

# The hidden effects of algorithmic recommendations

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*The views expressed here do not necessarily represent those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.*

# Algorithms in decision-making

- **Hiring:** resume scores
- **Consumer finance:** credit scores
- **Housing:** housing readiness
- **Health:** risk scores for mental health
- **Justice:** risk scores for pretrial misconduct

# Algorithms in decision-making

- **Hiring:** resume scores
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- **Health:** risk scores for mental health
- **Justice:** risk scores for pretrial misconduct

But human decision-makers often make the final decision

*(e.g., hiring managers, therapists, judges)*

# How are algorithms given to decision-makers?

Consider a hiring manager reviewing a job applicant...

*Resume score: high*

Algorithm output  
(prediction from algorithm)

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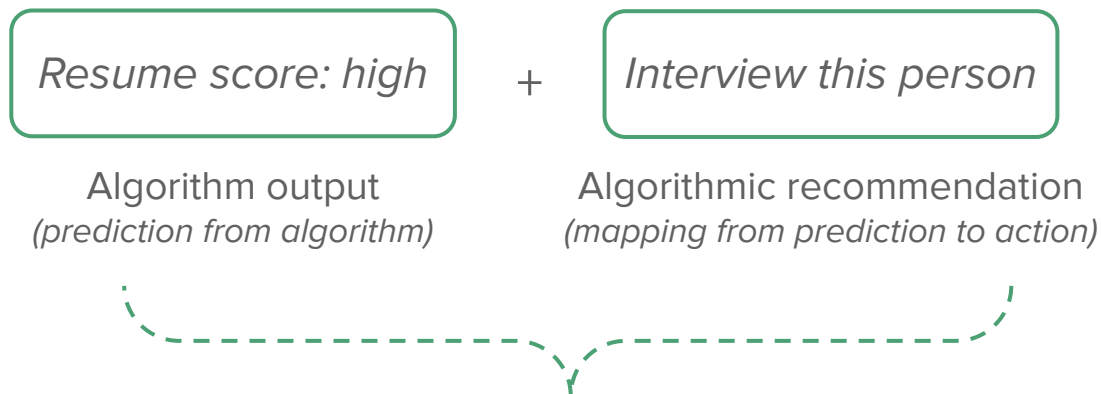
*Interview this person*

Algorithm output  
(prediction from algorithm)

Algorithmic recommendation  
(mapping from prediction to action)

# How are algorithms given to decision-makers?

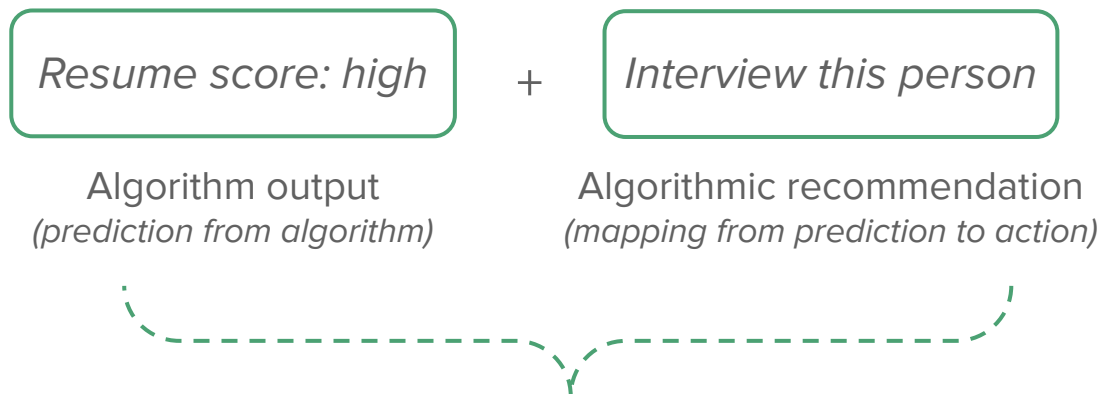
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**Studying “the effect of algorithms” on decisions often confounds these two components**

# How are algorithms given to decision-makers?

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*Empirical challenge: usually introduced at the same time*

# The hidden effects of algorithmic recommendations

- Predictions generated by algorithms are distinct from algorithmic recommendations, which are often overlooked
  - **This paper: isolate the effects of recommendations**



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- Predictions generated by algorithms are distinct from algorithmic recommendations, which are often overlooked
  - **This paper: isolate the effects of recommendations**

**How?** => Leverage a setting (*judges making bail decisions in CJS*) where

1. algorithmic predictions (*risk scores*) available to decision-makers stay the same
2. BUT algorithmic recommendations vary

# Preview of Results

## 1. Basic fact: **Recommendations matter**

- Algorithmic recommendations impact decisions  
*(a lenient recommendation increases lenient bail for marginal cases by 50+%)*
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*(lenient recommendations from a social planner provide “cover” for judges)*
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## 3. Heterogeneity: **Recommendations may not impact all groups equally**

- Judges deviate from lenient recommendation more for Black defendants than for white defendants with identical algorithmic scores

# Roadmap

1. Empirical setting: Kentucky bail decisions
2. What are the effects of algorithmic recommendations?
3. What is the mechanism behind the effect?
4. Heterogeneous effects of recommendations and implications for racial inequality

# Empirical Setting: Kentucky Bail Decisions

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# Criminal justice bail decisions and algorithms

**Judge objective:** minimize pretrial detention, minimize pretrial misconduct

**Lever:** setting money bail (requires defendant to post money for release from jail)

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STATE	TYPE/SCOPE OF USE
Alabama	VPRAI / Jefferson County
Alaska	State Created / Statewide
Arizona	PSA / Statewide   VPRAI / 2 County Superior Courts
Arkansas	State Created / Statewide
California (Sample risk assessment documents from San Francisco, and Napa County)	PSA / 3 counties   PRRS II / 2 Counties
Colorado (sample risk assessment documents)	CPAT / Statewide   ODARA for DV / Statewide
Connecticut	State created / Statewide
Delaware	State created (DELPAT) / Statewide
District of Columbia	Developed with Urban Institute and Maxarth
Florida	PSA / Volusia County   COMPAS - Sentencing / Statewide   State Created FPRAI Being piloted / 6 Counties

STATE	TYPE/SCOPE OF USE
Georgia	State created / Some counties
Hawaii	PSA / Statewide   ORAS-PAT / Statewide
Idaho (see FOI documents below)	State created / Statewide   Ada County / Revised IPRAI
Illinois	PSA / 4 counties   VPRAI/RVRA / Most Courts
Indiana (sample risk assessment documents)	Mandatory use of IRAS and IYAS / Statewide
Iowa	PSA / 4 Counties via Pilot Program   IRR
Kansas	State created / Johnson County
Kentucky	PSA / Statewide
Louisiana	PSA / New Orleans
Maine	ODARA (sex offenders) / Statewide   2019 Task Force for expansion
Maryland	State created / Most counties
Massachusetts	COMPAS / Statewide LS/CM / Statewide
Michigan	COMPAS for Sentencing / Statewide
Minnesota (see Pretrial Release Evaluation Form and Bench Card)	MNPAT / Statewide
Mississippi	CRJ (Crime Justice Institute) / Statewide
Missouri	PSA / 1 County   Statewide / State created   Separate statewide system for Juvenile and Sex Offenders   Use Oregon Public Safety Checklist for Sentencing

Montana	PSA / 2 Counties and 5 Pilot Counties
Nebraska	STRONG-R
Nevada	State created / Statewide Mar. 2019 by NV Supreme Court
New Hampshire	Yes
New Jersey	PSA / Statewide
New Mexico	PSA / 4 Counties   ODARA for DV
New York	(NYC) City Created / Citywide   State Created / State-wide for Parole
North Carolina	PSA / 1 County   Developing another statewide one
Ohio	PSA / 3 Counties   ORAS-PAT / Statewide
Oklahoma	ORAS for Pretrial Services Program + LSI/R / Statewide
Oregon (sample assessments)	Public Safety Checklist
Pennsylvania	PSA / Allegheny County   State created / 1 County
Rhode Island	PSA / Statewide
South Carolina	State Created - Cash Bail Use
South Dakota	PSA / 2 Counties
Tennessee	PSA / 2 Counties   State Created / One Judicial District Test
Texas (sample assessments)	PSA / Harris + Dallas County   PRAISTX (derivative of ORAS) / Statewide Parole Board
Utah	PSA / Statewide
Vermont	ORAS

Virginia	VPRAI revised by Luminosity / Statewide   Use Oregon Public Safety Checklist for Sentencing
Washington	PSA / 3 Counties
West Virginia	LS/CM
Wisconsin (See sample assessment documents)	PSA / 4 Counties   COMPAS / Statewide
Wyoming	COMPAS for Prisoners / Statewide
Federal	PTRA

Source: Epic (2020)



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Common risk score goal: "data-driven way to advance pretrial release"

and Napa County)	
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Predict misconduct based on observable data

Release Evaluation (Form and Bench Card)	MNPAT / Statewide
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# The Kentucky Algorithm

After person booked, pretrial services officer calculates a risk score

***Kentucky Pretrial Risk Assessment tool***  
*(March 2011-May 2013)*

# The Kentucky Algorithm

After person booked, pretrial services officer calculates a risk score

## ***Kentucky Pretrial Risk Assessment tool*** (March 2011-May 2013)

- Not complex black-box ML tool – it is a “checklist tool” (or “rule-based formula”)
- Total points and convert to levels:
  - 0-5: *low*
  - 6-13: *moderate*
  - 14-24: *high*
- Scores have relative, not absolute meaning (e.g., *high is riskier than low*)
- **Only levels shared with judges**

Risk Component	Points
No verified address	2
No verified means of support	1
ABC Felony charge	1
Pending case	7
Prior/active mis/felony FTA	2
Prior FTA traffic violation	1
Prior misdemeanors	2
Prior felonies	1
Prior violent convictions	1
History of drug/alcohol abuse	2
Prior felony escape conviction	3
On probation/parole	1

# House Bill introduces recommendation for some cases

Before June 2011:

- Judge receives info about defendant, incident, risk level and makes a bail decision in a few minutes
  - *Risk level: Kentucky Pretrial Risk Assessment tool*
  - Judge decides whether to set money bail

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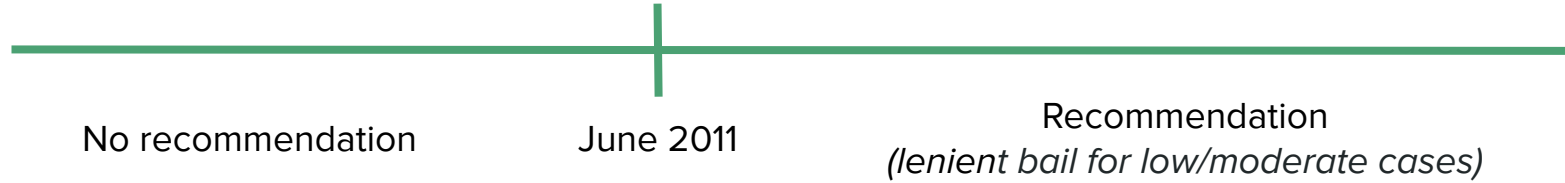
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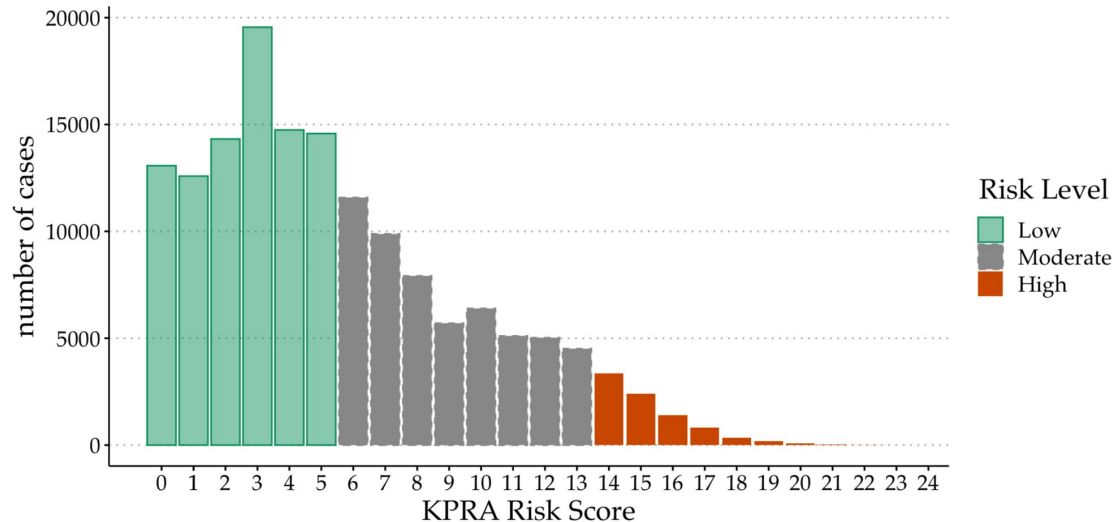
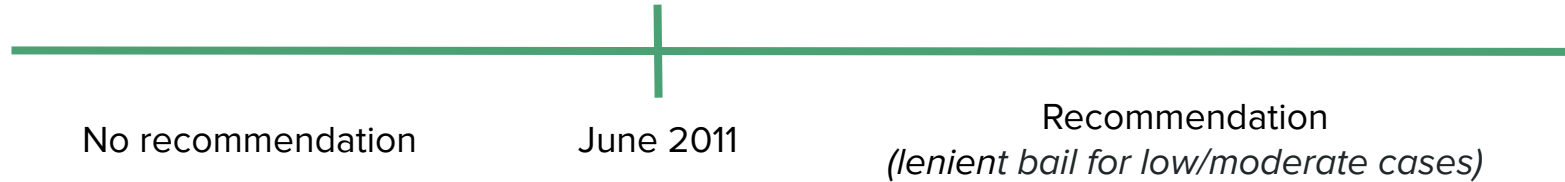
Starting June 2011:

- House Bill (*legislature action*) **recommends no money bail (“lenient bail”) for low and moderate risk level cases**
  - Judges could deviate by saying a few words (*no large admin cost*)
  - No recommendation for high risk cases

