Racial Bias

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Outline for Today

1. **Intro to Judge Fixed Effects**

2. **Summarize Papers on Racial Bias in Criminal Justice System**

3. **Summarize Papers on Racial Bias in Racial**

Next week

1. Racial bias group briefing note
2. Effect of incarceration on recidivism, education, and labor market outcomes

Readings

- Bhuller et al. (2020)
- Eren and Mocan (2021)

Judge Fixed Effects

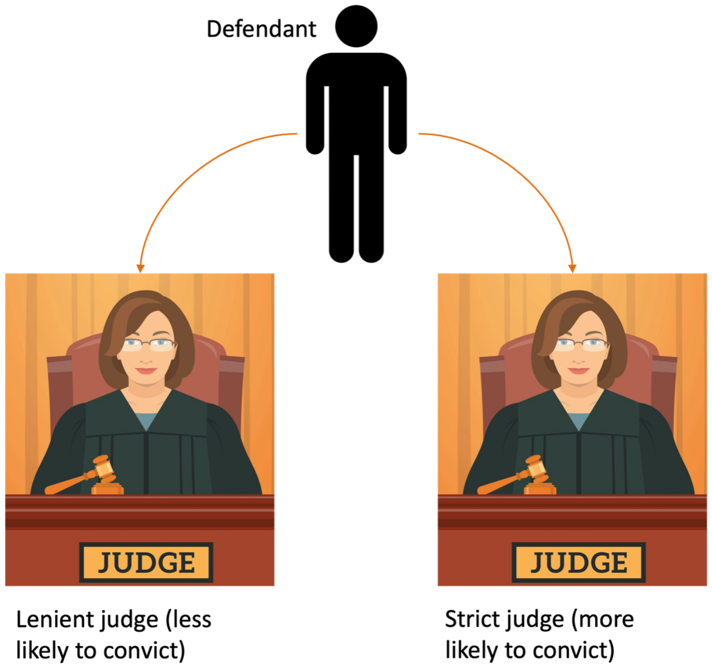
Judge Fixed Effects in a Nutshell

- **Conceptual Framework**: Judge fixed effects function akin to unobserved heterogeneity in econometric models, where the legal decisions—varies due to judge-specific traits and not solely due to the case specifics or legal arguments presented
- **Econometric Relevance**: In the econometric analysis of judicial behavior, judge fixed effects are capturing the intrinsic, idiosyncratic biases or tendencies of individual judges that might systematically affect case outcomes
- **Empirical Strategy**: To obtain unbiased estimators, it's critical to control for judge fixed effects in regression models. This approach isolates exogenous variation in legal decisions from endogenous judge characteristics.

What are Judge Fixed Effects?

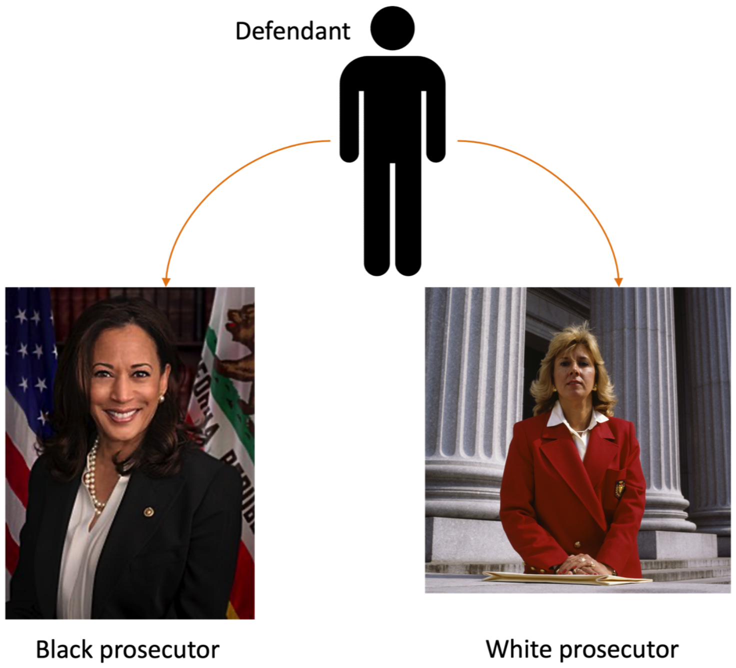
- It's a very common and well-regarded natural experiment that economists and social scientists use to study the casual effects of "treatment" within the criminal justice system
- It exploits the fact that judges/prosecutors are randomly assigned to cases
- Some judges/prosecutors are pickier and some are less picky
- This random assignment to picky/less picky judges leads to quasi-random variation in outcomes

Quasi-Experimental Approaches: Judges



- This quasi-random assignment of cases to judges creates quasi-random variation that can be used to study the causal effect of a conviction (or other judicial decision) on causal outcomes.
- Or random assignment to a judge/prosecutor of a particular race, to study racial bias.

Quasi-Experimental Approaches: Prosecutors



- Or random assignment to a judge/prosecutor of a particular race, to defendants, to study racial bias (Sloan, 2020)

Sloan (2020)

Judge Fixed Effects in Action

- CarlyWill Sloan, the author of this paper, just finished her Ph.D. in economics a few years ago and this was her dissertation research!

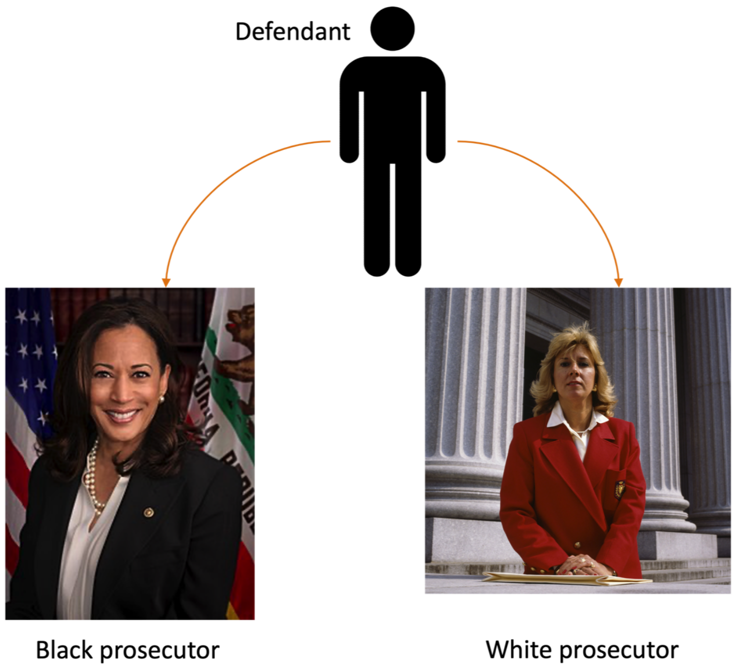
> Abstract: There is much interest in understanding the extent to which racial bias drives the large racial disparities in criminal justice outcomes. However, little is known about whether prosecutors exhibit racial bias, despite the widespread belief that prosecutors have more power and discretion than any other actor in the justice system. This paper uses data from New York County to test for racial bias in convictions by being the first to exploit the **conditionally random assignment of prosecutors to cases**. To overcome confounding factors associated with defendant and prosecutor race, I use a difference-in-differences to consider how much more black versus white defendants are convicted by white prosecutors, compared to the same difference for black prosecutors.

