
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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- I-95 “turnpike” studies in the mid-1990s raised public concern about racial profiling
- Public concern has led to widespread action
 - ❖ 26 states have passed legislation and hundreds of cities collect data
- The End of Racial Profiling Act of 2007 would mandate 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

Why is testing for racial profiling so hard?

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- ❖ A new approach

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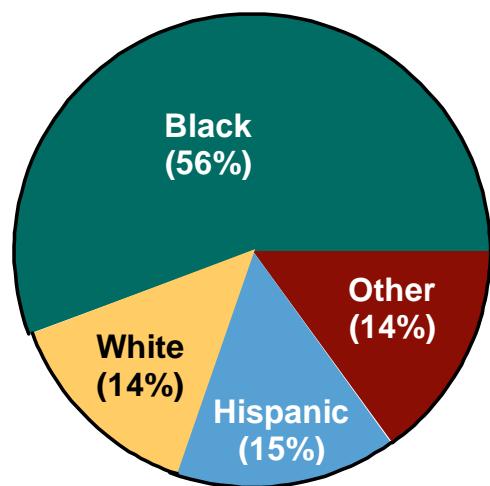
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Racial Distribution of People Stopped



Racial Distribution of People at Risk of Being Stopped

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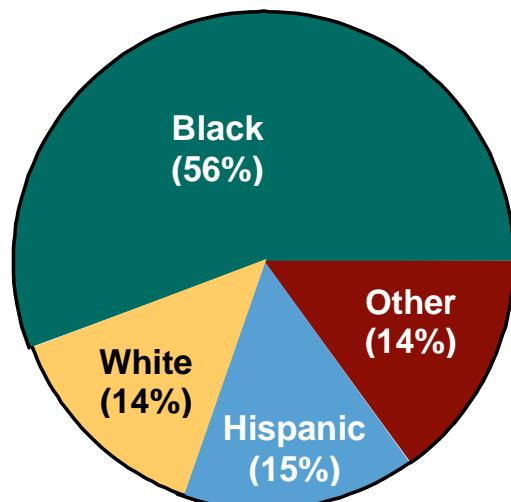
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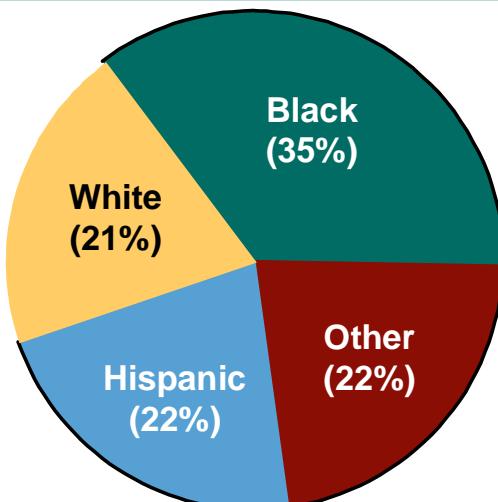
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Racial Distribution of People Stopped



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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- 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 to stop](#)

❖ Central question

❖ Simple veil of darkness test

❖ Adjusting for “clock time”

❖ Development of the test

❖ Accommodate underreporting

❖ Decomposition of the race effect

❖ Results

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Groger & Ridgeway (2006). “Testing for Racial Profiling in Traffic Stops from Behind a Veil of Darkness,” *JASA* 101(475):878-887. ASA 2007 Outstanding Statistical Application

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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❖ Accommodate underreporting

