
A Collection of Methods for Racial Profiling Analysis

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Racial profiling is a growing concern

Introduction

- ❖ Racial profiling is a growing concern
- ❖ Analytic quality is weak
- ❖ Why is testing for racial profiling so hard?
- ❖ Why is testing for racial profiling so hard?
- ❖ Why is testing for racial profiling so hard?
- ❖ A new approach

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Summary

- I-95 “turnpike” studies in the mid-1990s raised public concern about racial profiling
- Public concern has led to state and local-level action
 - ❖ At least 26 states have passed legislation
 - ❖ Hundreds of other localities collect data; some compelled by the Justice Department
- Congress considering the End of Racial Profiling Act mandating data collection to receive Federal funds
- Should officers use racial profiling?
 - ❖ Tenth Circuit: “unequal application of criminal law to white and black persons was one of the central evils addressed by the framers of the Fourteenth Amendment”

Analytic quality is weak

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- A growing number of studies claim racial profiling based on analysis of data collected
 - ❖ **Texas:** Concluded that “75% of agencies stop more black and Latino drivers than white drivers”
- And some studies hastily conclude no profiling occurs based on analyzed data
 - ❖ **Sacramento:**
% black drivers stopped =
% black crime suspect descriptions

Why is testing for racial profiling so hard?

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Racial Distribution of People Stopped

Racial Distribution of People at Risk of Being Stopped

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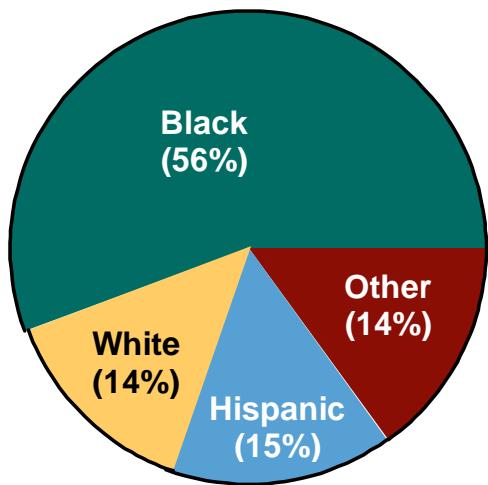
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Racial Distribution of People Stopped



Racial Distribution of People at Risk of Being Stopped

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Why is testing for racial profiling so hard?

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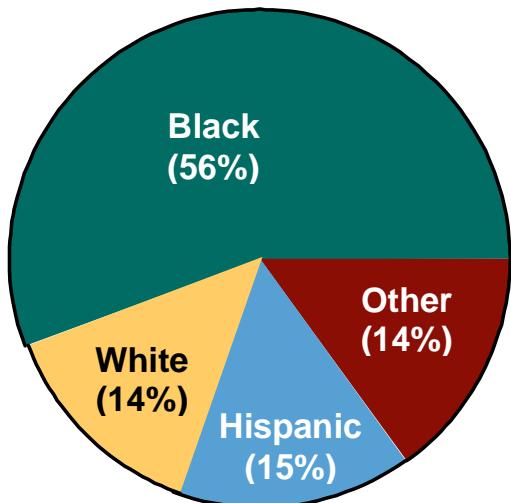
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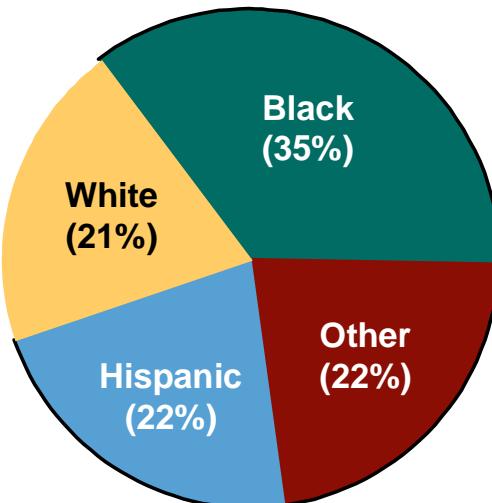
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Summary