Results show strong racial bias for property crimes

- Results indicate strong evidence of racial bias for property crimes but not for other crimes.
- Property crime results show white defendants have similar conviction rates regardless of prosecutor race
- However, while prosecutors of both races convict black defendants at higher rates, the difference in conviction rates across white and black defendants is 5 percentage points (8 percent) higher for white prosecutors than black prosecutors
- Additional results indicate this effect is driven by differences in dismissals and by defendants with no criminal history

Data and Methodology

- Sloan uses case-level data from the New York County District Attorney's Office
- Sloan has data on the race of the defendant, and the race of the prosecutor, and focuses on comparing white and black defendants who are randomly assigned prosecutors who are either white or black
- After controlling for screening date, assignment to prosecutors is as-good-as-random
- Primary outcome = was the defendant found guilty
- The research question is if the being quasi-randomly assigned a white or black prosecutor has a different effect on white vs. black defendants



- Or random assignment to a judge/prosecutor of a particular race, to defendants, to study racial bias (Sloan, 2020)

	Black Defendant	White Defendant
Black Prosecutor	Guilty conviction rate = C	Guilty conviction rate = D
White Prosecutor	Guilty conviction rate = A	Guilty conviction rate = B

- Difference-in-Differences Estimate = (A – B) – (C – D)
- Both black and white prosecutors may have higher guilty conviction rates for black defendants, but is this white-black gap in conviction rates higher for white prosecutors? This would suggest racial bias

Results

Table 2: Proportion Guilty by Prosecutor and Defendant Race

	(1) Black Prosecutors	(2) White Prosecutors
Panel A: White Defendants	0.4859	0.5045
Panel B: Black Defendants	0.5940	0.6354

Table 3: Proportion Guilty by Prosecutor and Defendant Race for Property Crimes

	(1) Black Prosecutors	(2) White Prosecutors
Panel A: White Defendants	0.5016	0.5021
Panel B: Black Defendants	0.6059	0.6546

Results

Table 6: Estimates of Opposite-Race Bias in Defendant Guilt by Crime Type

	(1)	(2)	(3)	(4)
Panel D: Property Crimes				
Outcome: Guilty				
Black Defendant*White Prosecutor	0.0481***	0.0448***	0.0459***	0.0500***
	(0.0159)	(0.0133)	(0.0134)	(0.0138)
Observations	29815	29815	29815	29815
Outcome Mean	0.615	0.615	0.615	0.615
FDR q-values	0.011	0.004	0.003	0.002
Prosecutor and Defendant Race Indicators	Y	Y	Y	Y
Screening Date FE	Y	Y	Y	Y
Case-Level Controls	-	Y	Y	Y
Prosecutor FE	-	-	Y	-
Interactions	-	-	-	Y

Standard errors in parentheses
* $p < .1$, ** $p < .05$, *** $p < .01$

If black defendants are quasi-randomly matched to white prosecutors, they are between 4.5 and 5 percentage points more likely to be deemed guilty, relative to:

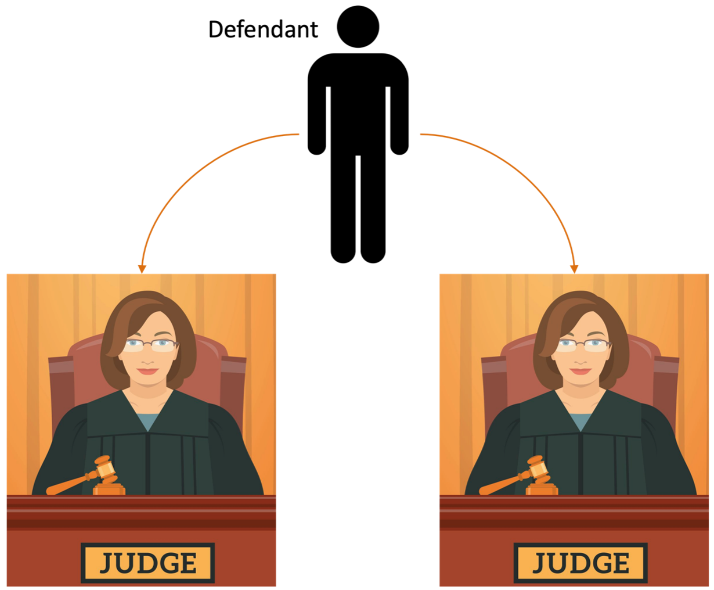
- Black defendants matched with black prosecutors
- White defendants matched with white prosecutors
- White defendants matched with white prosecutors

i.e. it's a difference-in-differences

Arnold, Dobbie and Yang (2018)

Racial Bias in Bail Decisions

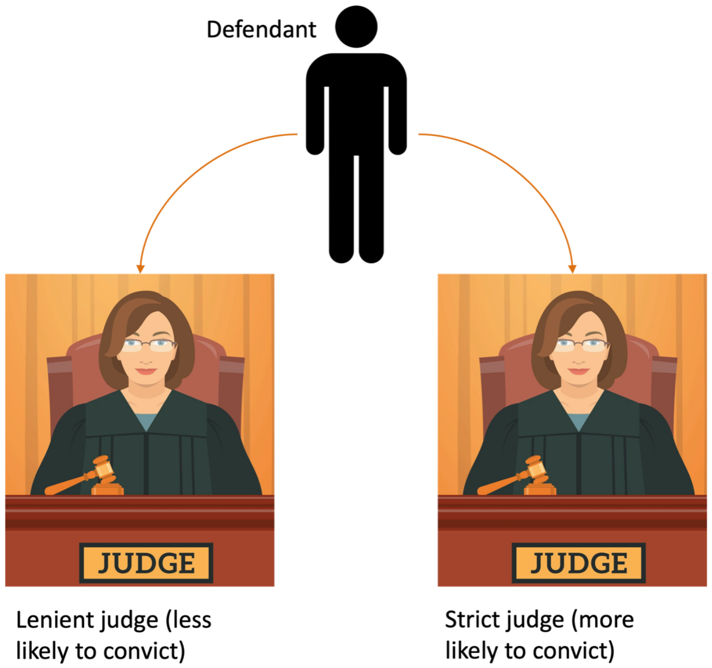
Abstract: This article develops a new test for identifying racial bias in the context of bail decisions—a high-stakes setting with large disparities between white and black defendants. We motivate our analysis using Becker's model of racial bias. Becker's model which predict that rates of pretrial misconduct will be identical for marginal white and marginal black defendants if bail judges are racially unbiased. In contrast, marginal white defendants will have higher rates of misconduct than marginal black defendants if bail judges are racially biased, whether that bias is driven by racial animus, inaccurate racial stereotypes, or any other form of bias. To test the model, we use the release tendencies of quasi-randomly assigned bail judges to identify the relevant race-specific misconduct rates. Estimates from Miami and Philadelphia show that bail judges are racially biased against black defendants, with substantially more racial bias among both inexperienced and part-time judges. We find suggestive evidence that this racial bias is driven by bail judges relying on inaccurate stereotypes that exaggerate the relative danger of releasing black defendants.