❖ Decomposition of the race effect

❖ Results

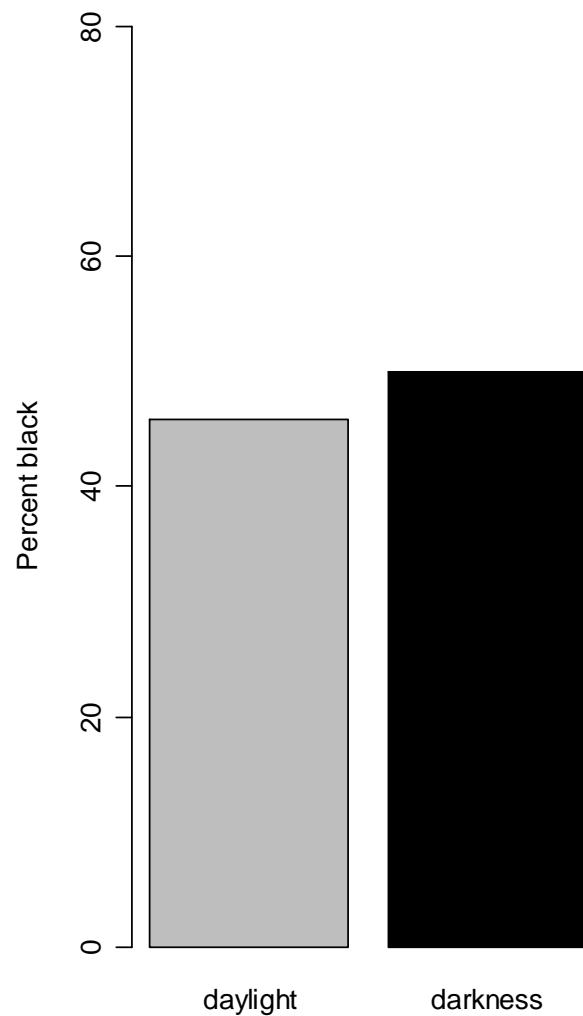
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- CPD officers stop a greater proportion of black drivers at night than during the day
- This is counter to the racial profiling hypothesis



Adjusting for “clock time”

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❖ Decomposition of the race effect

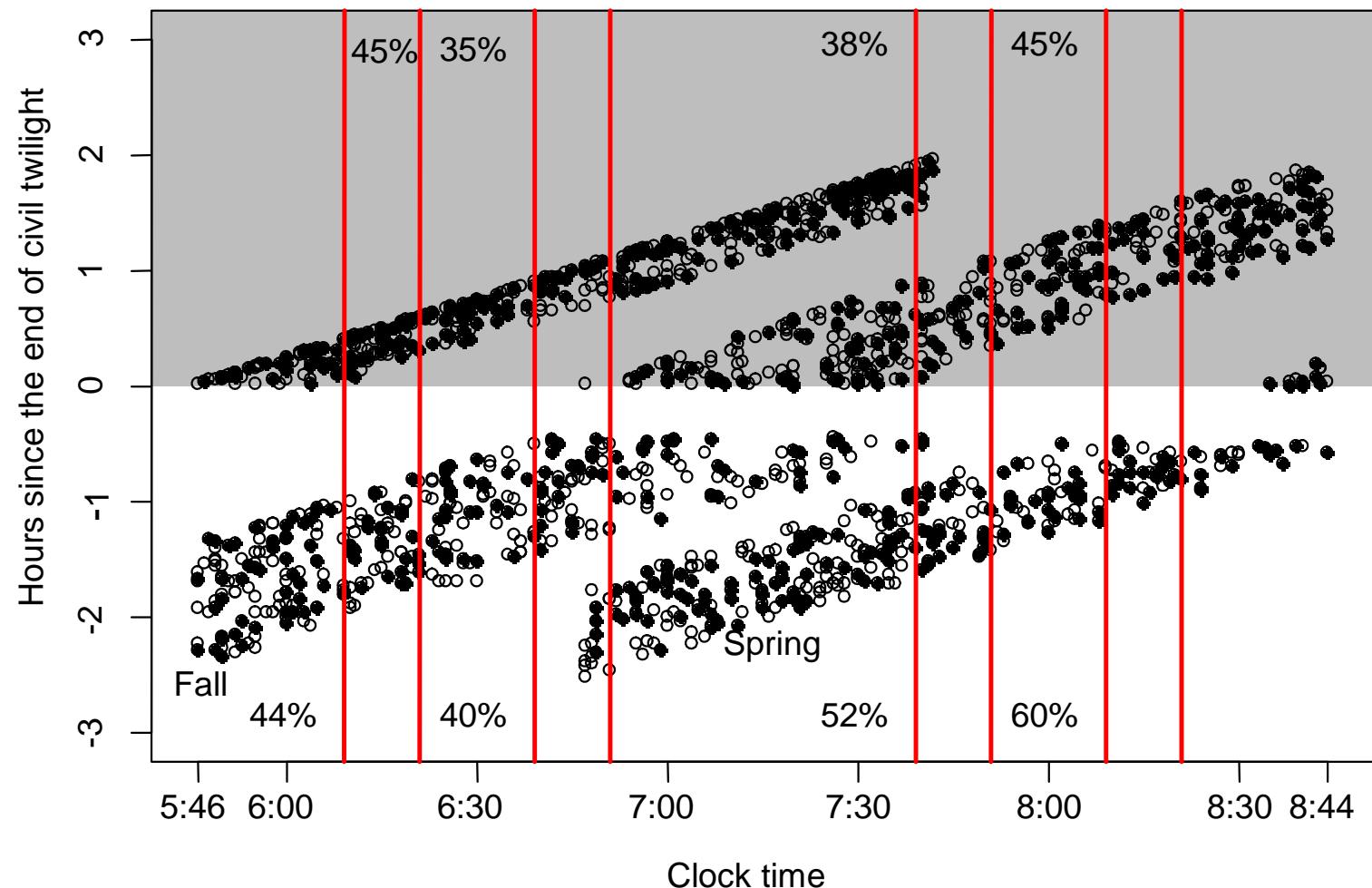
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Development of the test