Racial Distribution of People Stopped



Racial Distribution of Residents According to the Census



- The difference may result from:
 - ❖ A race bias
 - ❖ Car ownership, time on the road, and care
 - ❖ Exposure to police

A new approach

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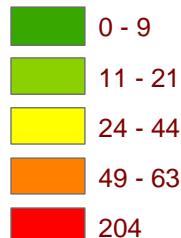
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Summary

- Gauge department wide racial bias in the decision to stop
- Identify potential problem officers with internal benchmarking
- Assess racial bias in post-stop activity with propensity scores

Use of force incidents



Step #1: Bias in the decision to stop

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Bias in the decision
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❖ Simple veil of
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❖ Adjusting for
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❖ Development of
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❖ Accommodate
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❖ Decomposition of
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❖ Results
❖ Results

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Summary

Groger & Ridgeway (2006). “Testing for Racial Profiling in Traffic Stops from Behind a Veil of Darkness,” *JASA* 101(475):878-887.

Central question: Does an officer’s ability to identify race of driver in advance influence which drivers he stops?

- The ability to discriminate requires officers identifying the race in advance (e.g. Goldin & Rouse, bias in orchestra auditions)
- The ability to identify race in advance of the stop decreases as it becomes dark
- We directly test whether the ability to identify the race affects the race distribution of the stopped drivers

Simple veil of darkness test

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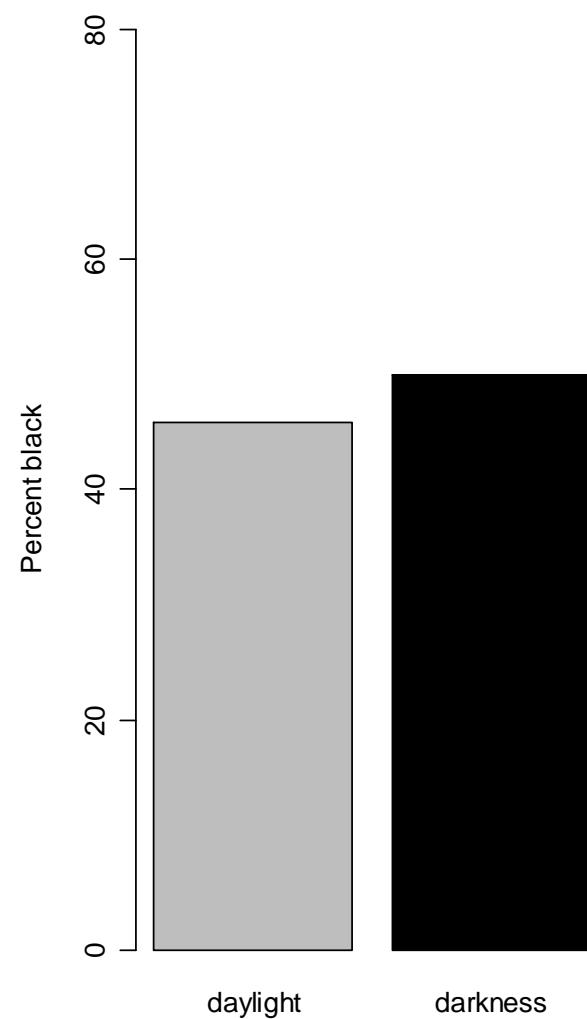
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Summary

- CPD officers stop a greater proportion of black drivers at night than during the day
- This is counter to the racial profiling hypothesis



Adjusting for “clock time”