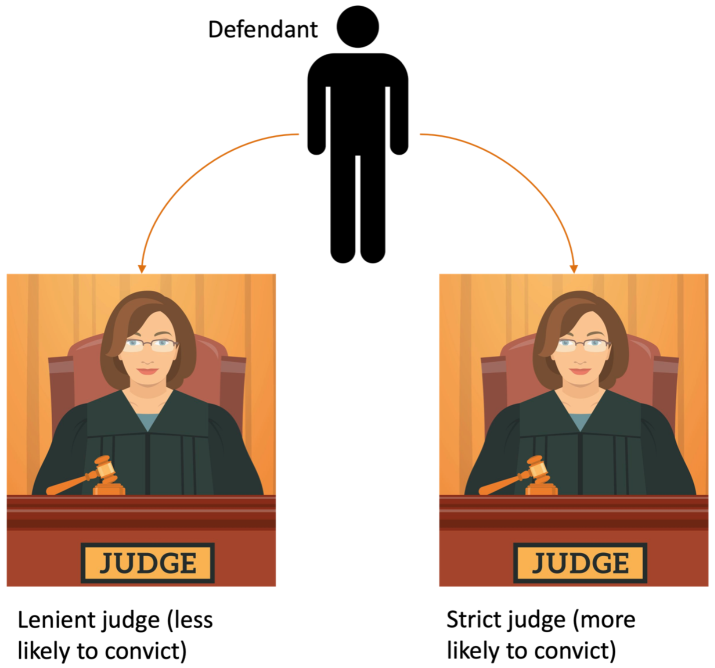
Lenient judge (less likely to convict)

Strict judge (more likely to convict)

- Most defendants would get pre-trail release (or not) regardless of the judge, but for a portion of defendants, they are “marginal”
- Defendants are “marginal defendants” if whether they get released or not depends on if they get quasi-randomly allocated to a lenient vs. a strict judge



- The quasi-random assignment to lenient vs. picky judges provides quasi-random variation in pre-trial release
- The idea is to see if those quasi-randomly assigned pre-trial release in this way re-commit crimes while on release



- The idea is to see if those quasi-randomly assigned pre-trial release in this way re-commit crimes while on release
- The key thing for this paper is to see if the re-commit rate differs between white and black defendants. If it does, it could suggest racial bias in how pre-trial release is allocated

Bias in Bail

RACIAL BIAS IN BAIL DECISIONS 1911

TABLE II
FIRST-STAGE RESULTS

	All defendants		White		Black	
	(1)	(2)	(3)	(4)	(5)	(6)
Pretrial Release	0.405***	0.389***	0.373***	0.360***	0.434***	0.415***
	(0.027)	(0.025)	(0.036)	(0.032)	(0.036)	(0.033)
	[0.698]	[0.698]	[0.711]	[0.711]	[0.688]	[0.688]
Court x year FE	Yes	Yes	Yes	Yes	Yes	Yes
Baseline controls	No	Yes	No	Yes	No	Yes
Observations	256,253	256,253	106,846	106,846	149,407	149,407

- First, does quasi-random assignment to a more lenient judge actually lead to pretrial release? If not, then we can't use this quasi-random assignment to them test the effect of quasi-randomly assigned pretrial release on criminal behavior while on release
- Thus, there needs to be a first stage that shows a relationship. We need to see a relationship between judge leniency and pretrial release

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- All instrumental variables papers, of which this is one, require a strong first stage, otherwise there is no way to do the study
- E.g., Levitt (1997) uses electoral cycles to measure the effect of police on crime and had to show that police hiring did in fact follow electoral cycles to some extent (the first stage)
- We see a strong first stage relationship here, which means we can then move to see how quasi-random assignment of pretrial release through lenient judges affects crimes committed while released

Bias in Bail

TABLE IV

PRETRIAL RELEASE AND CRIMINAL OUTCOMES

	IV results			MTE results		
	White (1)	Black (2)	D^{IV} (3)	White (4)	Black (5)	D^{MTE} (6)
Panel A: Rearrest for all crimes						
Rearrest prior to disposition	0.236***	0.014	0.222**	0.249***	0.017	0.231**
	(0.073)	(0.070)	(0.101)	(0.084)	(0.080)	(0.117)
	[0.172]	[0.182]	–	[0.172]	[0.182]	–
Panel B: Rearrest by crime type						
Rearrest for drug crime	0.067	0.019	0.047	0.074	−0.024	0.097
	(0.043)	(0.043)	(0.060)	(0.048)	(0.054)	(0.074)
	[0.077]	[0.081]	–	[0.077]	[0.081]	–
Rearrest for property crime	0.158***	−0.005	0.163**	0.149**	0.043	0.106
	(0.057)	(0.047)	(0.073)	(0.066)	(0.053)	(0.084)
	[0.065]	[0.068]	–	[0.065]	[0.068]	–
Rearrest for violent crime	0.079**	−0.000	0.080	0.082*	−0.001	0.083
	(0.039)	(0.042)	(0.058)	(0.044)	(0.050)	(0.068)
	[0.047]	[0.071]	–	[0.047]	[0.071]	–
Observations	106,846	149,407	–	106,846	149,407	–

- IV = Instrumental variable. We use quasi-randomly assigned “stricter” judges as a way to get quasi-random variation in pre-trial release
- Marginal defendant = those on the margins between getting pretrial release or not
- The idea is the random assignment of a pickier or less picky judge will create quasi-random variation in being released or not for this marginal group

Bias in Bail

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- White marginal defendants are much more likely to engage in pretrial misconduct compared to marginal black defendants
- For marginal black defendants, being quasi-randomly “assigned” pretrial release (via a less strict judge) or not (via a more strict judge) has no clear effect on pretrial misconduct (estimates are small and statistically insignificant)
- This not the case for marginal white defendants: they are significantly more likely to engage in pretrial misconduct

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- What does it mean that pretrial release has no effect on pretrial misconduct for black defendants, but significantly increases pretrial misconduct for white defendants?
- Judges are making inefficient (racist) decisions. They would make fewer mistakes (i.e. giving pretrial release to those less likely to commit pretrial misconduct) if they gave much fewer marginal or near-marginal white defendants release, and gave many more marginal and near-marginal black defendants release

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- i.e. judges over-release whites and under-release blacks
- This clearly implies racial bias: judges assume that marginal black defendants are more likely to commit pretrial misconduct, when that is not the case

Eren and Mocan (2018)

Other “natural experiments”

Abstract: Employing the universe of juvenile court decisions in Louisiana between 1996 and 2012, we analyze the effects of emotional shocks associated with unexpected outcomes of football games played by ~~a prominent college team in the state~~ **LSU**. We find that unexpected losses increase sentence lengths assigned by judges during the week following the game. The effects of these emotional shocks are asymmetrically borne by black defendants. The impact of upset losses on sentence lengths is larger for defendants if their cases are handled by judges who received their bachelor’s degrees from ~~the university with which the football team is affiliated~~ **LSU**. These results provide evidence for the impact of emotions in one domain on decisions in a completely unrelated domain among a uniformly highly educated group of individuals (judges) who make decisions after deliberation that involve high stakes (sentence lengths). They also point to the existence of a subtle and previously unnoticed capricious application of sentencing.