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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 and reporting terms are 0
- $\log K(t) = -\beta_1$

Results: VoD estimates of bias, Daylight Savings Time

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Year	$K(t)$	95% interval	N
2003	1.02	(0.70,1.47)	543
2004	1.19	(0.80,1.77)	465
2005	1.10	(0.81,1.51)	763
2006	0.71	(0.51,1.00)	606
2007	1.17	(0.87,1.60)	751
2008	0.83	(0.59,1.60)	598
Combined	0.96	(0.84,1.11)	3,726

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

Step #2: *Internal benchmarking*

G. Ridgeway and J.M. MacDonald (2009). “Doubly Robust Internal Benchmarking and False Discovery Rates for Detecting Racial Bias in Police Stops.” *JASA* 104:661–668.

- 83% of this officer's stops involve a black driver

Stop Characteristic	Example Officer (%) (n = 392)
Month	January
	February
	March
Day of the week	Monday
	Tuesday
	Wednesday
Time of day	(4-6 p.m.)
	(6-8 p.m.)
	(8-10 p.m.)
	(10 p.m. -12 a.m.)
Patrol borough	Brooklyn North
Precinct	B
	C
Outside	96
In uniform	Yes
Radio run	Yes

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Bias in the decision to stop

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❖ Central question

❖ Internal benchmark

❖ Stop locations are well matched

❖ Propensity score weighting

❖ Common approach

❖ Estimating the false discovery rate

❖ Flagged officers show large disparities

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- 78% of similarly situated stops made by other officers involved black drivers

Stop Characteristic	Example Officer (%) (n = 392)	Internal Benchmark (%) (ESS = 3,676)
Month	January	3
	February	4
	March	8
Day of the week	Monday	13
	Tuesday	11
	Wednesday	14
Time of day	(4-6 p.m.]	9
	(6-8 p.m.]	8
	(8-10 p.m.]	23
	(10 p.m. -12 a.m.]	17
Patrol borough	Brooklyn North	100
Precinct	B	98
	C	1
Outside		96
In uniform	Yes	99
Radio run	Yes	1
		3