# Variation in recommendation over time and scores



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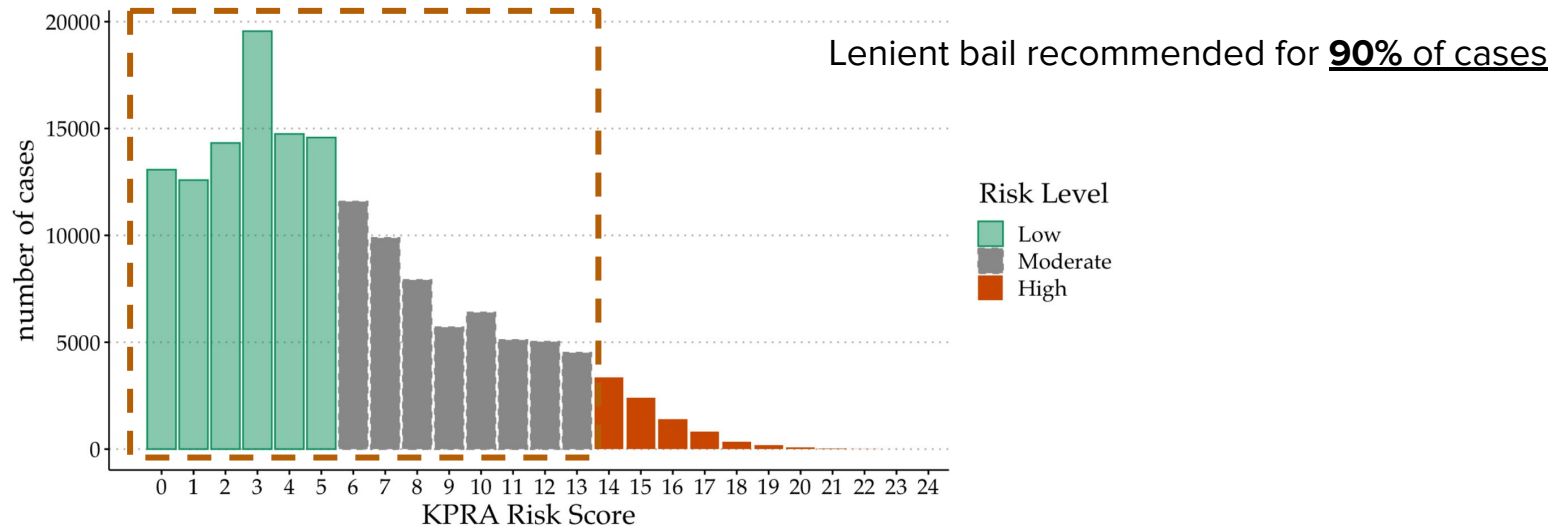


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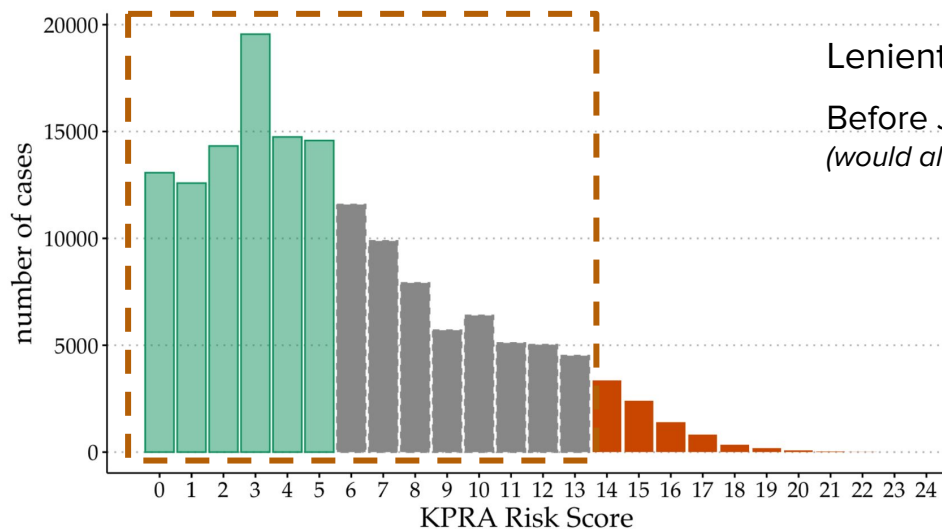


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June 2011

Recommendation  
(lenient bail for low/moderate cases)



Lenient bail recommended for 90% of cases

Before June 2011, only 32% got lenient bail  
(would align with a threshold of score <4)

Risk Level

Low  
Moderate  
High

What are the effects of recommendations?

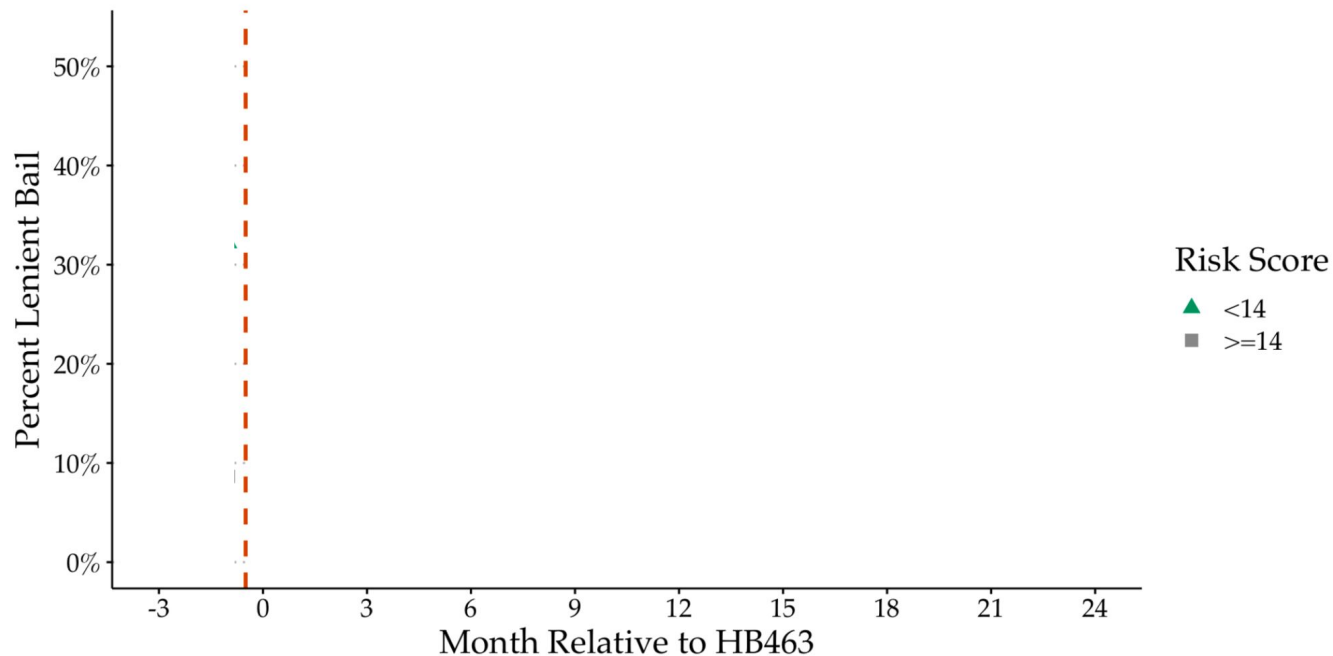
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# Difference-in-differences approach

- Cases with scores  $< 14$  get a lenient recommendation
- Cases with scores  $\geq 14$  do not

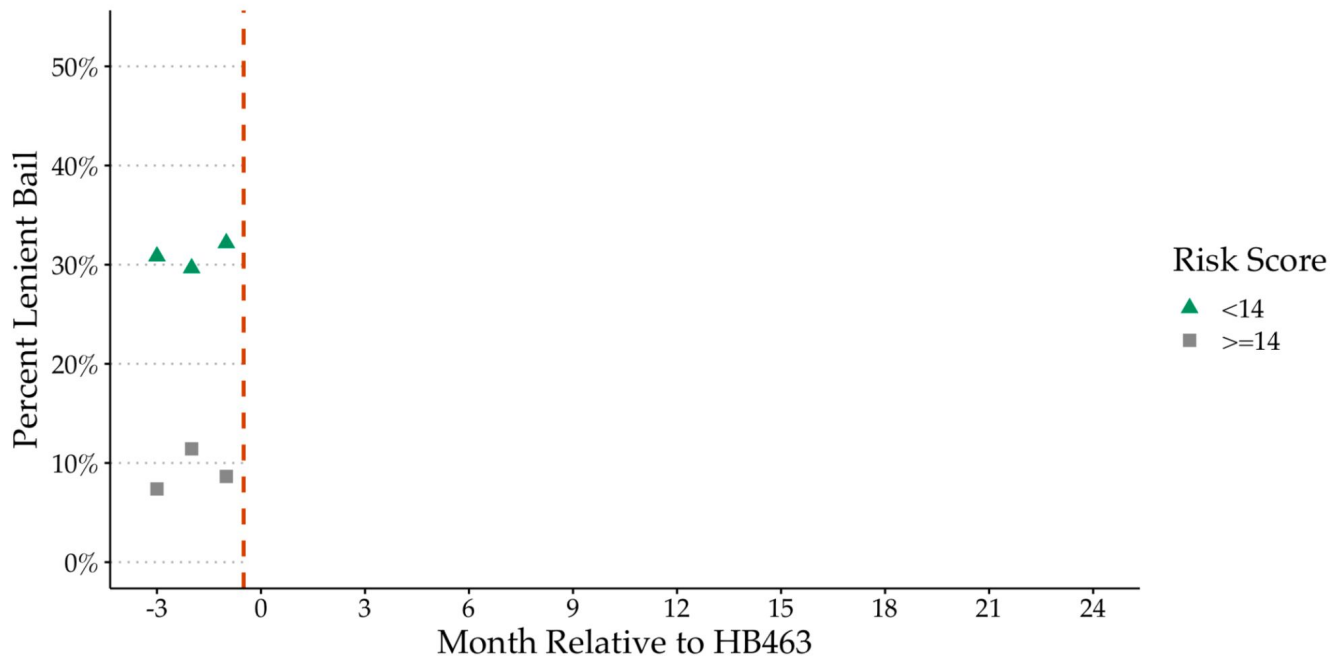
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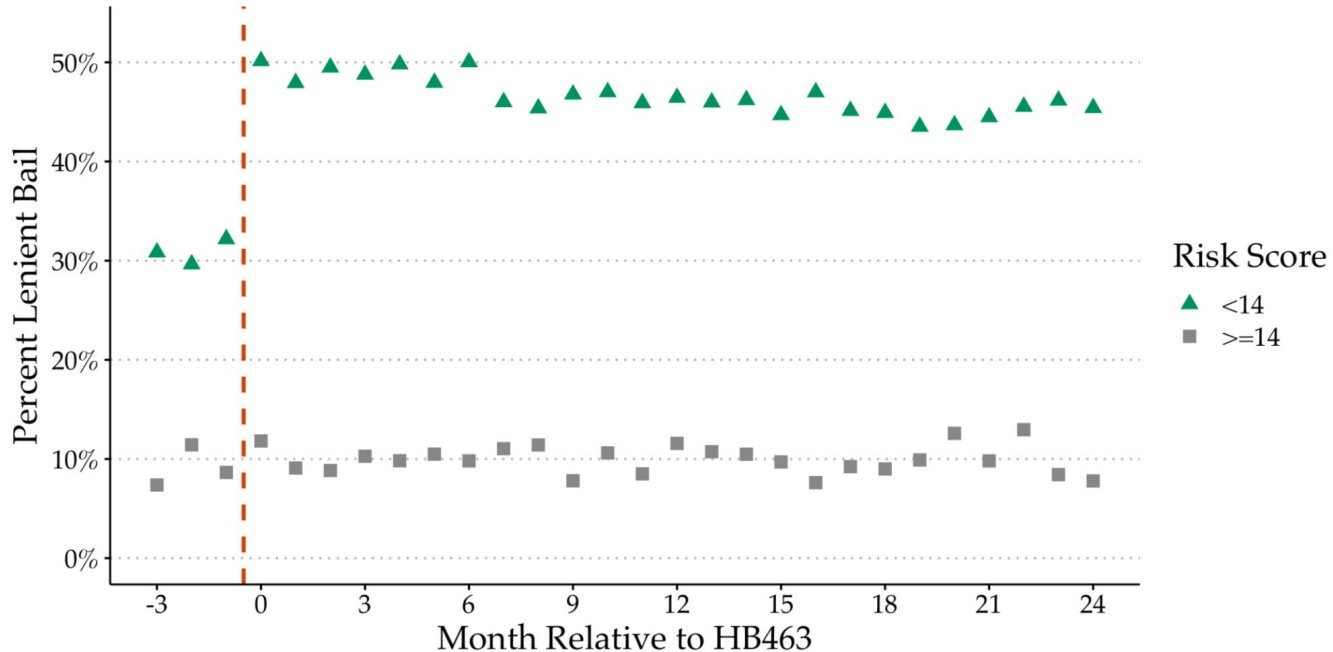
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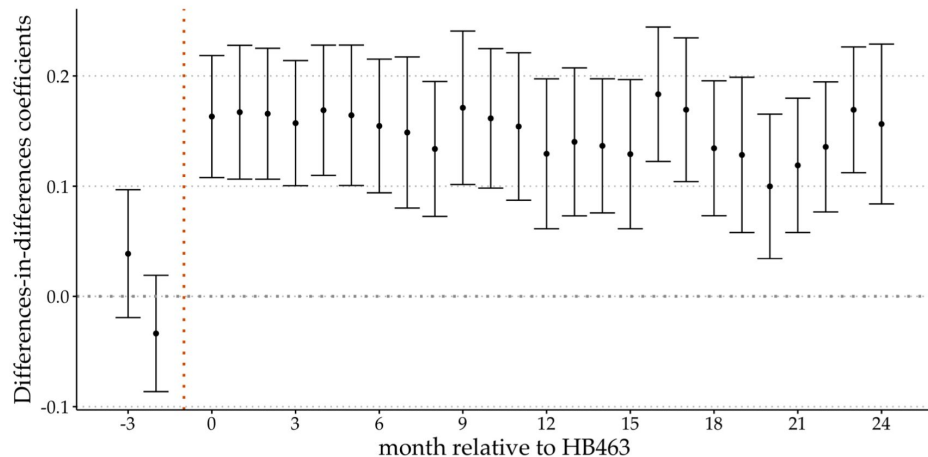
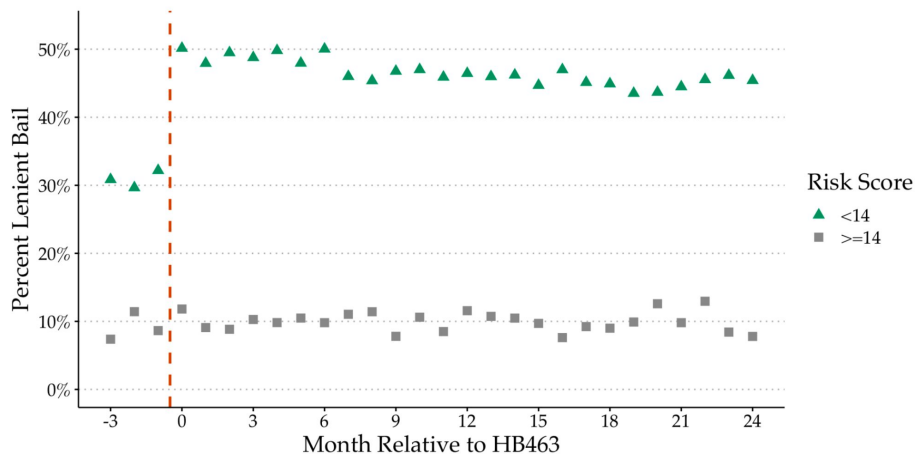
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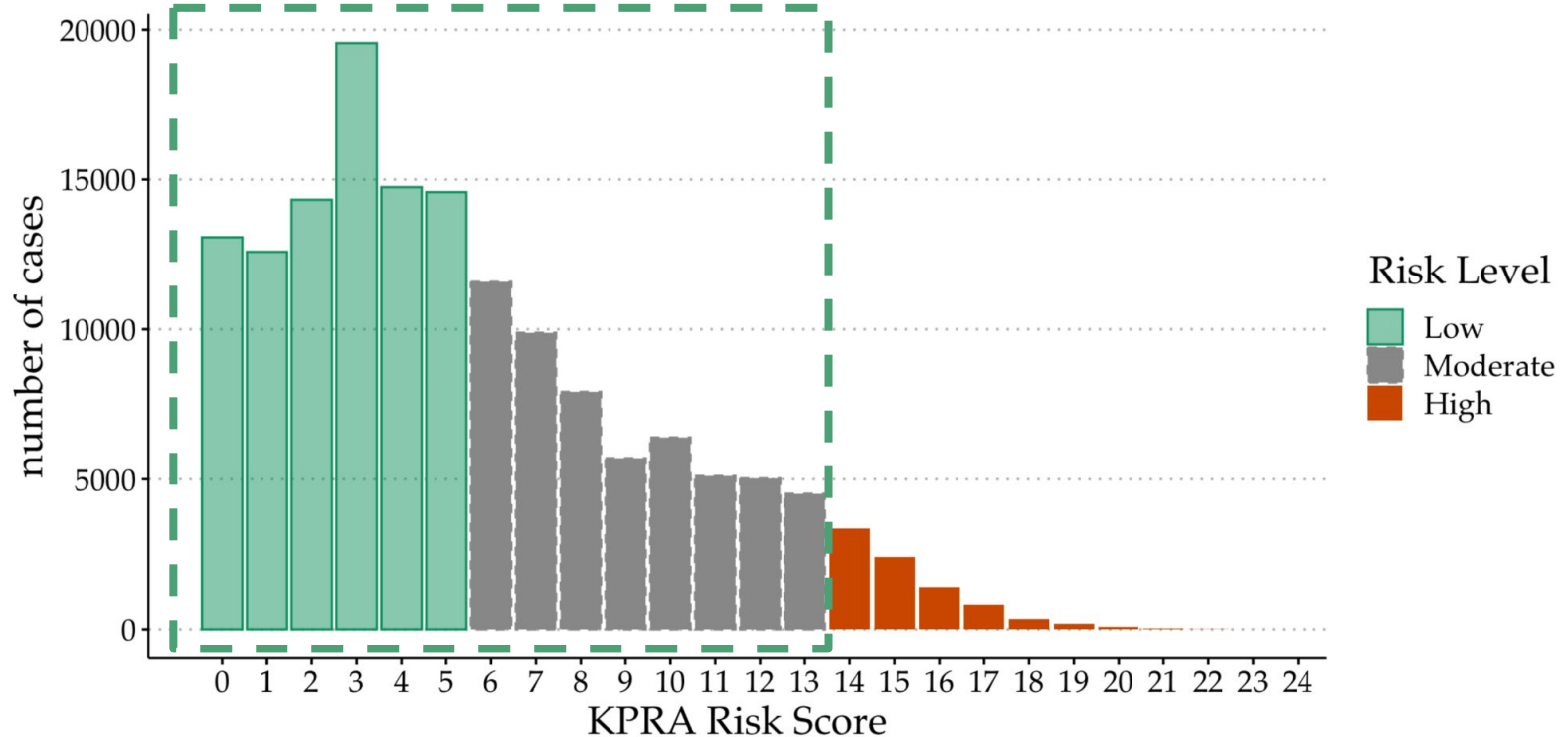
$$\text{lenient}_{itj} = \sum_{m \neq -1} [\beta_m \times I(\text{score}_i < 14)] + X_{itj} + \epsilon_{itj}$$