LSU as a Natural Experiment

- In this paper, the authors use LSU winning or loses as quasi-random variation of negative emotions, to see how this differentially affects black versus white juvenile defendants.
- The comparison is a difference-in-difference of sorts:
- Upset loss (negative emotional shock) vs. not an upset loss (no shock)
- Black juvenile defendant vs. white juvenile defendant

LSU game outcome	Defendant Race	
	Black	White
Not an upset loss (no shock)	Average sentence length = C	Average sentence length = D
Upset loss (negative shock)	Average sentence length = A	Average sentence length = B

- Difference-in-Differences Estimate = (A – B) – (C – D)
- Black juvenile defendants may face a higher sentence length anyways (so, C > D), but if this increases after an upset loss, then it suggests that judges react to negative emotional shocks in racist ways

Results

TABLE 7—THE EFFECT OF EMOTIONAL SHOCKS FROM LSU FOOTBALL GAMES ON DISPOSITION LENGTH IMPOSED BY JUDGES: BY TYPE OF GAME, TYPE OF CRIME, AND THE RACE OF THE JUVENILE

	Game type		Offense type		Juvenile race	
	LSU ranks in top 10	LSU ranks below top 10	Felony	Non-felony	Black	White
	(1)	(2)	(3)	(4)	(5)	(6)
Upset loss	49.537	24.564	32.854	28.327	42.902	4.815
	(19.450)	(23.197)	(21.756)	(17.672)	(14.894)	(21.963)
Close loss	12.763	3.276	15.617	8.622	−0.017	12.610
	(34.201)	(28.978)	(38.650)	(22.456)	(23.320)	(34.936)
Upset win	37.564	−23.079	−32.895	4.525	−10.166	−2.588
	(62.036)	(24.703)	(40.784)	(22.278)	(28.592)	(31.103)
Predicted win	−6.020	19.200	28.050	0.620	14.915	3.735
	(18.022)	(20.118)	(26.907)	(15.873)	(16.680)	(26.023)
Predicted close	−3.640	1.918	12.243	−9.635	−2.607	6.339
	(22.158)	(22.134)	(31.515)	(17.507)	(20.236)	(28.700)
Predicted loss	−29.094	32.942	25.749	11.321	15.108	28.234
	(27.550)	(21.949)	(33.548)	(19.654)	(23.645)	(28.835)
Average disposition length	476.29	539.26	634.61	426.53	521.46	499.64
Sample Size	4,484	5,756	3,876	5,358	5,781	3,272
Controls						
Season, week, and days of week	Yes	Yes	Yes	Yes	Yes	Yes
Judge	No	No	No	No	No	No
Juvenile	Yes	Yes	Yes	Yes	Yes	Yes
Game	Yes	Yes	Yes	Yes	Yes	Yes
Offense fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Judge fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors, which are clustered at the judge level, are reported in parentheses. Columns 1 and 2 include all bye weeks irrespective of ranking during the bye weeks. Offense classifications (felony and non-felony) are based on the Louisiana Office of Juvenile Justice categorization. See notes to Table 4 and the text for data and control variable details.

- Disposition length increases by 42.9 days for black defendants, and only 4.8 days for white defendants after the negative shock of an upset game
- No statistically significant effects for any other types of game outcomes other than "upset loss"

Coviello and Persico (2015)

NYC Stop and Frisk

Abstract: We introduce a model to explore the identification of two distinct sources of bias in the New York Police Department's [former] stop-and-frisk program: the police officer making the stop decisions and the police chief allocating personnel across precincts. We analyze 10 years of data from the stop-and-frisk program in light of this theoretical framework. We find that white pedestrians are slightly less likely than African American pedestrians to be arrested conditional on being stopped. We interpret this finding as evidence that the officers making the stops are on average not biased against African Americans relative to whites, because the latter are stopped despite being a less productive stop for a police officer. We find suggestive evidence of police bias in the decision to frisk Further research is needed.

Summary Statistics

Table 1. Descriptive Statistics (%)

	Mean	SD
Arrest made	5.8	23
African American	84	37
Recorded crime:		
Possession of a weapon	27	44
Robbery	17	37
Criminal trespass	12	32
Grand larceny auto	9.1	29
Burglary	8.9	28
Grand larceny	4.3	20
Assault	4	20
Illegal possession of substances	3.6	19
Possession of marijuana	3.3	18
Illegal sales of substances	2.9	17
Petit larceny	2.5	16
Mischief	1.2	11
Graffiti	1.1	10
Other	4.3	20

Note. The crime categories represent 95 percent of the crimes recorded in the sample. Years 2003–5 have missing values for the recorded crimes. $N = 2{,}947{,}865$ observations and 2,496,267 recorded crimes.

- Summary statistical table of 2,947,865 stop and frisk events in NYC
- 5.8% of stops lead to arrests
- African Americans make up 84% of people stopped

L: police pressure (stops/pop)

R: Hit rate (arrests/stops)

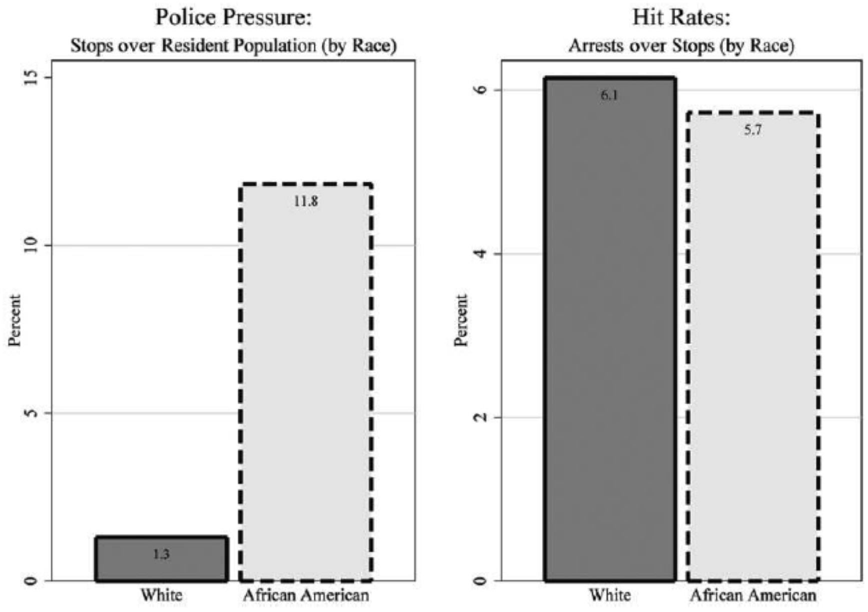

Figure 1. Average annual police pressure and hit rates in New York City, 2003–12

Left figure:

African Americans were disproportionately more likely to have been stopped, compared to their population.