Stop locations are well matched

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❖ Common approach

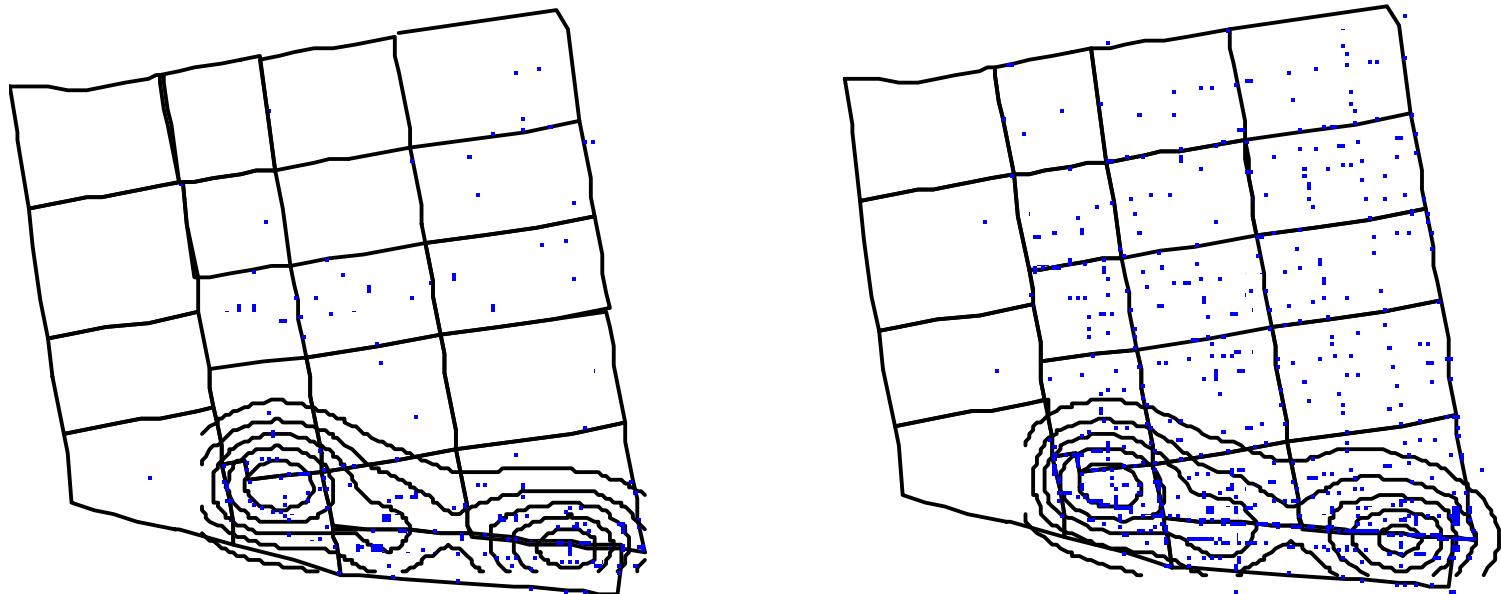
❖ Estimating the false discovery rate

❖ Flagged officers show large disparities

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- The internal benchmarking method also matches on the higher dimensional margins

Propensity score weighting

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❖ Propensity score weighting

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- ❖ Estimating the false discovery rate
- ❖ Flagged officers show large disparities

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- 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 2,756 officers and 2,756 correlated z s an appropriate reference distribution can be much wider (Efron 2006).

Estimating the false discovery rate

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- ❖ Stop locations are well matched
- ❖ Propensity score weighting

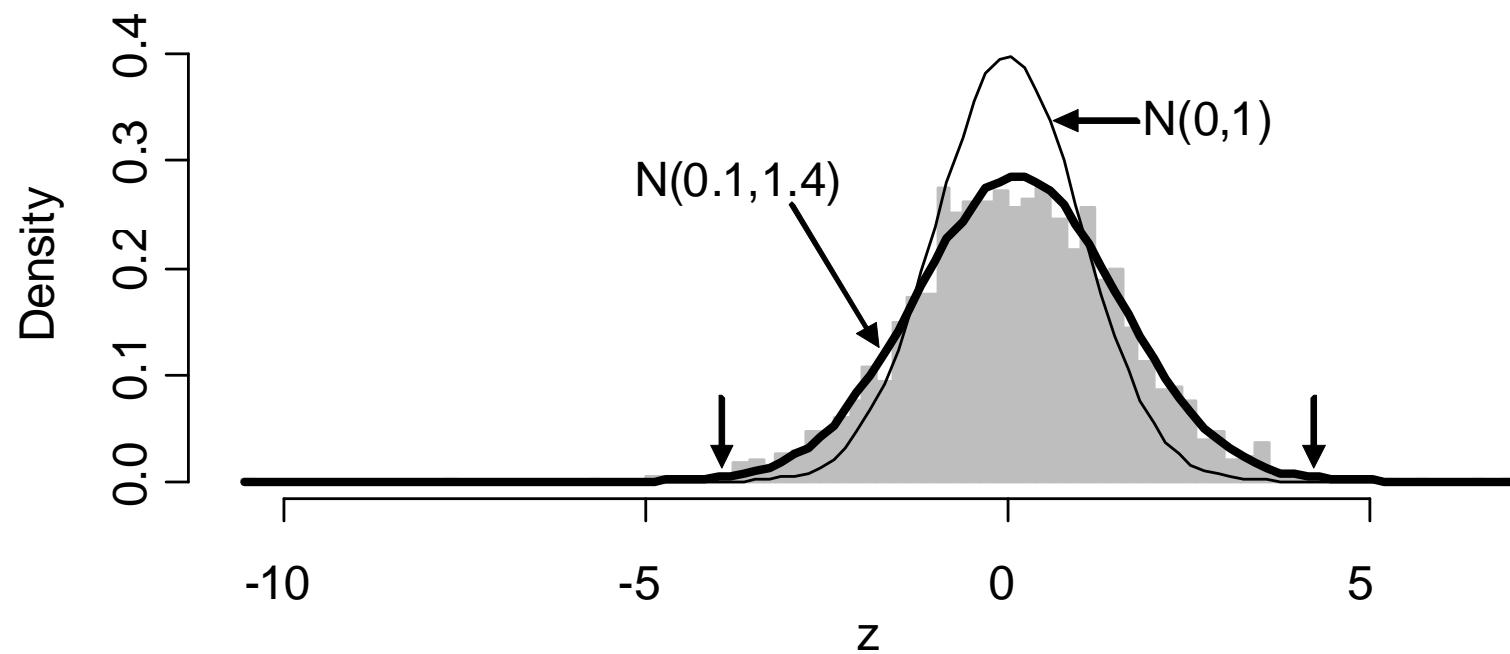
- ❖ Common approach
- ❖ Estimating the false discovery rate