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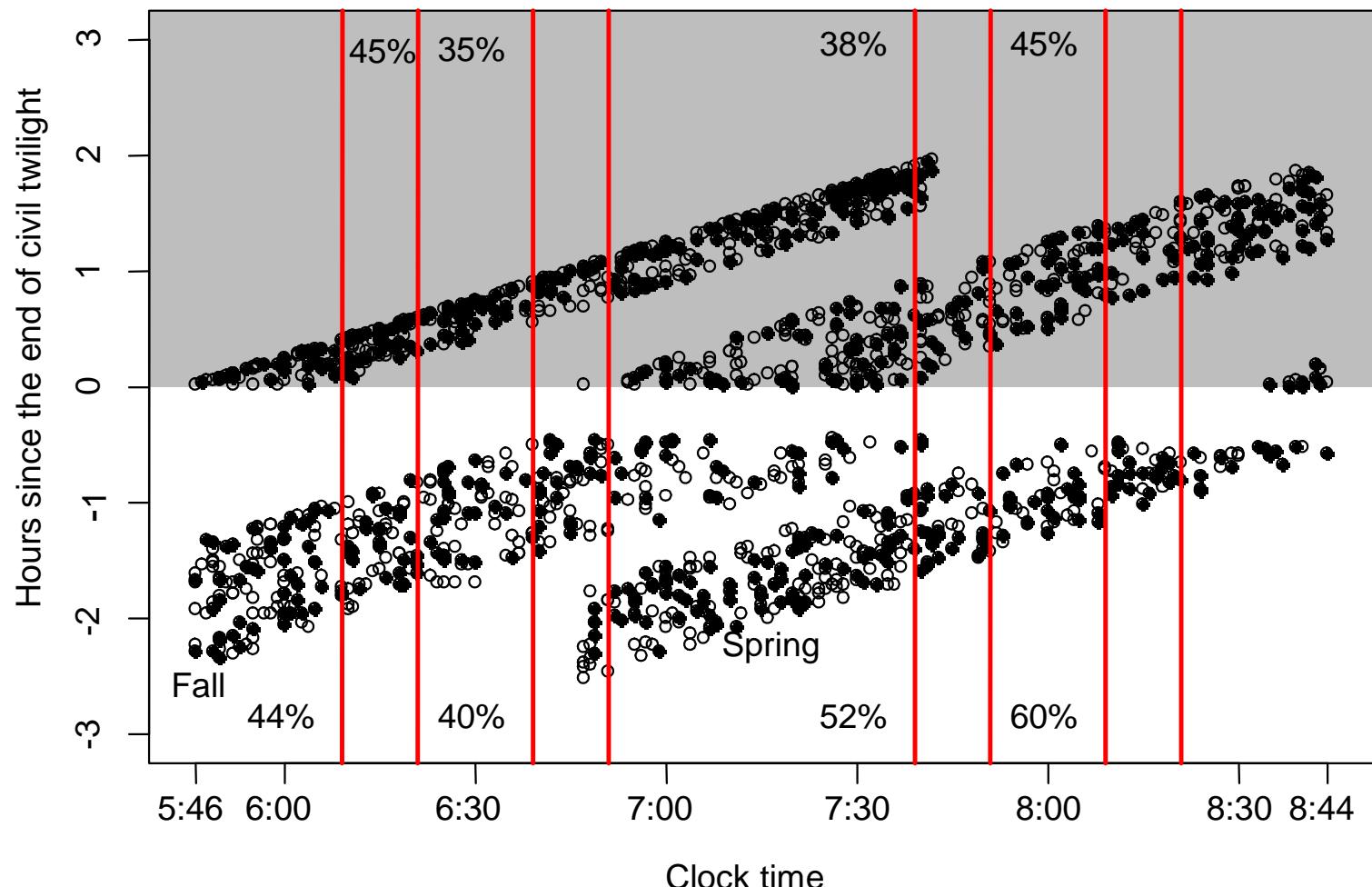
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Development of the test

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- In the absence of a race bias $K(t) = 1$

$$\frac{P(S|B, t, d = 0)}{P(S|\bar{B}, t, d = 0)} = K(t) \frac{P(S|B, t, d = 1)}{P(S|\bar{B}, t, d = 1)}$$

- Bayes' Theorem and some algebra yield

$$K(t) = \frac{P(B|S, t, d = 0)}{P(\bar{B}|S, t, d = 0)} \frac{P(\bar{B}|S, t, d = 1)}{P(B|S, t, d = 1)} \\ = \frac{P(\bar{B}|t, d = 0)}{P(B|t, d = 0)} \frac{P(B|t, d = 1)}{P(\bar{B}|t, d = 1)}$$