African Americans were stopped and frisked about 9x as often.

L: police pressure (stops/pop)

R: Hit rate (arrests/stops)

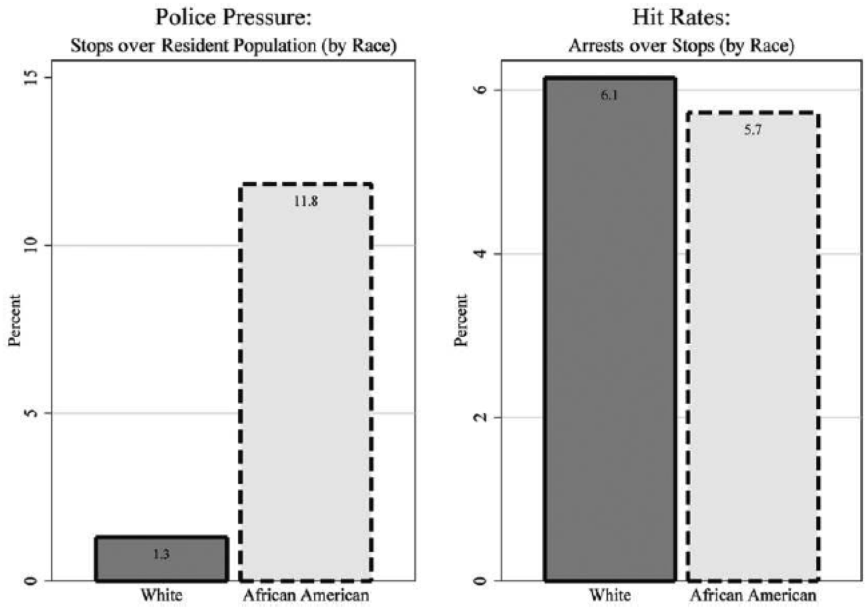

Figure 1. Average annual police pressure and hit rates in New York City, 2003–12

Right figure:

Hit rate = how often a stop leads to an arrest

Hit rates are similar between white and African American citizens

The hit rate for whites is a bit higher, suggesting that the average white person stopped and frisked may be slightly more likely to be arrested

L: police pressure (stops/pop)

R: Hit rate (arrests/stops)

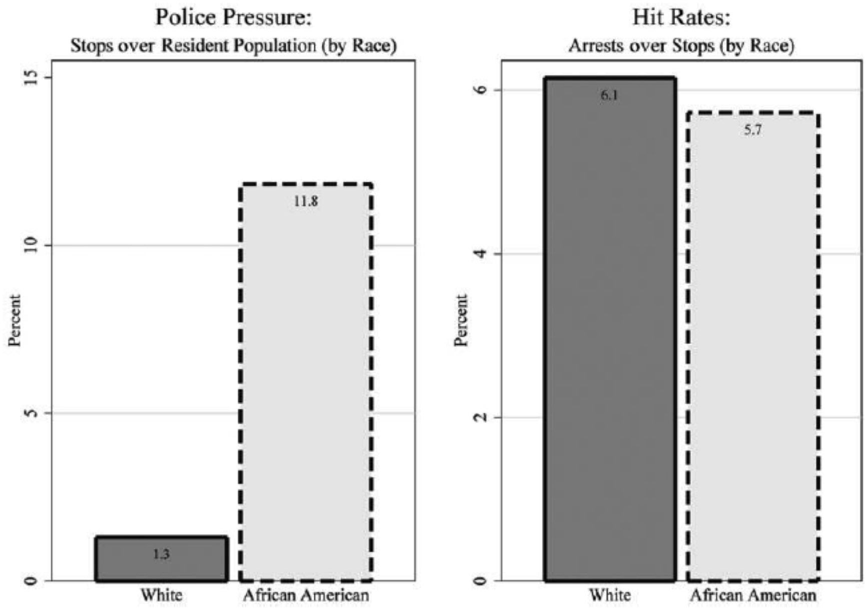

Figure 1. Average annual police pressure and hit rates in New York City, 2003–12

Regardless, this is **not** suggestive of statistical discrimination, where African Americans are searched because they are more likely to have done something that requires arrest

If this were the case, then the hit rates for African Americans would be higher

Instead, these results are suggestive of taste-based discrimination, where officers are choosing to search African Americans for reasons of personal preference (animus) and not due to the average criminality by race

What Correlates with Relative Police Pressure?

Table 2. Correlates of Relative Police Pressure in New York City

	(1)	(2)	(3)
% African American	−.222**	−.057	−.066
	(.073)	(.055)	(.049)
Income		.365**	.307**
		(.119)	(.115)
Constant	23.118**	−2.910	−10.874
	(3.857)	(6.473)	(24.535)
Average relative police pressure			17
% African Americans in average precinct			26.78
Adjusted R^2	.083	.266	.467
Precinct controls	No	No	Yes
Year fixed effects	No	Yes	Yes

Note. Estimates are from ordinary least squares regressions on 75 precincts. The dependent variable is (relative) police pressure (arrests of American Americans/African American population)/(arrests of whites/white population). Column 3 includes the variable for the margin of Mayor Michael Bloomberg's victory. Missing years are computed using moving averages for the variables for the fraction of African Americans, income, age, fraction of females, fraction of college degrees, serious crime, graffiti, social capital, and African American commanding officers. Regressions with year fixed effects (nine dummies) control for possible time trends in the dependent variable and precinct-specific characteristics. Standard errors, in parentheses, are clustered at the precinct level. $N = 750$ observations.

** Significant at the 1% level.

This table shows how stop and frisk activity is allocated by the 75 precincts.

Outcome variable = relative police pressure

This is calculated as:

If > 1, more arrests per capita for African Americans.

What Correlates with Relative Police Pressure?

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** Significant at the 1% level.

Column (1) shows that precincts with a higher % African American residents have per capita arrest rates that are lower for African Americans relative to whites.

(Could suggest, e.g., that in whiter precincts, African Americans are relatively more likely to get stopped.)

What Correlates with Relative Police Pressure?

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% African American	–.222**	–.057	–.066
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** Significant at the 1% level.

Adding precinct resident income estimates (column 2) makes this relationship between % American American and relative pressure disappear.

Instead, we see a strong positive relationship between income and relative pressure.

Interpretation: precincts where the residents are on-average richer have more relative police pressure on African Americans.

(So, you can think of this as police being more likely to stop and frisk African Americans in wealthier – often whiter – neighborhoods.)

How arrest rates, conditional on stop, vary by race?

