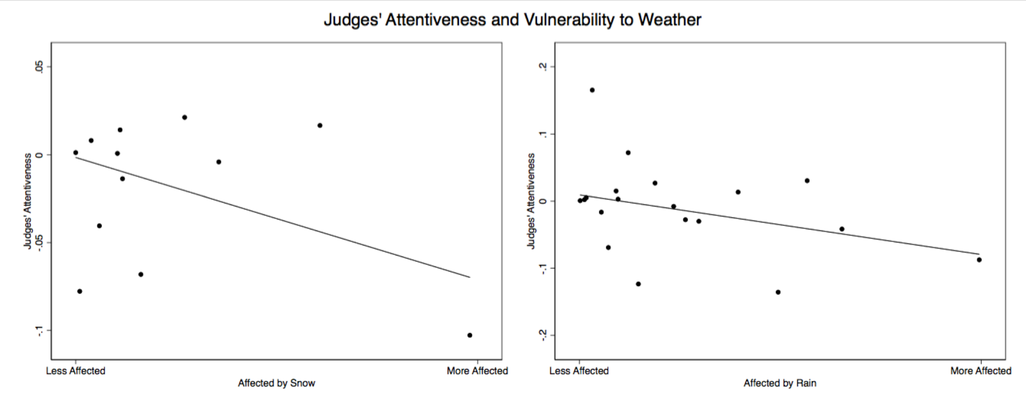

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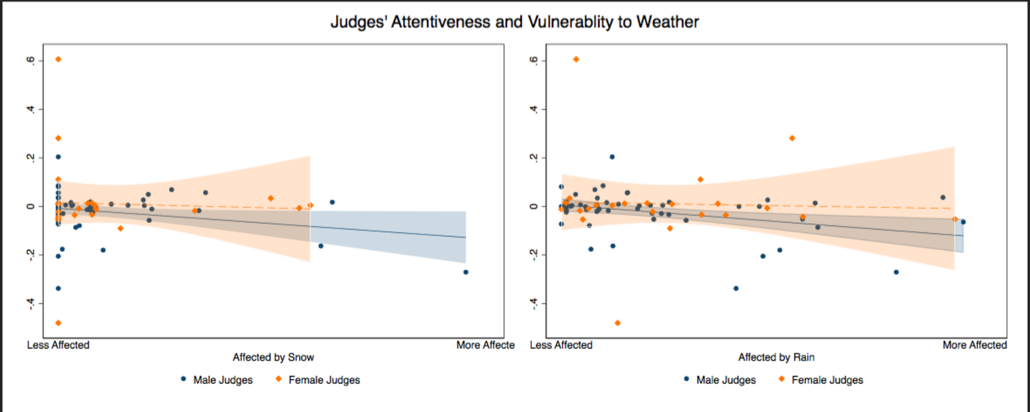

Next Step

Estimating Bias of Judges

Following Arnold et al. (2018), consider for asylum applicants of country c, and for judge j

- α_c^j: pretrial grant rates at the margin
- w^j: weight across all judges $j = 1, \cdots, J$

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Weighted average of the treatment effects for asylum applicants of country c at the margin of granting asylum across all judges is

$$\alpha_c^{w,*} = \sum_{j=1}^{J} w^j \alpha_c^j = \sum_{j=1}^{J} w^j t_c^j$$

Estimating Bias of Judges

To estimate the **average bias among judges**

$$D^{w,*}_{c_1,c_2} = \sum_{j=1}^{J} w^j \left(t^j_{c_1} - t^j_{c_2}\right) = \sum_{j=1}^{J} w^j t^j_{c,1} - \sum_{j=1}^{J} w^j t^j_{c,2} = \alpha^{w,*}_{c,1} - \alpha^{w,*}_{c,2}$$

2 strategies could be considered:

- IV: use judge leave-out leniency as the instrument

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2 strategies could be considered:

- IV: use judge leave-out leniency as the instrument
- MTE: following the framework developed by Heckman and Vytlacil (2005)

Potential RCTs

- **Judges' side**:
  - individual nudging scheme: inspection, record keeping
  - ruling scheme improvement: group ruling by multiple judges

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  - individual nudging scheme: inspection, record keeping
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- **Appeal court**:
  - encourage appealing: by aiding appeals after lower court asylum rejection to increase the *pressure* on judges

References I

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Thank you!