Accommodate underreporting

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- There is some potential underreporting

$$P(B|S, t, d) = \frac{P(B|R, S, t, d)P(R|S, t, d)}{P(R|B, S, t, d)}$$

$$\log K(t) =$$

$$\log \frac{P(B|R, S, t, d = 0)}{1 - P(B|R, S, t, d = 0)} - \log \frac{P(B|R, S, t, d = 1)}{1 - P(B|R, S, t, d = 1)} +$$
$$\log \frac{P(\bar{B}|t, d = 0)}{P(B|t, d = 0)} \frac{P(B|t, d = 1)}{P(\bar{B}|t, d = 1)} +$$
$$\log \frac{P(R|\bar{B}, S, t, d = 0)}{P(R|\bar{B}, S, t, d = 1)} \frac{P(R|B, S, t, d = 1)}{P(R|B, S, t, d = 0)}$$

Decomposition of the race effect

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$$\log K(t) = \text{stop distribution} + \text{exposure} + \text{reporting}$$

- We can estimate the stop ratio using logistic regression

$$\log \frac{P(B|R, S, d, t)}{1 - P(B|R, S, d, t)} = \beta_0 + \beta_1 d + g(t)$$

- $g(t)$ is some flexible function of t (e.g. $t + t^2 + t^3$)
- Assume exposure term is 0
- Assume reporting term is 0
- $\log K(t) = -\beta_1$

Results: VoD estimates of bias, all months

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Year	$K(t)$	95% interval	N
2003	1.01	(0.88,1.16)	4,013
2004	0.98	(0.86,1.12)	4,589
2005	1.07	(0.98,1.16)	10,890
Combined	1.02	(0.95,1.09)	19,492

- Includes all stops during the evening intertwilight period

Results: VoD estimates of bias, Daylight Savings Time

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Year	$K(t)$	95% interval	N
2003	1.15	(0.79,1.68)	470
2004	1.19	(0.79,1.80)	403
2005	1.11	(0.81,1.52)	764
Combined	1.10	(0.91,1.33)	1,637

- Includes all stops occurring within four weeks of the spring or fall Daylight Saving Time change during the evening intertwilight period

Step #2: Internal benchmarking

- Consider a particular officer #534
- 71% of this officer's stops involve a black driver

		Percentage
Time	(12-4pm]	9
	(4-8pm]	57
	(8pm-12am]	34
Day	Mon	20
	Tue	12
	Wed	12
	:	:
	Month	
Month	Jan	12
	Feb	14
	Mar	7
	Apr	6
	May	8
Area	:	:
	J	49
	K	33
	L	5
	M	11

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❖ Common
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❖ Estimating the
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Internal benchmark

- 46% of similarly situated stops made by other officers involved black drivers

		Percentage	Comparison
Time	(12-4pm]	9	9
	(4-8pm]	57	56
	(8pm-12am]	34	35
Day	Mon	20	20
	Tue	12	11
	Wed	12	12
	:	:	:
	Month	12	12
	Jan	12	12
	Feb	14	15
	Mar	7	7
	Apr	6	6
	May	8	7
Area	:	:	:
	J	49	48
	K	33	34
	L	5	5
	M	11	11

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Summary

- Reweight stops that other officers made so that they have the same distribution of features

$$f(\mathbf{x}|t = 1) = w(\mathbf{x})f(\mathbf{x}|t = 0)$$

- Solving for $w(\mathbf{x})$ yields the propensity score weight

$$w(\mathbf{x}) = \frac{f(t = 1|\mathbf{x})}{f(t = 0|\mathbf{x})}K = \frac{p(\mathbf{x})}{1 - p(\mathbf{x})}K$$

where $p(\mathbf{x})$ is the probability that a stop with features \mathbf{x} involves the officer in question