Table 3. Arrests Made

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
African American	−.420**	−.437**	−.437	.379**	.355**	.355+	.340+
	(.037)	(.037)	(.469)	(.046)	(.046)	(.207)	(.204)
Constant	6.140**						
	(.034)						
Mean outcome							5.79
% African American							84
P-value				.001	.001	.001	.001
Year fixed effects	No	Yes	Yes	No	Yes	Yes	Yes
Precinct fixed effects	No	No	No	Yes	Yes	Yes	Yes
Year × precinct fixed effects	No	No	No	No	No	No	Yes

Note. Estimates are from ordinary least squares regressions. The dependent variable is the probability of being arrested conditional on being stopped in New York City (in %). Regressions with year fixed effects (nine dummies) and precinct fixed effects on 76 precincts (75 dummies) control for a possible time trend in the dependent variable and precinct-specific characteristics, respectively. Standard errors, in parentheses, are clustered at the precinct level in columns 3, 5, and 7. The *P*-value is for the joint test of all the precinct fixed effects equal to 0. $N = 2{,}947{,}865$.

+ Significant at the 10% level.

** Significant at the 1% level.

Outcome variable = arrests made conditional being stopped (i.e. arrests divided by stops, arrest rate given that a stop occurred) Key independent variable = African American The idea here is to see how being African American associates with arrest rates.

Columns (1) to (3) do not include precinct fixed effects.

Columns (4) to (7) do include precinct fixed effects.

How arrest rates, conditional on stop, vary by race?

Table 3. Arrests Made

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
African American	−.420**	−.437**	−.437	.379**	.355**	.355+	.340+
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Note. Estimates are from ordinary least squares regressions. The dependent variable is the probability of being arrested conditional on being stopped in New York City (in %). Regressions with year fixed effects (nine dummies) and precinct fixed effects on 76 precincts (75 dummies) control for a possible time trend in the dependent variable and precinct-specific characteristics, respectively. Standard errors, in parentheses, are clustered at the precinct level in columns 3, 5, and 7. The *P*-value is for the joint test of all the precinct fixed effects equal to 0. $N = 2{,}947{,}865$.

+ Significant at the 10% level.

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Precinct fixed effects means controlling for average differences between precincts in the outcome variable

In this case, controlling for average differences by precinct in arrest made

Columns (1) to (3) do not include precinct fixed effects

Columns (4) to (7) do include precinct fixed effects

How arrest rates, conditional on stop, vary by race?

Table 3. Arrests Made

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
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Constant	6.140**						
	(.034)						
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P-value				.001	.001	.001	.001
Year fixed effects	No	Yes	Yes	No	Yes	Yes	Yes
Precinct fixed effects	No	No	No	Yes	Yes	Yes	Yes
Year × precinct fixed effects	No	No	No	No	No	No	Yes

Note. Estimates are from ordinary least squares regressions. The dependent variable is the probability of being arrested conditional on being stopped in New York City (in %). Regressions with year fixed effects (nine dummies) and precinct fixed effects on 76 precincts (75 dummies) control for a possible time trend in the dependent variable and precinct-specific characteristics, respectively. Standard errors, in parentheses, are clustered at the precinct level in columns 3, 5, and 7. The *P*-value is for the joint test of all the precinct fixed effects equal to 0. $N = 2{,}947{,}865$.

+ Significant at the 10% level.

** Significant at the 1% level.

Without precinct fixed effects (col. 1 to 3), the data shows that African Americans are less likely to be arrested (conditional on stop)

With precinct fixed effects (col. 4 to 7), …. African Americans more likely to be arrested (conditional on stop)

How arrest rates, conditional on stop, vary by race?

Table 3. Arrests Made

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
African American	−.420**	−.437**	−.437	.379**	.355**	.355+	.340+
	(.037)	(.037)	(.469)	(.046)	(.046)	(.207)	(.204)
Constant	6.140**						
	(.034)						
Mean outcome							5.79
% African American							84
P-value				.001	.001	.001	.001
Year fixed effects	No	Yes	Yes	No	Yes	Yes	Yes
Precinct fixed effects	No	No	No	Yes	Yes	Yes	Yes
Year × precinct fixed effects	No	No	No	No	No	No	Yes

Note. Estimates are from ordinary least squares regressions. The dependent variable is the probability of being arrested conditional on being stopped in New York City (in %). Regressions with year fixed effects (nine dummies) and precinct fixed effects on 76 precincts (75 dummies) control for a possible time trend in the dependent variable and precinct-specific characteristics, respectively. Standard errors, in parentheses, are clustered at the precinct level in columns 3, 5, and 7. The *P*-value is for the joint test of all the precinct fixed effects equal to 0. $N = 2{,}947{,}865$.
+ Significant at the 10% level.
** Significant at the 1% level.

Interpretation: With precinct fixed effects, the idea is that <u>within the same precinct</u>, an African-American person is more likely to be arrested than a white person.

How arrest rates, conditional on stop, vary by race?

Table 3. Arrests Made

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
African American	−.420**	−.437**	−.437	.379**	.355**	.355+	.340+
	(.037)	(.037)	(.469)	(.046)	(.046)	(.207)	(.204)
Constant	6.140**						
	(.034)						
Mean outcome							5.79
% African American							84
P-value				.001	.001	.001	.001
Year fixed effects	No	Yes	Yes	No	Yes	Yes	Yes
Precinct fixed effects	No	No	No	Yes	Yes	Yes	Yes
Year × precinct fixed effects	No	No	No	No	No	No	Yes

Note. Estimates are from ordinary least squares regressions. The dependent variable is the probability of being arrested conditional on being stopped in New York City (in %). Regressions with year fixed effects (nine dummies) and precinct fixed effects on 76 precincts (75 dummies) control for a possible time trend in the dependent variable and precinct-specific characteristics, respectively. Standard errors, in parentheses, are clustered at the precinct level in columns 3, 5, and 7. The *P*-value is for the joint test of all the precinct fixed effects equal to 0. $N = 2{,}947{,}865$.

+ Significant at the 10% level.

** Significant at the 1% level.

Without the precinct fixed effects, we are comparing white and African American pedestrians both within the same precinct and between different precincts

If African Americans tend to more often be in precincts where they are often stopped and frisked, but not arrested, then that explain the negative estimates in columns (1) to (3)

Frisks, for pedestrians suspected of weapons possession

Table B5. Frisks, for Pedestrians Suspected of Weapons Possession

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
African American	4.900**	4.937**	4.938**	2.972**	2.996**	2.996+	2.900+
	(.164)	(.164)	(1.265)	(.184)	(.184)	(1.643)	(1.526)
Constant	83.058**						
	(.158)						
Mean outcome (%)	87.64						
% African American	93.5						
P-value				.001	.001	.001	.001
Year fixed effects	No	Yes	Yes	No	Yes	Yes	Yes
Precinct fixed effects	No	No	No	Yes	Yes	Yes	Yes
Year × precincts fixed effects	No	No	No	No	No	No	Yes

Note. Estimates are from ordinary least squares regressions. The dependent variable is the probability of being frisked in the sub-sample of stops on suspicion of weapons possession in New York City (in %). Regressions with year fixed effects (nine dummies) and precinct fixed effects for 76 precincts (75 dummies) control for a possible time trend in the dependent variable and precinct-specific characteristics, respectively. Standard errors, in parentheses, are clustered at the precinct level in columns 3, 6, and 7. The *P*-value is for the joint test of all the precinct fixed effects equal to 0.