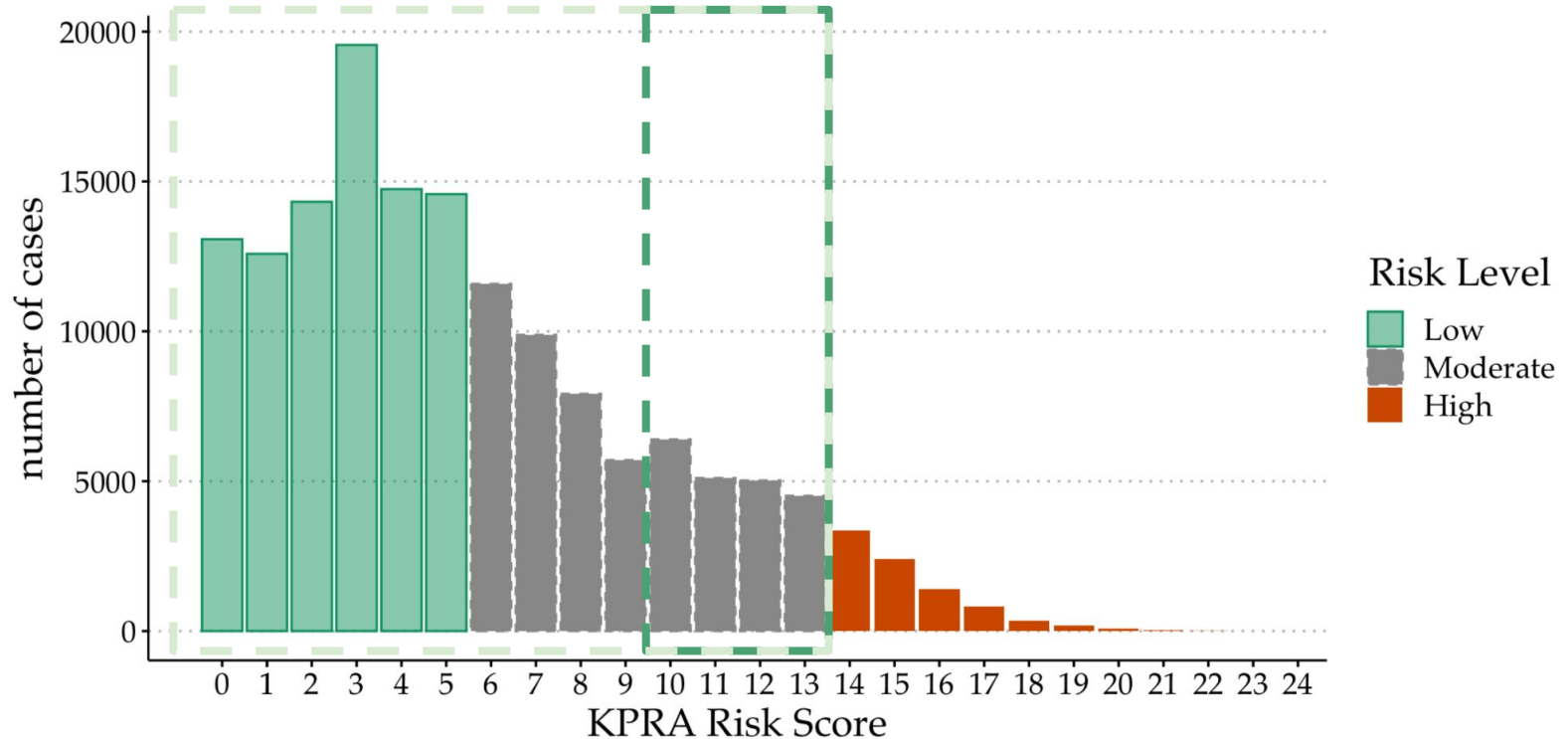
**Pooled DD: 15 pp increase / 50% increase (off the 30% baseline)**