- Estimate $p(\mathbf{x})$ using a flexible, non-parametric version of logistic regression
- Compare the percentage of black drivers among the officer's stops with the weighted percentage of black drivers among other stops using weights

$$w_i = p(\mathbf{x}_i)/(1 - p(\mathbf{x}_i))$$

Common approach

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- A common approach is to compute z-statistics for each officer

$$z = \frac{p_t - p_c}{\sqrt{\frac{p_t(1-p_t)}{n_t} + \frac{p_c(1-p_c)}{ESS}}}$$

- In the absence of racial bias this would be distributed $N(0,1)$ and a cutoff of 2.0 would be reasonable
- With 133 officers and 133 correlated zs an appropriate reference distribution can be much wider (Efron 2006).

Estimating the false discovery rate

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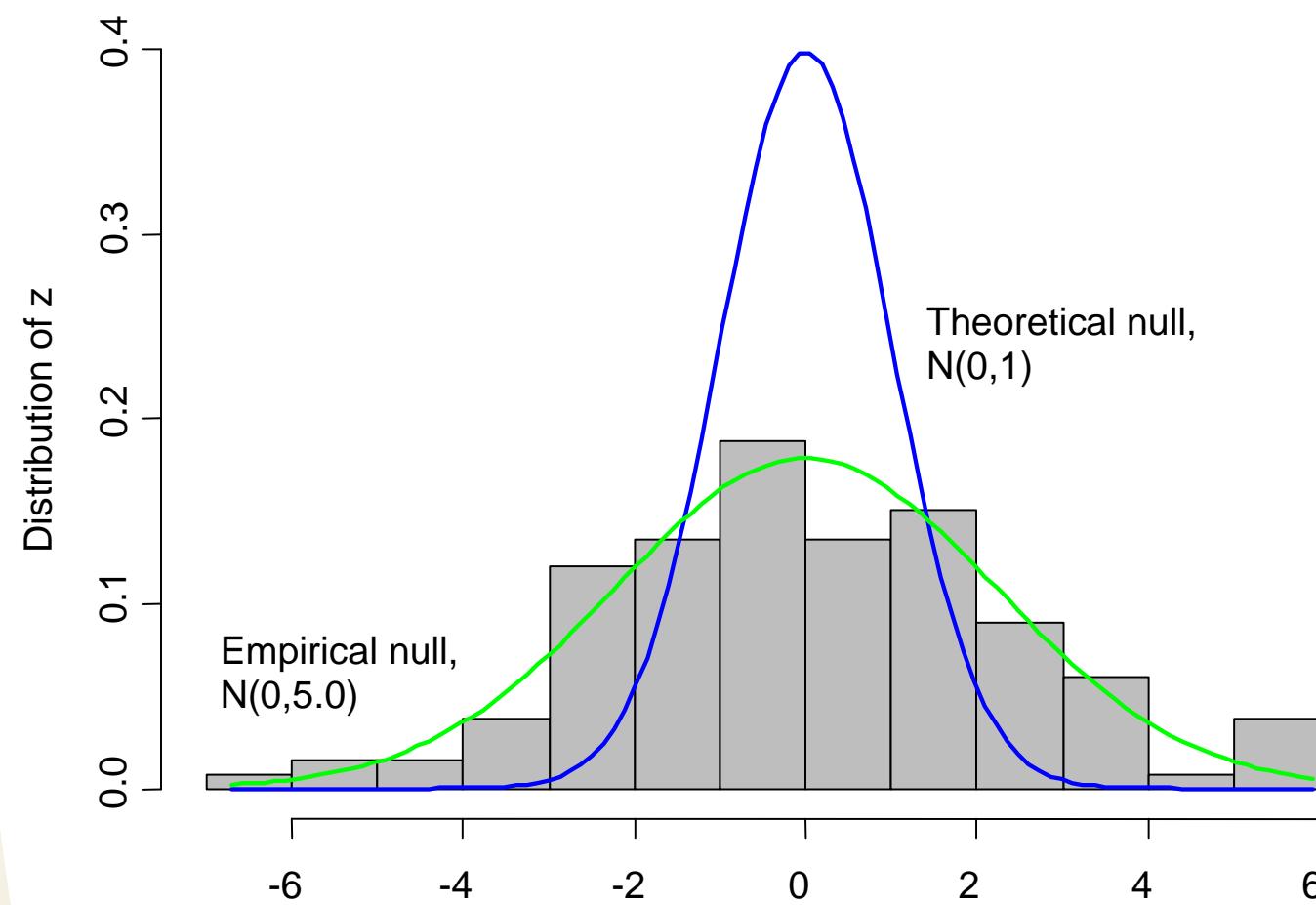
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Summary