+ Significant at the 10% level.

** Significant at the 1% level.

In all case (with and without precinct fixed effects) there is strong or at least weak evidence that African Americans are more likely to be frisks compared to whites

Summary of Results

- African Americans were about 9x more likely to be stopped and frisked
- About 53.7% (39.3%) of stops of African Americans (whites) develop into frisks
- After controlling for precinct-level fixed effects (average differences between precincts, so comparing white vs. African American in the same precinct), they find that white pedestrians are slightly less likely than African American pedestrians to be arrested conditional on being stopped
- Two interpretations of this point
- white pedestrians are slightly less likely than African American pedestrians in the same precinct to be arrested conditional on being stopped
- Interpretation 1) Suggestive in this case of no bias against African Americans, because whites are being stopped despite being slightly less productive stops for police officers (slightly lower arrest rate). Officers slightly "over stop" white pedestrians
- Interpretation 2) Another interpretation could be that officers are biased in their decisions to arrest, and are more likely to arrest African Americans
- It's difficult to determine to what extent it's 1) or 2) or a combination of both

Summary of Results

- When analyzing frisking, they find that after controlling for precinct-level fixed effects (so, comparing white vs. African American in the same precinct), African Americans are less likely than white pedestrians to be arrested conditional on being frisked
- In this case, this is suggestive of bias against African Americans in the decision to frisk
- Police may have been "over frisking" African American pedestrians
- But the authors note that further research is needed on this point

Antonovics and Knight (2009)

Boston Police Car Searching

Abstract: This paper provides new evidence on racial profiling using information on the race of both motorists and police officers in Boston. We develop a new test for distinguishing between preference-based (taste-based) and statistical discrimination. Our test is based on the notion that if search decisions are driven purely by statistical discrimination, then they should be independent of officer race. Our results, by contrast, demonstrate that officers are more likely to search if officer race and driver race differ. We then investigate and rule out two alternative explanations for our finding

Background

- The authors use a unique data set where they match the race of the police officer (white, black, Hispanic) with the race of the driver (white, black, Hispanic)
- They observe these officer-driver pairs for every traffic stop made by officers in the Boston Police Department from about April 2001 to April 2003
- They can use this data to determine:
    1. if certain racial groups are more likely to be searched
    2. if officers of certain races are more likely to search vehicles in general
    3. if officers of certain races are more likely to search drivers of certain races

Theory

- The authors observe that black drivers are more likely to be searched after being stopped
- The authors use this data on car stops and searches by driver and officer race to test to what extent discrimination in car searches is due to preference-based discrimination (**taste-based discrimination**) or **statistical discrimination**

What is animus?

- Also called preference-based discrimination
- Discrimination that occurs due to not liking or having animus against a group
  - Think outright racism, homophobia, sexism, transphobia, ageism, etc.
- The term was coined by Gary Becker, a famous labor economist who is known for being one of the first to apply economics to study discrimination in the labor market
- Unsurprisingly, taste-based discrimination is seen as uniformly bad, both because it is inequitable, but it also creates inefficiencies (e.g., inefficiently searching cars/people)

What is statistical discrimination?

- This theory is typically attributed to Kenneth Arrow's 1973 work The Theory of Discrimination and to Edmund Phelp's 1972 paper The Statistical Theory of Racism and Sexism
- The idea is that some discrimination is based on individuals using actual or perceived information about the differences between groups – i.e. actual or perceived statistical differences between groups
- Minority status – such as race or ethnicity – is used a proxy for something else

Statistical Discrimination: Policing

- Police offers could (and likely do) statistically discriminate in interactions with citizens
- They may, for example, be more likely to assume that people of color have done something wrong, have drugs in their car, etc.
- For these “reasons”, police may be more likely to search people of color through car searches, “stop and frisk” etc.
- In this example, race is used as a proxy for assumptions about criminality

Distinction between Taste-Based and Statistical Discrimination

- Antonovics and Knight (2009) use their data on traffics stops, and to what extent there were searches of vehicles by driver and officer rate to determine to what extent the discrimination they observe (higher search rates for black drivers) is due to taste-based discrimination or statistical discrimination
- If black/Hispanic drivers, conditional on being pulled over, are more likely to be searched than white drivers, and this **does not vary by officer race**, this is likely suggestive of statistical discrimination
  - All officers are assuming that those groups are more likely to have drugs, weapons, etc.
- If black/Hispanic drivers, conditional on being pulled over, are more likely to be searched than white drivers, and this **does vary by officer race**, this is likely suggestive of taste-based discrimination
- Officers of a particular race prefer to search motorists of a particular race more often, which likely reflects taste-based discrimination, since, otherwise, we would see similar behavior by officers of other races

Distinction between Taste-Based and Statistical Discrimination

- Antonovics and Knight (2009) thus conduct two tests:

1. Conditional on being stopped, do we see that black and/or Hispanic motorists are more likely to be searched, regardless of officer race? *If yes, there is statistical discrimination*
2. Conditional on being stopped, do we see that black and/or Hispanic motorists are more likely to be searched by white officers? *If yes, white officers exhibit taste-based discrimination against black and/or Hispanic motorists.*

Summary Statistics

TABLE 1.—PROBABILITY OF SEARCH BY OFFICER RACE AND DRIVER RACE
(standard deviation of sample mean in parentheses)

	Officer Race			
Driver Race	White	Black	Hispanic	All
White	0.40%	0.62%	0.25%	0.46%
	(0.04%)	(0.07%)	(0.09%)	(0.04%)
	n = 22,471	n = 11,132	n = 3,256	n = 36,859
Black	0.97%	0.82%	0.49%	0.87%
	(0.09%)	(0.09%)	(0.15%)	(0.06%)
	n = 13,131	n = 9,116	n = 2,258	n = 24,505
Hispanic	0.97%	0.82%	0.38%	0.85%
	(0.14%)	(0.16%)	(0.19%)	(0.10%)
	n = 5,058	n = 3,164	n = 1,066	n = 9,288
All	0.65%	0.73%	0.35%	0.65%
	(0.04%)	(0.06%)	(0.07%)	(0.03%)
	n = 40,660	n = 23,412	n = 6,580	n = 70,652

Note: Includes only officers for whom the search variable is missing for at most 10% of all citations. Stops involving drivers from other racial groups are not included.

1) Black and Hispanic drivers are more likely to be searched (rates of 0.87% and 0.85% versus 0.46%), and

2) In this raw data, Black officers are more likely than White officers to search (0.73% to 0.65%) and White officers are more likely than Hispanic officers to search (0.65% to 0.35%)

Summary Statistics

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	n = 40,660	n = 23,412	n = 6,580	n = 70,652

Note: Includes only officers for whom the search variable is missing for at most 10% of all citations. Stops involving drivers from other racial groups are not included.