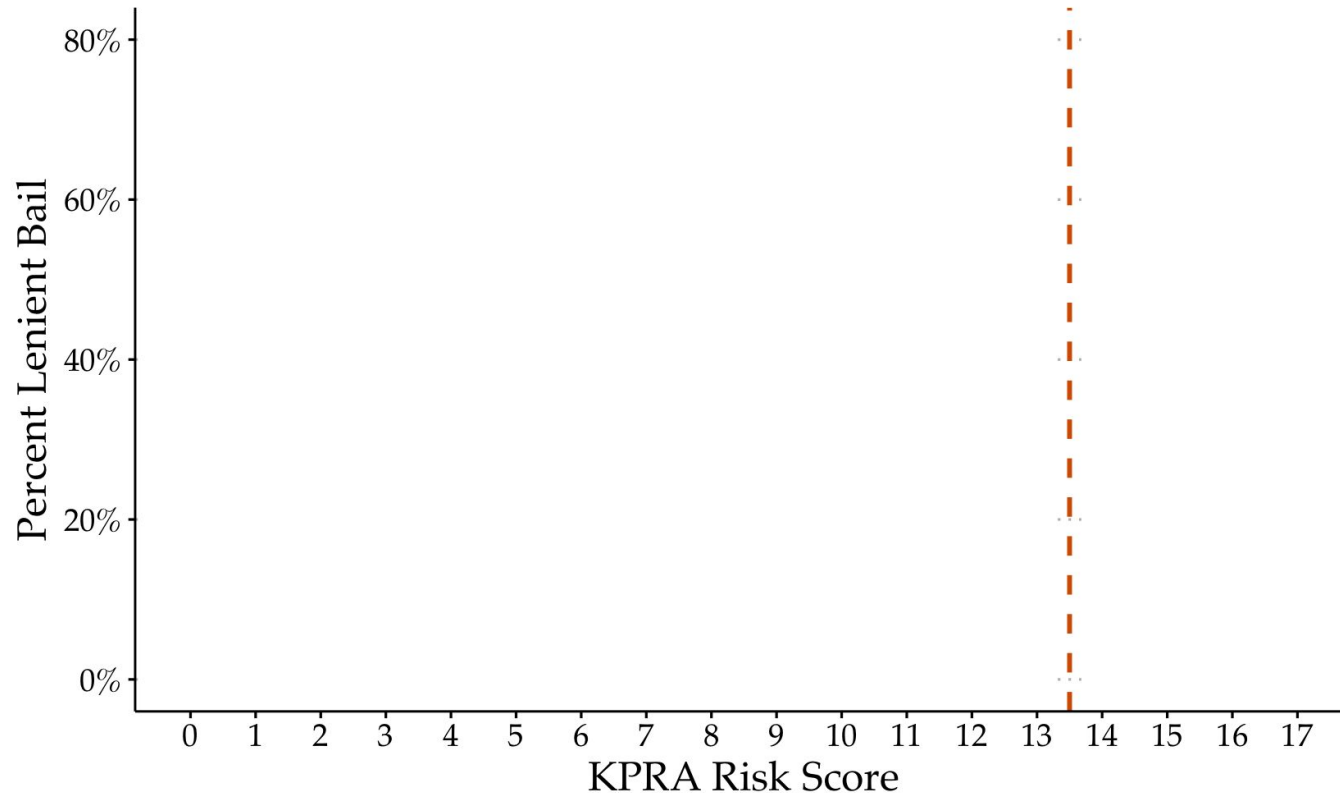
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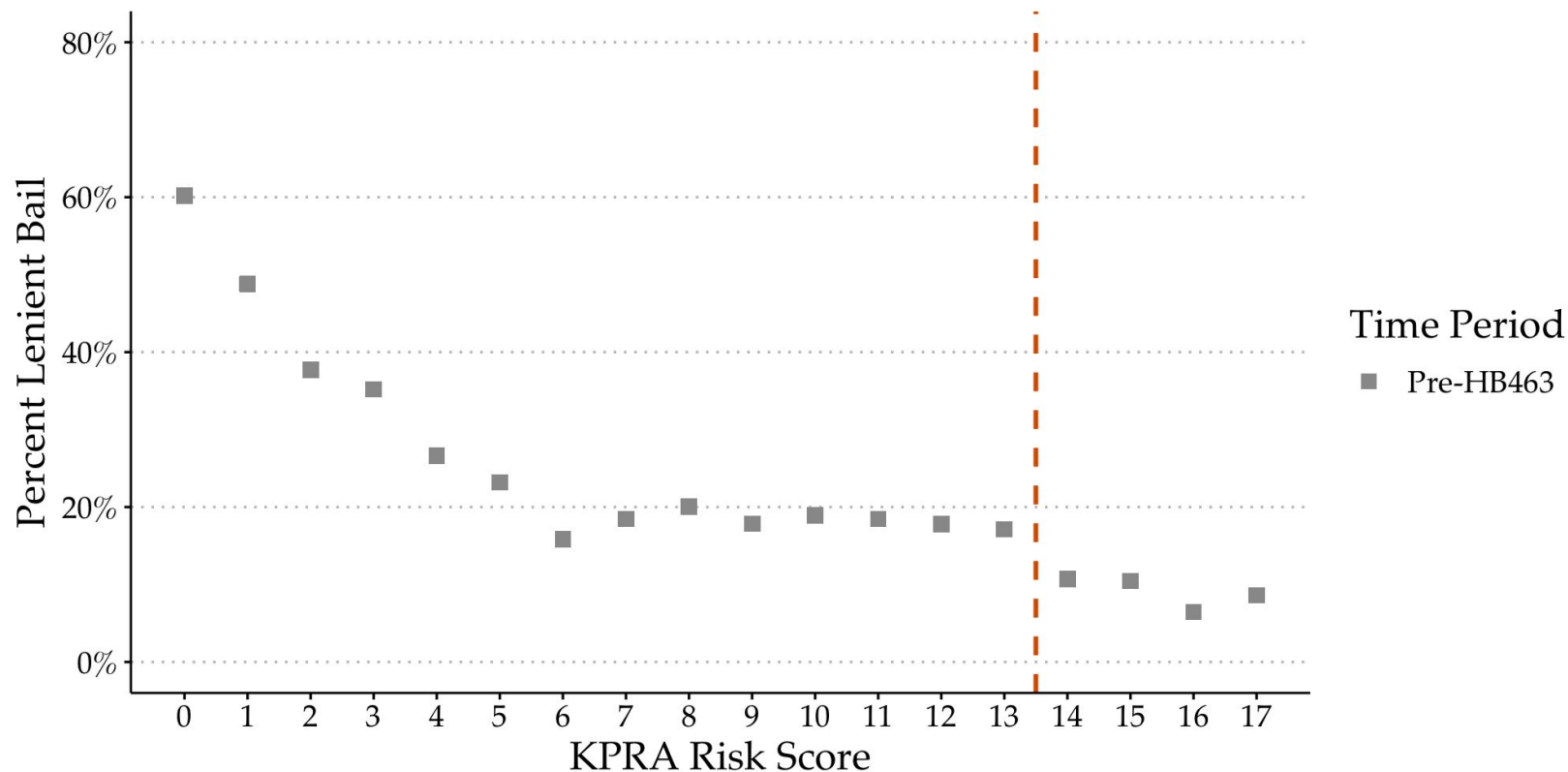
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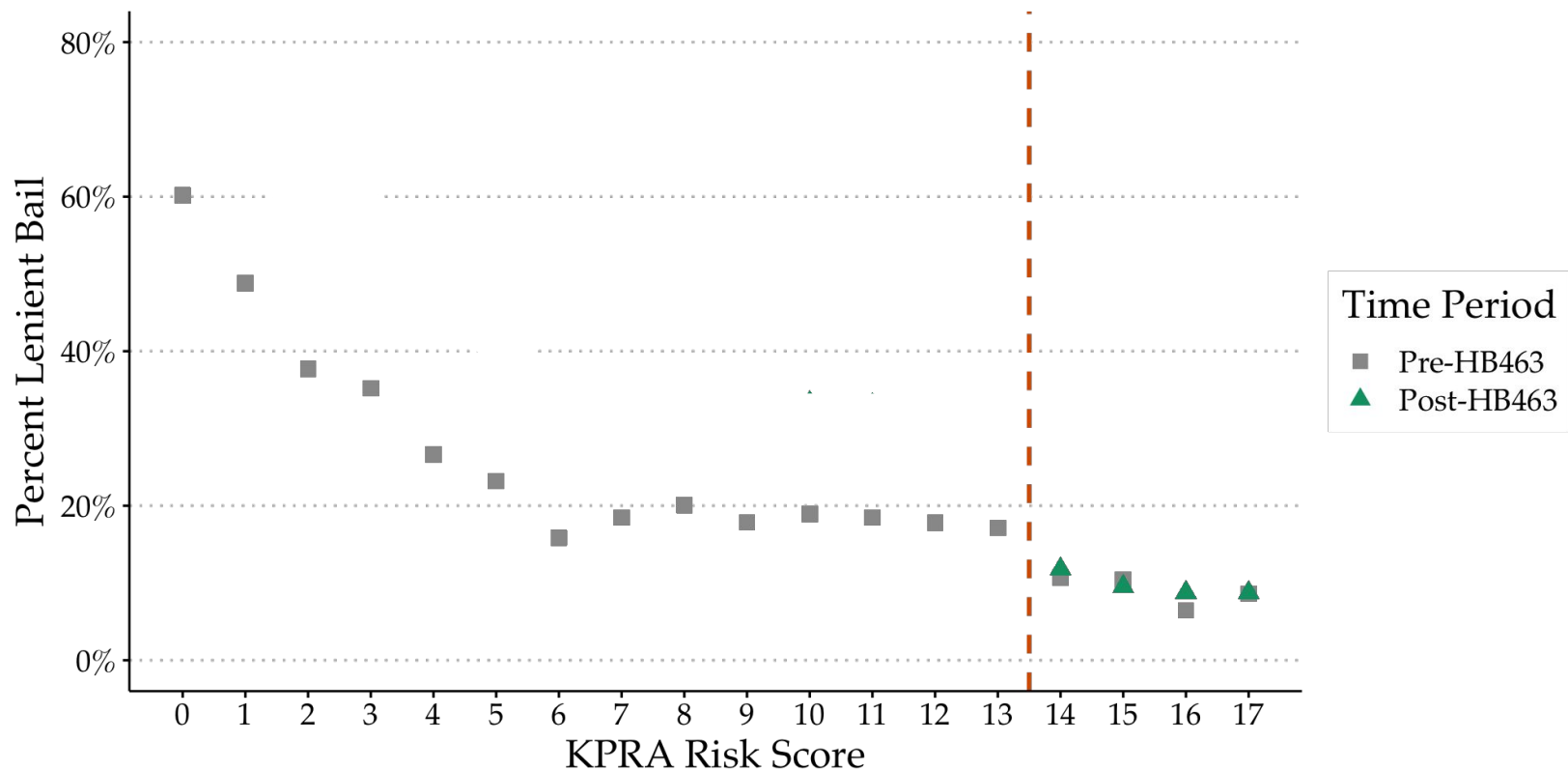
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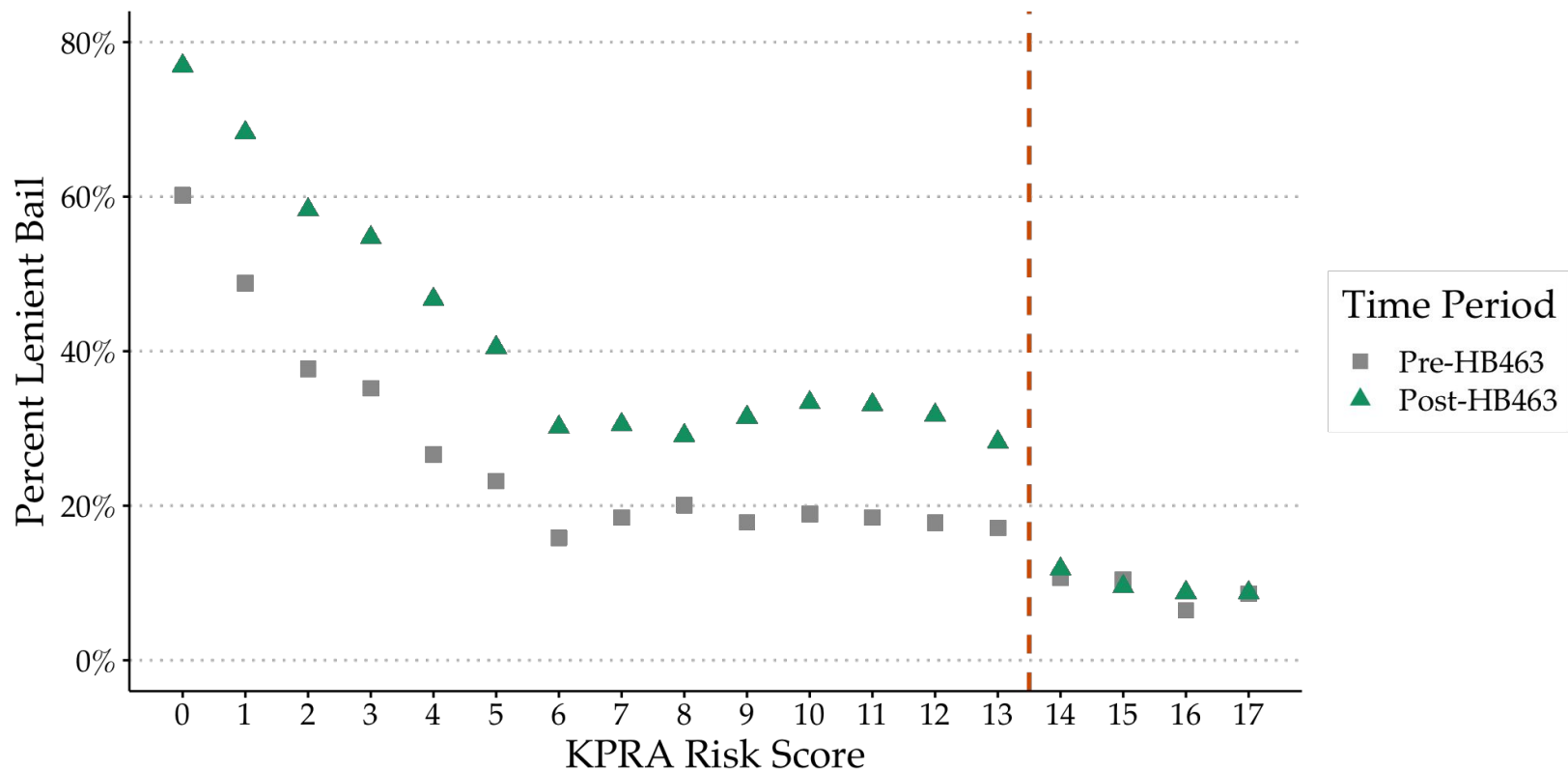
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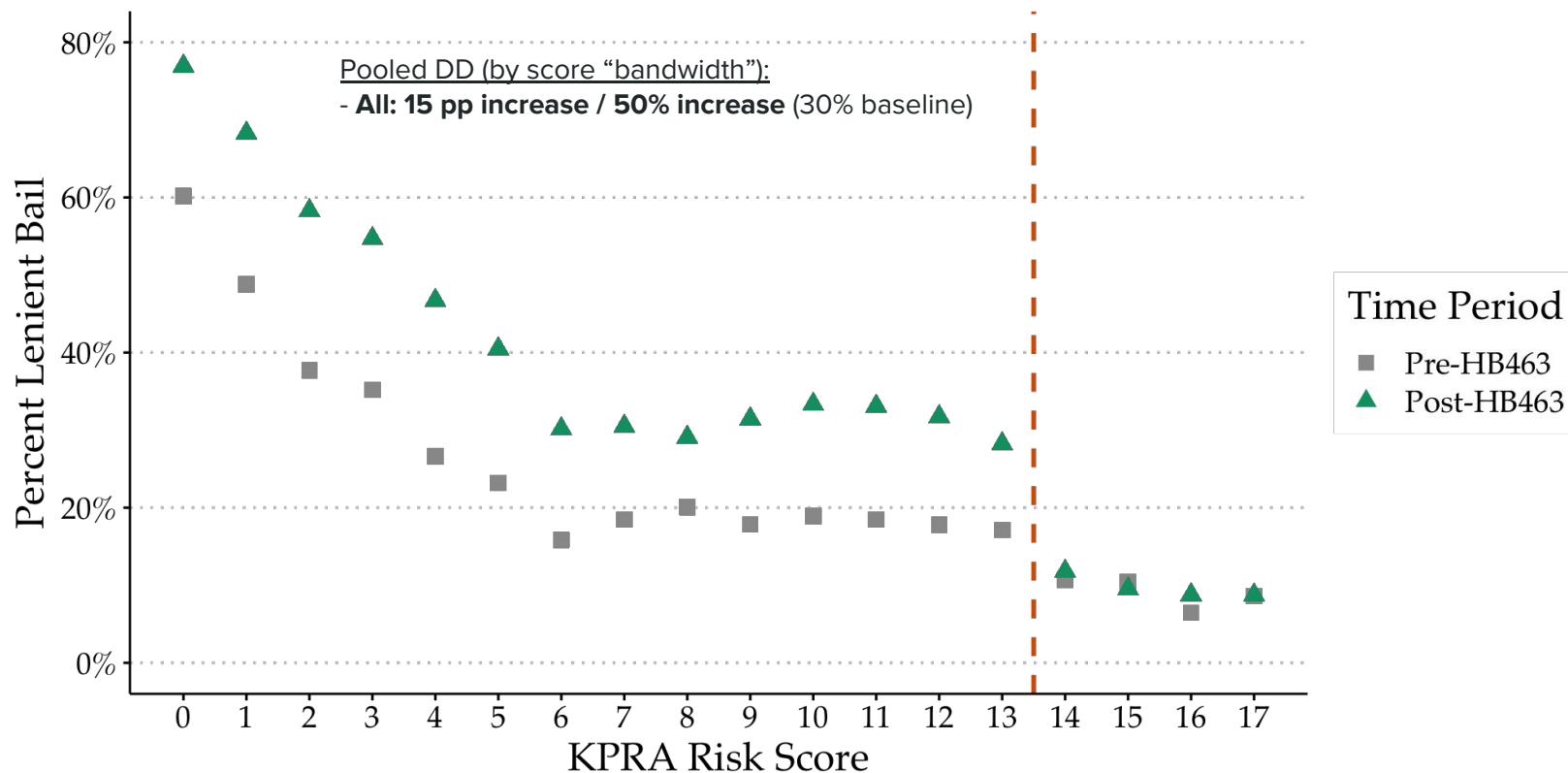
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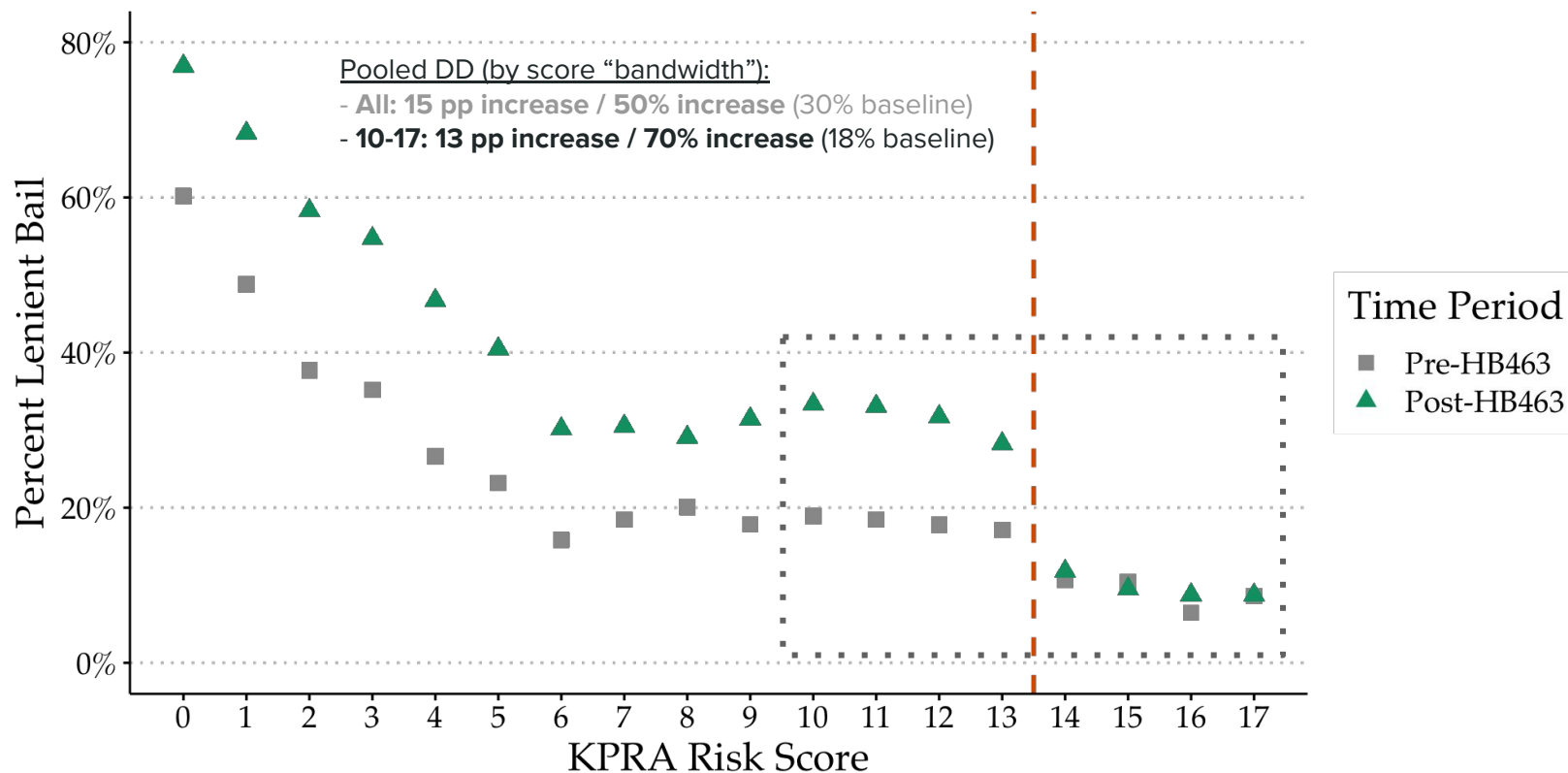
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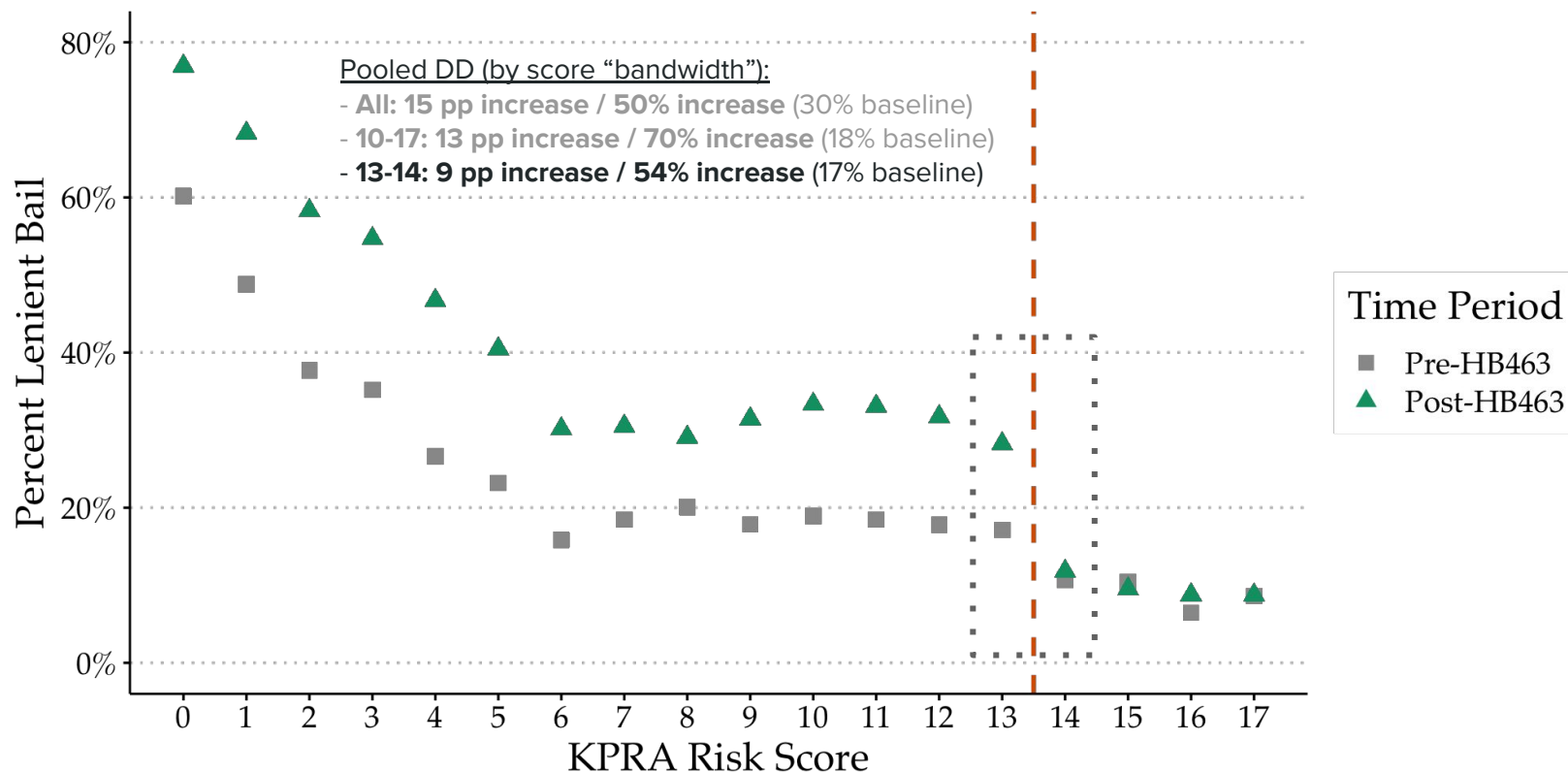