- Estimate $f_0(z)$ and $f(z)$ from the observed zs
- Right tail consists of 5 officers with “problem officer” probabilities ranging from 70% to 86%



Step #3: Assessing race bias post-stop

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❖ Reweighting balances the group

❖ Results:
Cincinnati stop duration

❖ Results:
Cincinnati search rates

Summary

G. Ridgeway (2006). "Assessing the effect of race bias in post-traffic stop outcomes using propensity scores," *JQC* 22(1):1-29.

- **Central question:** Are black drivers more/less likely to be cited, have long stop durations, or be searched?

Stop feature	% Black drivers (N=3,703)	% Nonblack drivers (N=3,033)
Region A	32%	14%
Time of day 12am-4am	16%	8%
Resident	76%	64%
Age 18-29	47%	38%
Reason Mechanical/ Registration	26%	16%
Male	75%	74%

Reweighting balances the group

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❖ Results:
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Summary

● $w(\mathbf{x}) = \frac{P(\text{black}|\mathbf{x})}{1-P(\text{black}|\mathbf{x})}$

Stop feature	% Black drivers (N=3,703)	% Nonblack drivers weighted (ESS=1,689.2)	% Nonblack drivers (N=3,033)
Region			
A	32%	33%	14%
Time of day			
12am-4am	16%	16%	8%
Resident	76%	76%	64%
Age			
18-29	47%	48%	38%
Reason			
Mechanical/ Registration	26%	26%	16%
Male	75%	76%	74%

Results: Cincinnati stop duration

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Year	Stop Duration (Minutes)	Black Drivers	Nonblack (reweighted)	Nonblack (unweighted)
2003	$n =$ (0,10)	16,708 40%	4,881 43%	18,548 56%
2004	$n =$ (0,10)	18,721 40%	5,190 44%	20,390 59%
2005	$n =$ (0,10)	15,571 45%	4,965 47%	20,431 60%

- Black drivers in 2005 were three times more likely to have invalid licenses than white drivers (23% vs. 7%)

Results: Cincinnati search rates

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Summary

Year	Discretion (Minutes)	Black Drivers	Nonblack (reweighted)	Nonblack (unweighted)
2003	$n =$	16,708	4,881	18,548
	High	5.9%	5.4%	2.8%
	Low	8.1%	5.5%	2.7%
2004	$n =$	18,721	5,190	20,390
	High	6.7%	6.2%	3.2%
	Low	10.7%	7.0%	3.9%
2005	$n =$	19,375	6,141	25,163
	High	6.1%	5.2%	2.8%
	Low	4.4%	3.5%	1.6%

- Hit rates for black and white drivers are about 28% for high discretion searches.

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- Racial profiling analyses have generally confused the issue by studying irrelevant comparisons
- Credible and relevant comparisons are not difficult
 - ❖ Assess whether the ability to identify race in advance influences who gets stopped
 - ❖ Compare similarly situated officers
 - ❖ Equalize race groups on the obvious features on which they might legitimately differ

For more information

- Oakland 2003 report endorsed by OPD, the ACLU, the NAACP, and the Oakland CPRB
- Oakland Tribune reported “blacks are more likely than other races to be pulled over by police”
- Cincinnati Enquirer “Study: No bias in traffic stops, But many perceive discrimination based on race”

More available at <http://www.i-pensieri.com/gregr/rp.shtml> or Google “racial profiling analysis” or “Greg Ridgeway”

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