These trends could be affected by neighborhoods, however, where perhaps black officers work in neighborhoods where search rates happen to be higher (e.g., higher crime areas)

For this reason, it's important to add neighborhood fixed effects

These fixed effects control for neighborhoods, which will have different search rates, and police officers of different races will be allocated to different neighborhoods

Summary Statistics

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Note: Includes only officers for whom the search variable is missing for at most 10% of all citations. Stops involving drivers from other racial groups are not included.

Once neighborhood fixed effects are added, the interpretation is a comparison between white, black, and Hispanic drivers pulled over at stops <u>within the same neighborhood</u> by white, black, or Hispanic officers working in that same <u>neighborhood</u>.

Results

Table 4.—Probability of Search and Guilt Conditional on Search, Officer Race Excluded

	Unweighted Probits		Weighted Probits	
	Search	Guilt	Search	Guilt
Black driver	0.213***	−0.472	0.387***	−0.622
	(0.059)	(0.388)	(0.144)	(0.464)
Hispanic driver	0.144	−0.228	0.219	0.262
	(0.108)	(0.409)	(0.163)	(0.452)
Stop at night	0.154	0.012	0.201*	−0.487
	(0.101)	(0.329)	(0.116)	(0.349)
Young driver (Age $<$ 26)	0.087**	−0.314	0.110	−0.413
	(0.038)	(0.236)	(0.129)	(0.367)
Male driver	0.064	−0.188	0.096	−0.062
	(0.046)	(0.261)	(0.123)	(0.365)
In-state driver	0.084		0.246	
	(0.092)		(0.194)	
In-town driver	0.028	−0.030	0.032	0.045
	(0.036)	(0.335)	(0.105)	(0.402)
Accident	0.854***	−0.138	0.022	0.481
	(0.153)	(0.433)	(0.188)	(0.531)
Neighborhood controls	YES	YES	YES	YES
Observations	70,652	369	70,652	369

Heteroskedasticity-robust standard errors clustered at the officer level in parentheses.
*significant at 10%; **significant at 5%; ***significant at 1%.

Without looking at the race of the police officer, these results show that black drivers are more likely to be searched (significant at the 1% level)

But are NOT more likely to be guilty, suggesting that this extra searching of black drivers is inefficient. (The coefficient is actually negative, although the SE is large so its insignificant)

No clear evidence that Hispanics are more likely to be searched (coefficient is positive but SE is quite large)

Results

PECIFICATION

	Weighted Probits		
	(4)	(5)	(6)
Black driver	0.167	0.144	0.204
	(0.126)	(0.126)	(0.142)
Hispanic driver	0.061	0.023	−0.006
	(0.166)	(0.174)	(0.176)
Black officer	−0.134	−0.115	−0.085
	(0.134)	(0.134)	(0.135)
Hispanic officer	−0.487*	−0.511*	−0.501**
	(0.279)	(0.269)	(0.249)
Mismatch	0.354***	0.355***	0.345***
	(0.126)	(0.125)	(0.121)
Stop at night		0.207*	0.208*
		(0.123)	(0.117)
Young driver (Age $<$ 26)		0.101	0.106
		(0.128)	(0.126)
Male driver		0.100	0.088
		(0.128)	(0.122)
In-state driver		0.255	0.254
		(0.182)	(0.185)
In-town driver		−0.015	0.025
		(0.099)	(0.105)
Accident		0.036	0.018
		(0.179)	(0.188)
Neighborhood controls	NO	NO	YES
Observations	70,652	70,652	70,652

This table adds in officer race and a mismatch variable

The coefficient on black (Hispanic) driver tells you how the search probability differs compared to white drivers. Positive = more likely to be searched than white drivers

The coefficient on black (Hispanic) officer tells you how the search probability differs compared to white officer. Positive = more likely to search than white officers

Mismatch = 1 if the driver and officer race are not the same, 0 otherwise

We also see that Hispanic officers, compared to white officers, are much less likely to search drivers, regardless of the driver's race

Results

PECIFICATION

	Weighted Probits		
	(4)	(5)	(6)
Black driver	0.167	0.144	0.204
	(0.126)	(0.126)	(0.142)
Hispanic driver	0.061	0.023	−0.006
	(0.166)	(0.174)	(0.176)
Black officer	−0.134	−0.115	−0.085
	(0.134)	(0.134)	(0.135)
Hispanic officer	−0.487*	−0.511*	−0.501**
	(0.279)	(0.269)	(0.249)
Mismatch	0.354***	0.355***	0.345***
	(0.126)	(0.125)	(0.121)
Stop at night		0.207*	0.208*
		(0.123)	(0.117)
Young driver (Age < 26)		0.101	0.106
		(0.128)	(0.126)
Male driver		0.100	0.088
		(0.128)	(0.122)
In-state driver		0.255	0.254
		(0.182)	(0.185)
In-town driver		−0.015	0.025
		(0.099)	(0.105)
Accident		0.036	0.018
		(0.179)	(0.188)
Neighborhood controls	NO	NO	YES
Observations	70,652	70,652	70,652

We see that the coefficient on black driver is now insignificant compared to earlier

This means that we don't have enough evidence to suggest that black drivers are searched more often when there is NOT a race mismatch between driver and officer (i.e., mismatch = 0)

When we do have a mismatch (mismatch = 1), then searches are significantly more likely

This suggests that what is driving the additional searches done against black drivers is officers of a different race

This is most likely driven by extra searches by white officers since (1) there are more white officers than Hispanic officers in Boston, by far, and (2) white officers are more likely to search

Results

PECIFICATION

	Weighted Probits		
	(4)	(5)	(6)
Black driver	0.167	0.144	0.204
	(0.126)	(0.126)	(0.142)
Hispanic driver	0.061	0.023	−0.006
	(0.166)	(0.174)	(0.176)
Black officer	−0.134	−0.115	−0.085
	(0.134)	(0.134)	(0.135)
Hispanic officer	−0.487*	−0.511*	−0.501**
	(0.279)	(0.269)	(0.249)
Mismatch	0.354***	0.355***	0.345***
	(0.126)	(0.125)	(0.121)
Stop at night		0.207*	0.208*
		(0.123)	(0.117)
Young driver (Age $<$ 26)		0.101	0.106
		(0.128)	(0.126)
Male driver		0.100	0.088
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		(0.179)	(0.188)
Neighborhood controls	NO	NO	YES
Observations	70,652	70,652	70,652

These extra searches of black drivers by white officers suggests taste-based discrimination since if it were statistical discrimination, then officers of other races would be searching at similar rates

These extra searches, driven by taste-based discrimination, are inefficient since, as we saw earlier, black drivers are no more likely (and are perhaps less likely) to be guilty

There is no statistical reason to search black drivers more, suggesting again that these extra searches stem from taste-based discrimination