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What is the mechanism behind the effect?

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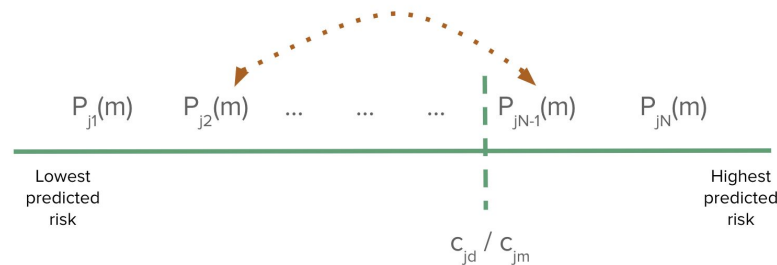
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## NEWS

### Darrell Brooks Should Not Have Been Released on Low Bail, Milwaukee DA Admits

BY KATHERINE FUNG ON 11/22/21 AT 2:02 PM EST

*"[Bail] in this case is not consistent with ... the risk assessment of the defendant prior to the setting of bail."*

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*In New York City court observations,*

***“judges routinely stated that they only ordered people to be released [...] because the law forced them to.”***  
(Corvert 2022)

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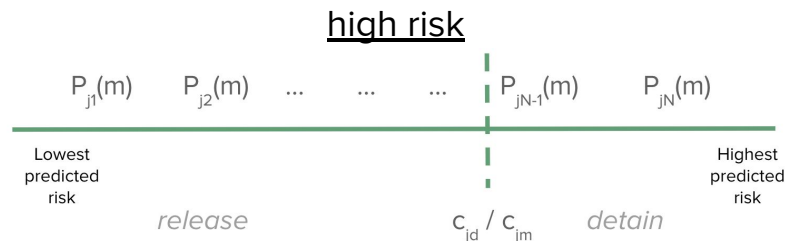
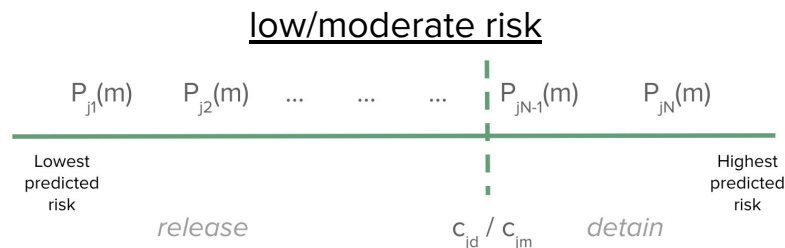
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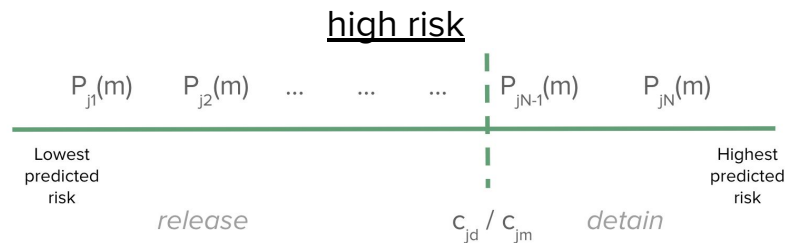
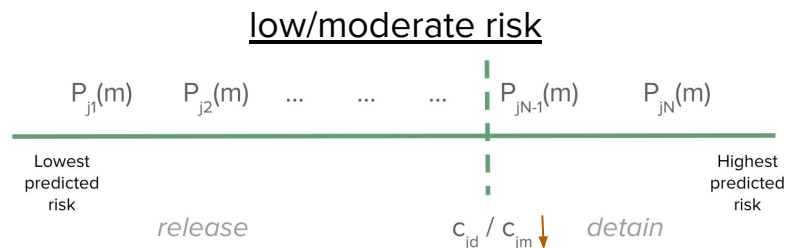
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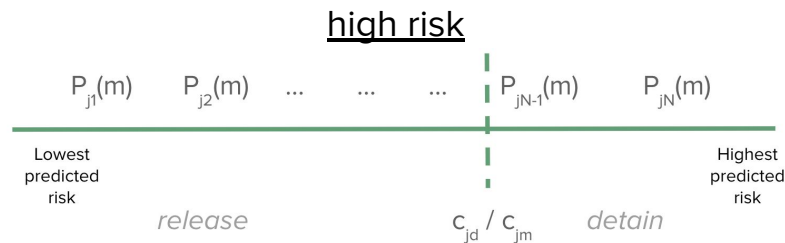
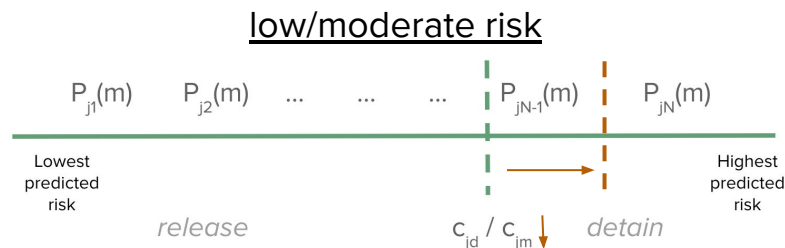
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- **Not as risky if recommended release (algorithm designer gives reputational cover)**

=> change in *composition* of decisions, no effect for high risk



# Testing the dueling predictions

Want to estimate effect of recommendation introduction on high risk group (*not covered by recommendation*)

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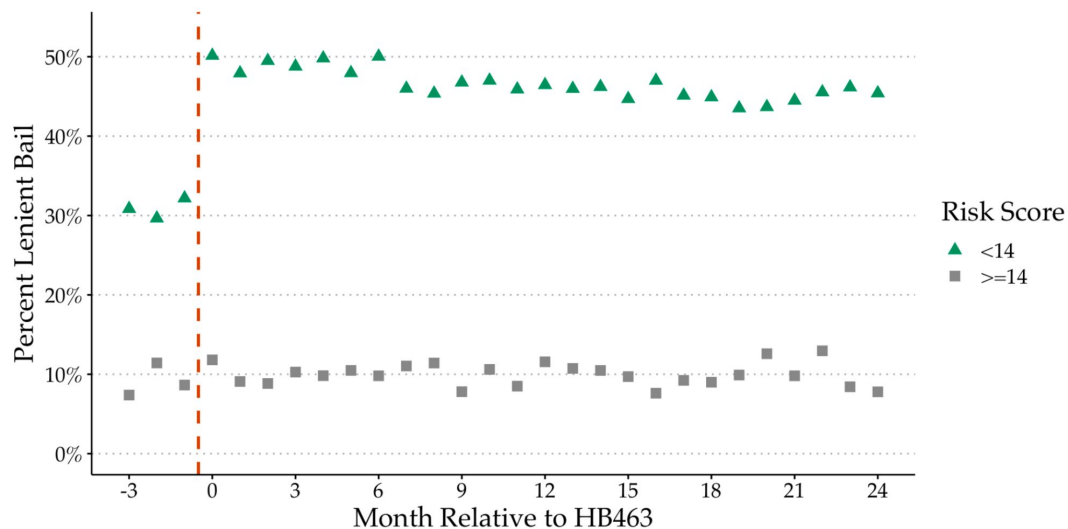
Methodology = **leverage variation over time (RD in time)**



# Testing the dueling predictions

Want to estimate effect of recommendation introduction on high risk group (*not covered by recommendation*)

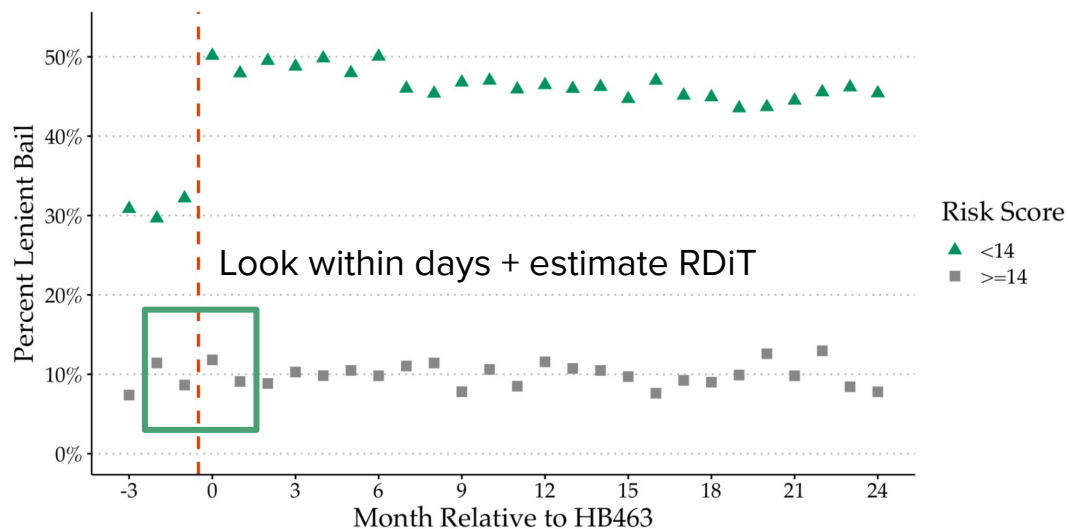
Methodology = **leverage variation over time (RD in time)**



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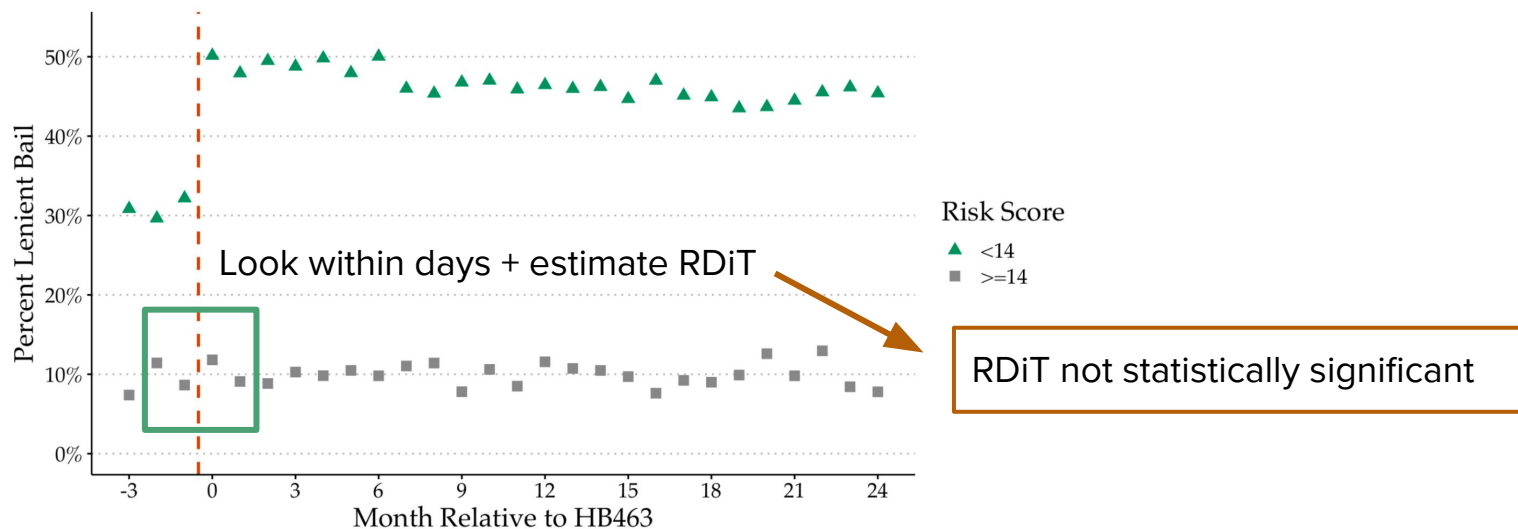
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Methodology = **leverage variation over time (RD in time)**



# Why might recommendations *change judge decisions*?

1. ~~Administrative cost to deviate~~
2. Recommendations increase algorithms use in setting perceived probabilities (upweight algorithm output)

=> change in *allocation* but not *composition* of decisions, decrease in lenient bail for high risk

3. Recommendations change misconduct costs in the event of a bad outcome (*someone was released and commits misconduct; “type II errors”*)
  - Sticking neck out more if recommended detention (additional penalty)
  - **Not as risky if recommended release (algorithm designer gives reputational cover)**

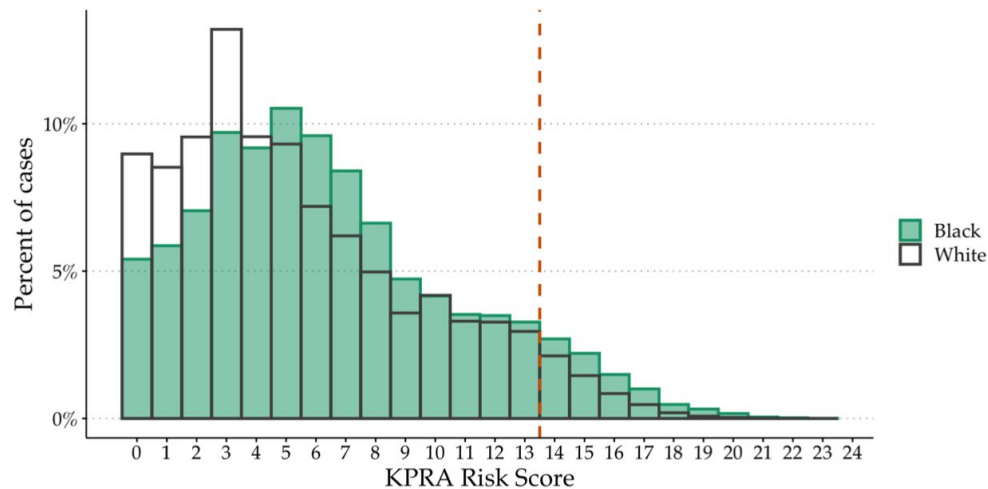
=> change in *composition* of decisions, no effect for high risk

# Heterogeneous recommendation effects and implications for racial inequality

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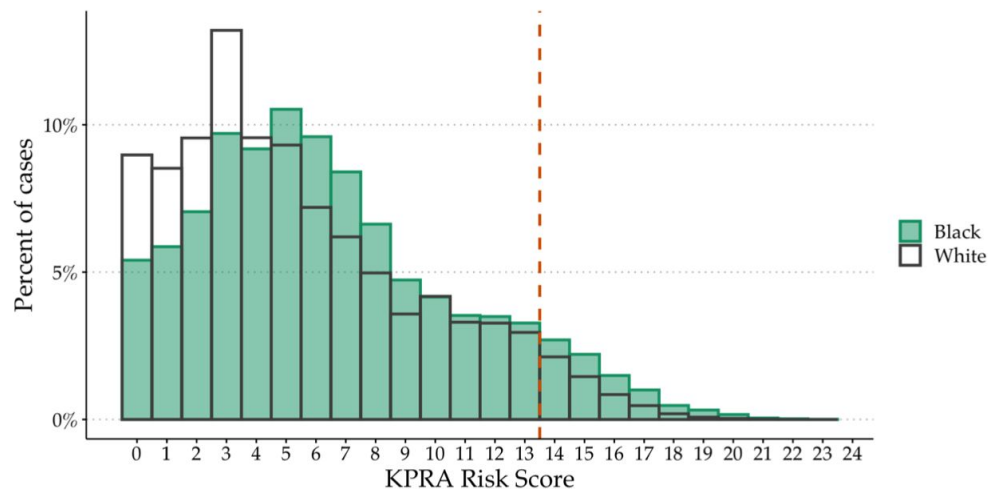
# Racial disparities in risk scores, recommendations, and outcomes

Concern about the algorithm distribution:  
usage might widen racial disparities



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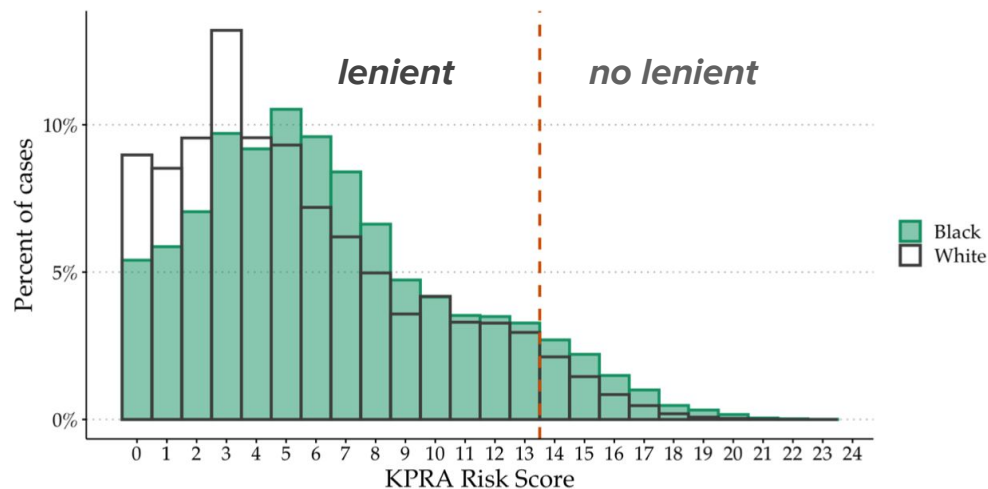
After the recommendations implemented,

Black people were **9.3 pp less likely** to get lenient bail (36.7% vs. 46%) than white people

***How much is due to different recommendations?***

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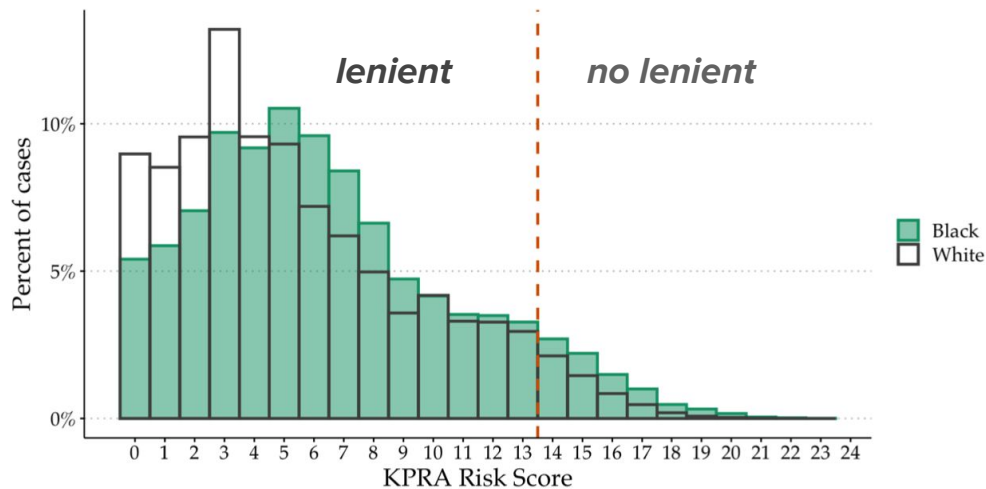
*If bail automatically set by recommendations (low/mod => lenient; high => no lenient),*

Black people would've been **3.3 pp less likely** to get lenient bail (91.5% vs. 94.8%) than white people



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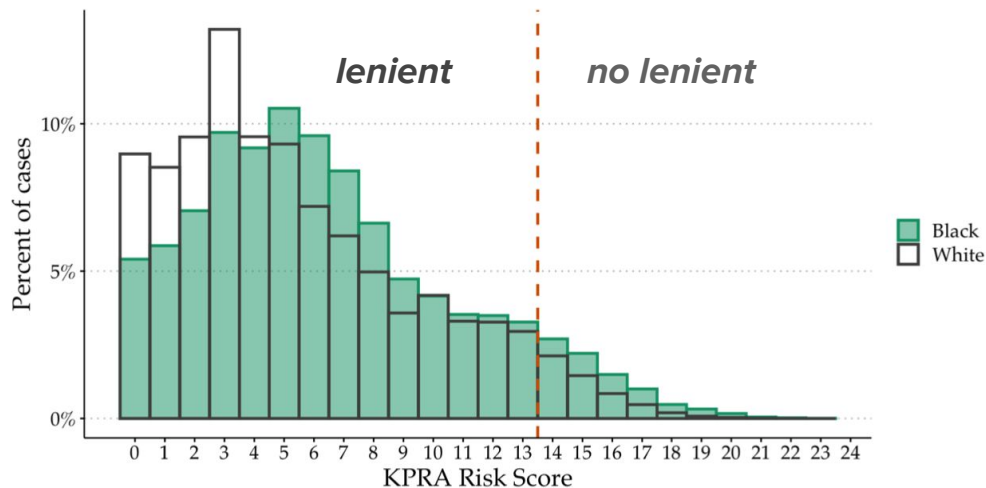
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*(automating to recommendation generates a 65%  
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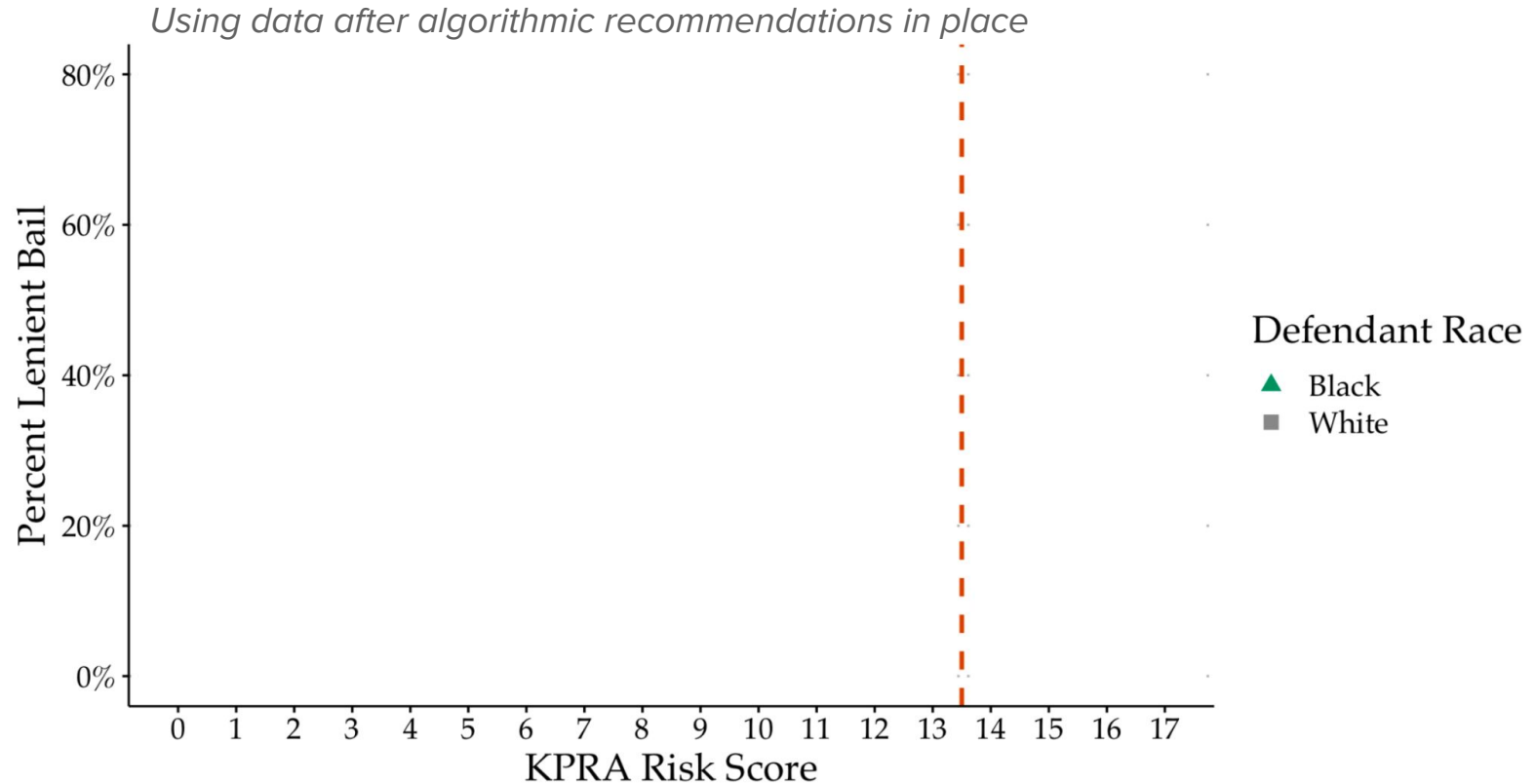
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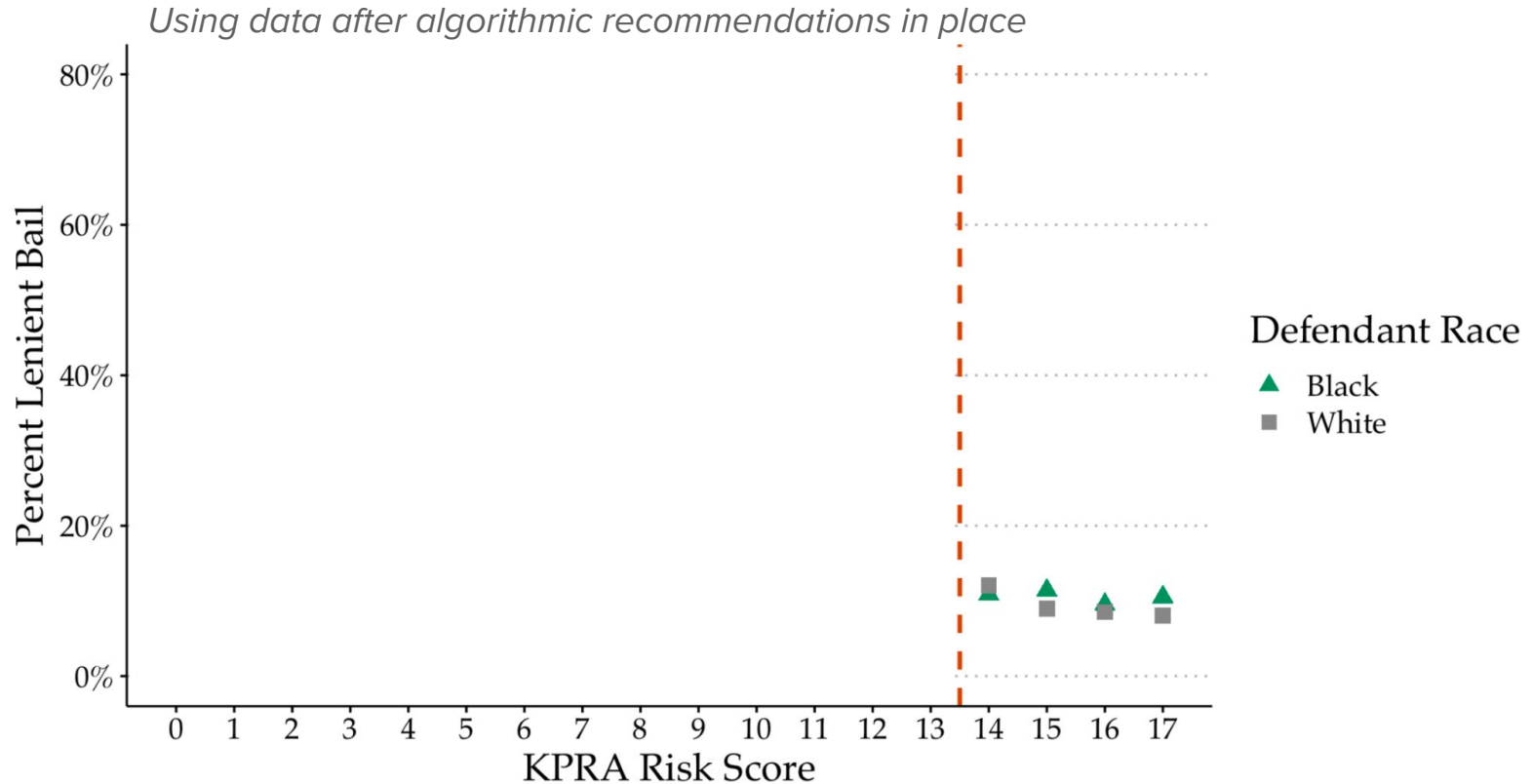
*(automating to recommendation generates a 65% smaller racial gap than observed)*

**corollary: deviations from lenient recommendation vary by defendant race**

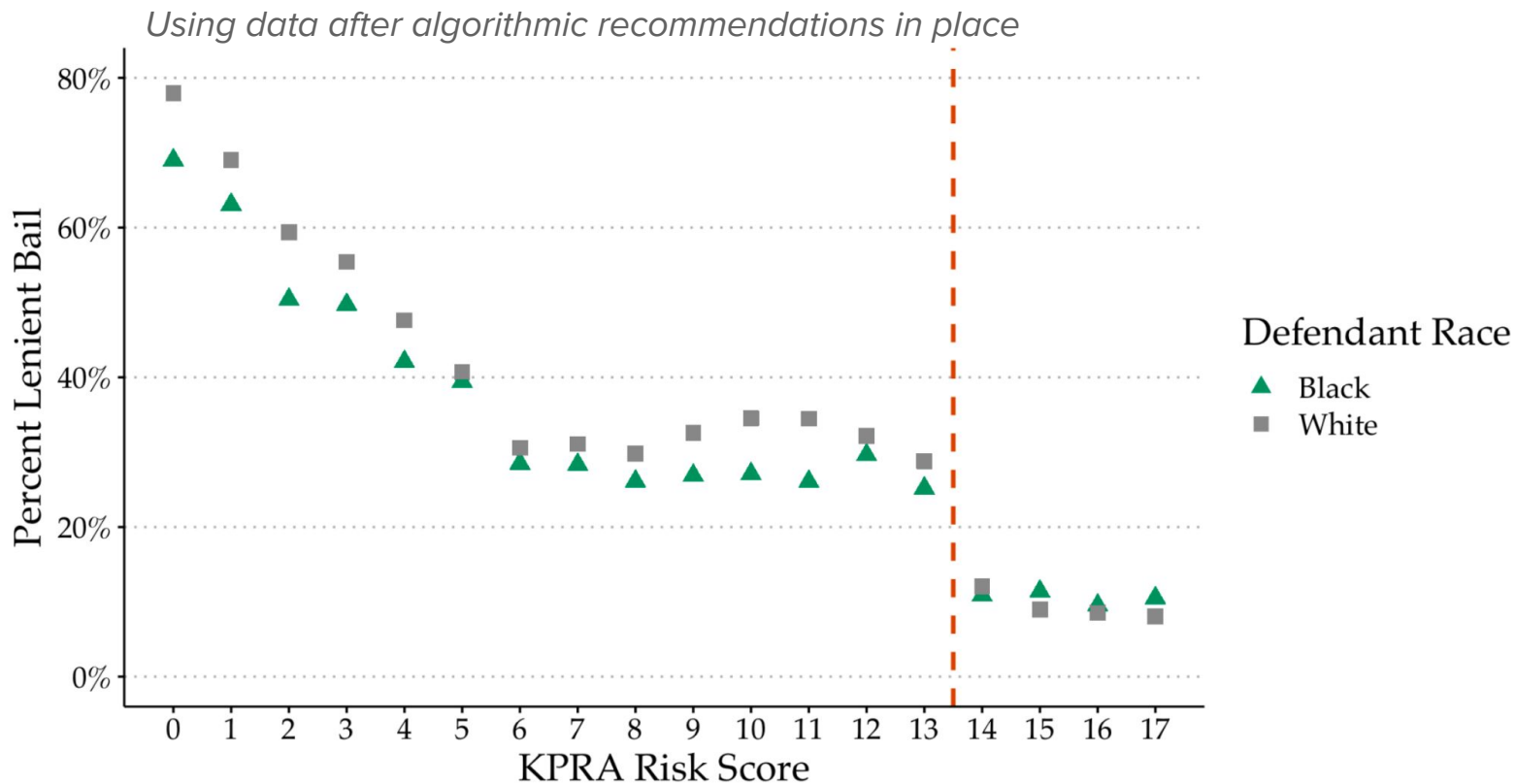
# Are differences in deviations due to different risk score distributions?



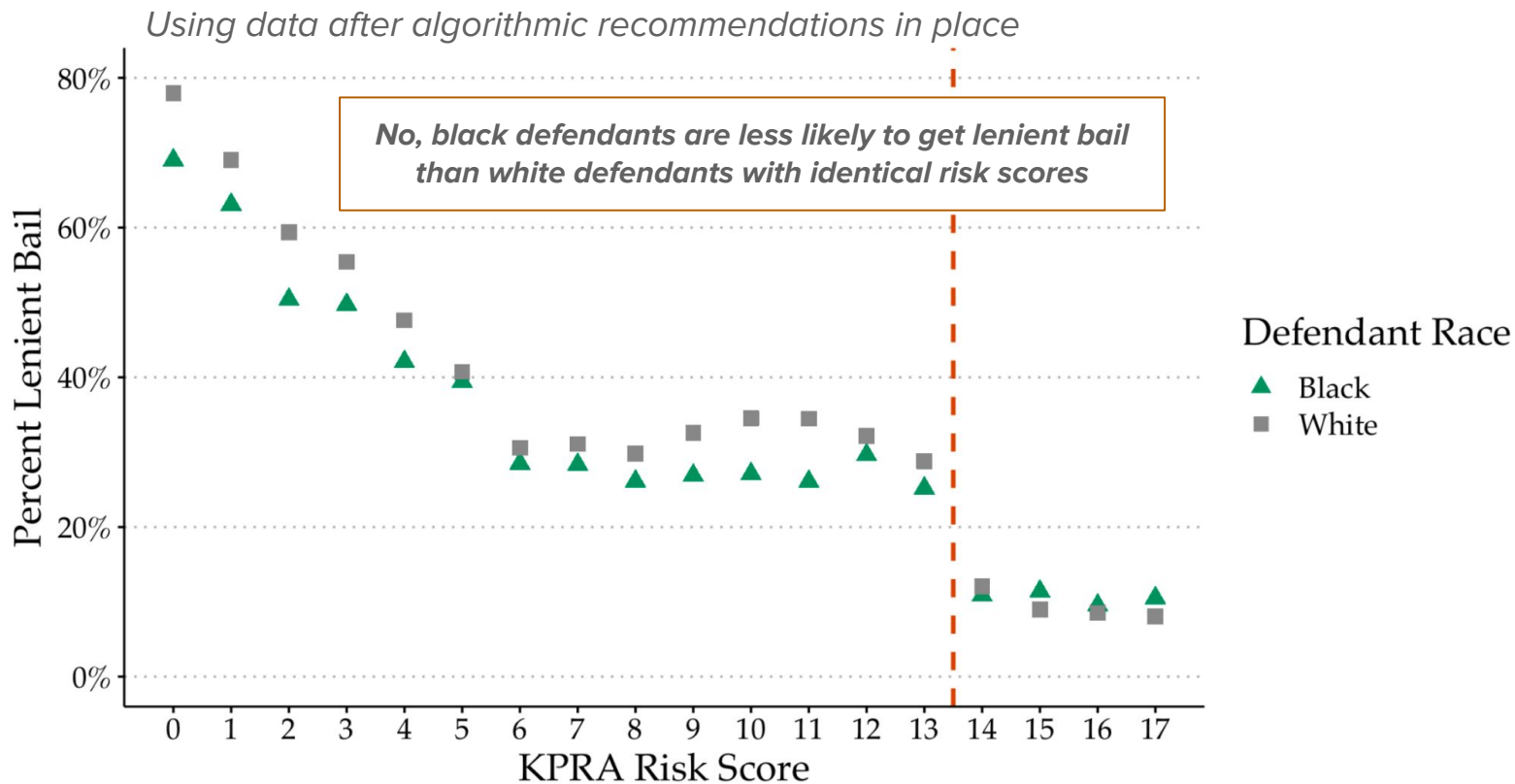
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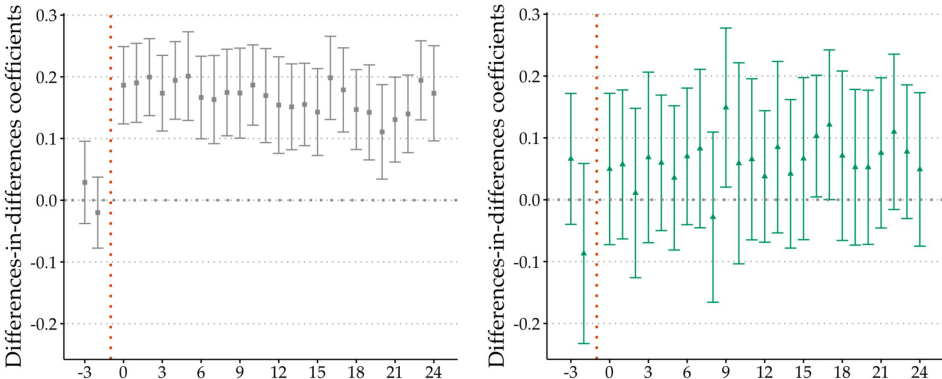
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# Effects of algorithmic recommendation differ by defendant race

<i>Dependent variable: I(lenient bail)</i>		
	DD (White Defendants) (1)	DD (Black Defendants) (2)
I(score<14) x Post	0.168*** (0.020)	0.088*** (0.034)
		
Avg Dep Var (Pre-HB463)	0.312	0.297

## Effects of algorithmic recommendation differ by defendant race

	<i>Dependent variable: I(lenient bail)</i>		
	DD ( <i>White Defendants</i> )	DD ( <i>Black Defendants</i> )	DDD
	(1)	(2)	(3)
I(score<14) x Post	0.168*** (0.020)	0.088*** (0.034)	0.167*** (0.020)
I(score<14) x Black			0.032 (0.029)
Post x Black			0.009 (0.031)
I(score<14) x Post x Black			−0.083** (0.033)
Avg Dep Var (Pre-HB463)	0.312	0.297	0.309



# What explains this heterogeneity?

	<i>Dependent variable: I(lenient bail)</i>	
	DDD	
	(1)	
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I(score<14) x Post x Black	−0.083** (0.034)	Are these differences <b><i>within</i></b> judges or <b><i>between</i></b> judges?
Extra FEs	NA	

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	DDD	DDD	DDD
	(1)	(2)	(3)
I(score<14) x Post	0.167*** (0.020)		
I(score<14) x Black	0.032 (0.030)	<b><i>Allow for time-score-varying judge FEs</i></b>	<b><i>Allow for time-score-varying county FEs</i></b>
Post x Black	0.009 (0.031)		
I(score<14) x Post x Black	-0.083** (0.034)		
Extra FEs	NA	judge x under14 x post	county x under14 x post

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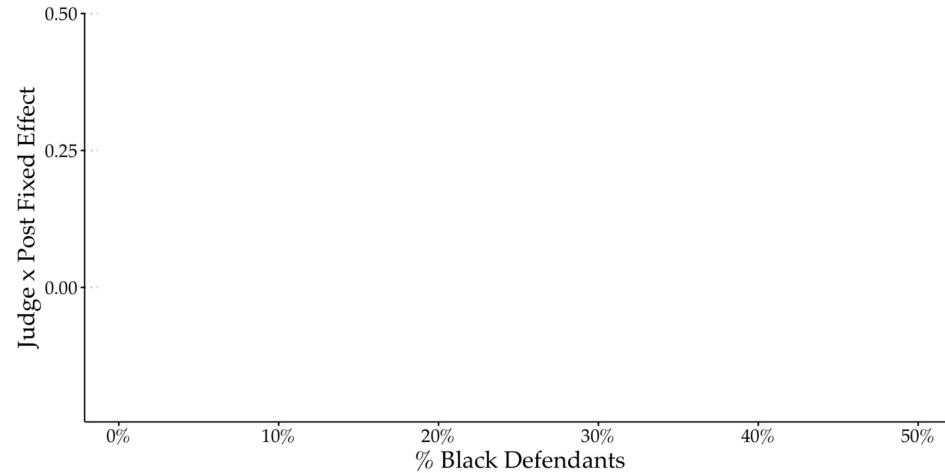
# Judges with more Black defendants respond less to lenient recommendations

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*Subset to cases with score <14,  
Estimate judge x post FEs  
(judge FE for post period)*

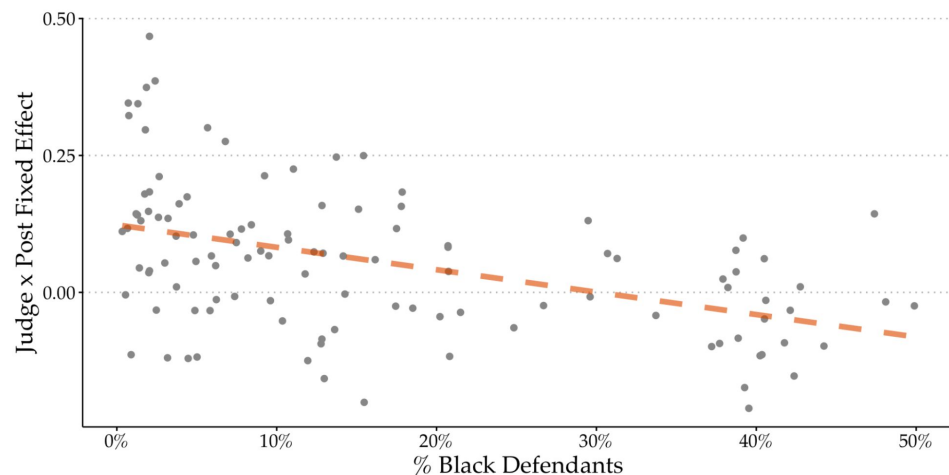
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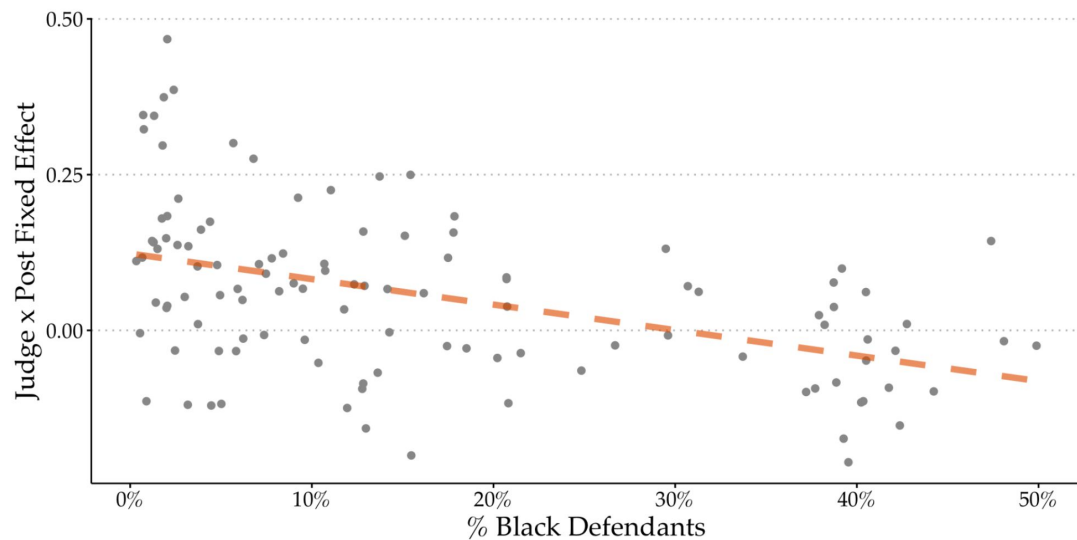
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# Why do they respond less?



Could this relationship be explained by...

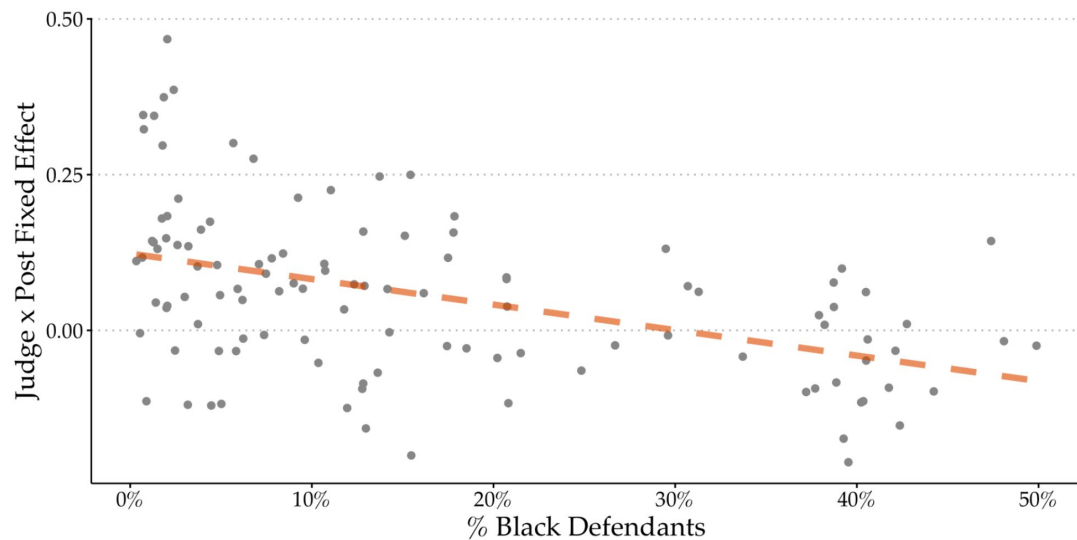
## Judge characteristics?

- *Demographics (race, gender)*
- *Experience (years as judge)*
- *Election competitiveness*
- *Misconduct rates*

## County characteristics?

- *Population*
- *Crime rates*

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## County characteristics?

- *Population*
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Data sources:

- **Judge demographics/experience:** hand-collect data from public profiles online, interviews with staff
- **Election competitiveness:** hand-collect data on 2010 local election PDFs
- **Misconduct rates:** calculate FTA/re-arrest rates by judge in pre-period
- **Population and crime rates:** county-level data from 2010 UCR data



## Why do they respond less?

*Dependent Variable = Judge x Post FE*

	(1)	(2)	(3)	(4)	(5)	(6)
Share Black Defendants	-0.374*** (0.081)					

**Judges who see 10 pp more Black defendants  
respond to the recommendation 3.7 pp less**

(25% drop from the 15 pp baseline effect)

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			+ Election contest + Contest in district + log(voters)	+ Election contest + Contest in district + log(voters)	+ Election contest + Contest in district + log(voters)	+ Election contest + Contest in district + log(voters)
				+ FTA rate pre- + Rearrest rate pre-	+ FTA rate pre- + Rearrest rate pre-	+ FTA rate pre- + Rearrest rate pre-
					+ County pop + Rural indicator	+ County pop + Rural indicator
						+ Crime rate + Index crime rate + Prop crime rate + Violent crime rate

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## Other judge- and county-level covariates do not explain this

*Dependent Variable = Judge x Post FE*

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Share Black Defendants	-0.374*** (0.081)	-0.384*** (0.085)	-0.377** (0.144)	-0.323** (0.149)	-0.307* (0.169)	-0.374** (0.178)
		+ Judge race + Judge gender + Years as judge	+ Judge race + Judge gender + Years as judge	+ Judge race + Judge gender + Years as judge	+ Judge race + Judge gender + Years as judge	+ Judge race + Judge gender + Years as judge
			+ Election contest + Contest in district + log(voters)	+ Election contest + Contest in district + log(voters)	+ Election contest + Contest in district + log(voters)	+ Election contest + Contest in district + log(voters)
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**(25% drop from the 15 pp baseline effect)**

Suggestive evidence:

Reputational cover recommendations provide depends on county demographics

similar to Feigenberg + Miller (2021) finding of higher CJS severity in more racially heterogeneous places

# Wrap-up

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- Algorithmic recommendations are common practice in decision-making settings
- Effects of algorithmic recommendations are often hidden in study of effects of algorithms

This paper:

- ***Algorithmic recommendations have independent, economically meaningful effects***
- Why? ***Recommendations can change costs of mistakes***
- Deviations from recommendations can complicate effects on group inequality
  - ***Discretion matters even though algorithmic systems aim to limit its importance***

\end{talk}

Thanks for  
coming!

You can email me here:

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*More info:*

*[albrightalex.com](http://albrightalex.com)*

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