- ❖ Flagged officers show large disparities

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- Estimate $f_0(z)$ and $f(z)$ from the observed zs
- Right tail consists of 5 officers with “problem officer” probabilities in excess of 50%
- Standard cutoff of $z > 2.0$ flags 242 officers, 90% of which have fdr estimated to be greater than 0.999

Flagged officers show large disparities

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Officer	Black (%)	Officer	Stops (n)	fdr
	Benchmark		Benchmark	
86	55	151	773	0.03
85	67	218	473	0.38
77	56	237	1,081	0.14
75	51	178	483	0.22
64	20	59	695	0.02

Several current systems have statistical flaws

- LAPD's TEAMS II Risk Management Information System
- Pittsburgh's Performance Assessment and Review System
- Cincinnati's Risk Management System
- Phoenix's Personnel Assessment System

Step #3: Assessing race bias post-stop

G. Ridgeway (2006). "Assessing the effect of race bias in post-traffic stop outcomes using propensity scores," *J. Quantitative Criminology* 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=26,941)	% Nonblack drivers (N=25,149)
Invalid license	22%	7%
Male	65%	66%
Neighborhood		
Over-the-Rhine	9%	5%
Avondale	5%	1%
Downtown	2%	4%
I-75	4%	11%
Residence		
Cincinnati	93%	61%
Date & Time		
12am-4am	16%	8%
Monday	15%	14%
August	9%	11%
Age		
18-25	33%	29%
Reason		
Equipment violation	27%	16%
Moving violation	51%	76%

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❖ Central question

❖ Reweighting balances the group

❖ Results: Stop durations in Cincinnati

❖ Results: Search rates in Cincinnati

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Reweighting balances the group

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

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❖ Central question

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❖ Results: Stop durations in Cincinnati

❖ Results: Search rates in Cincinnati

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Stop feature	% Black drivers (N=26,941)	% Nonblack drivers weighted (ESS=4,952)	% Nonblack drivers (N=25,149)
Invalid license	22%	20%	7%
Male	65%	65%	66%
Neighborhood			
Over-the-Rhine	9%	10%	5%
Avondale	5%	5%	1%
Downtown	2%	2%	4%
I-75	4%	5%	11%
Residence			
Cincinnati	93%	92%	61%
Date & Time			
12am-4am	16%	16%	8%
Monday	15%	15%	14%
August	9%	9%	11%
Age			
18-25	33%	32%	29%
Reason			
Equipment violation	27%	28%	16%
Moving violation	51%	52%	76%

Results: Stop durations in Cincinnati

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❖ Central question

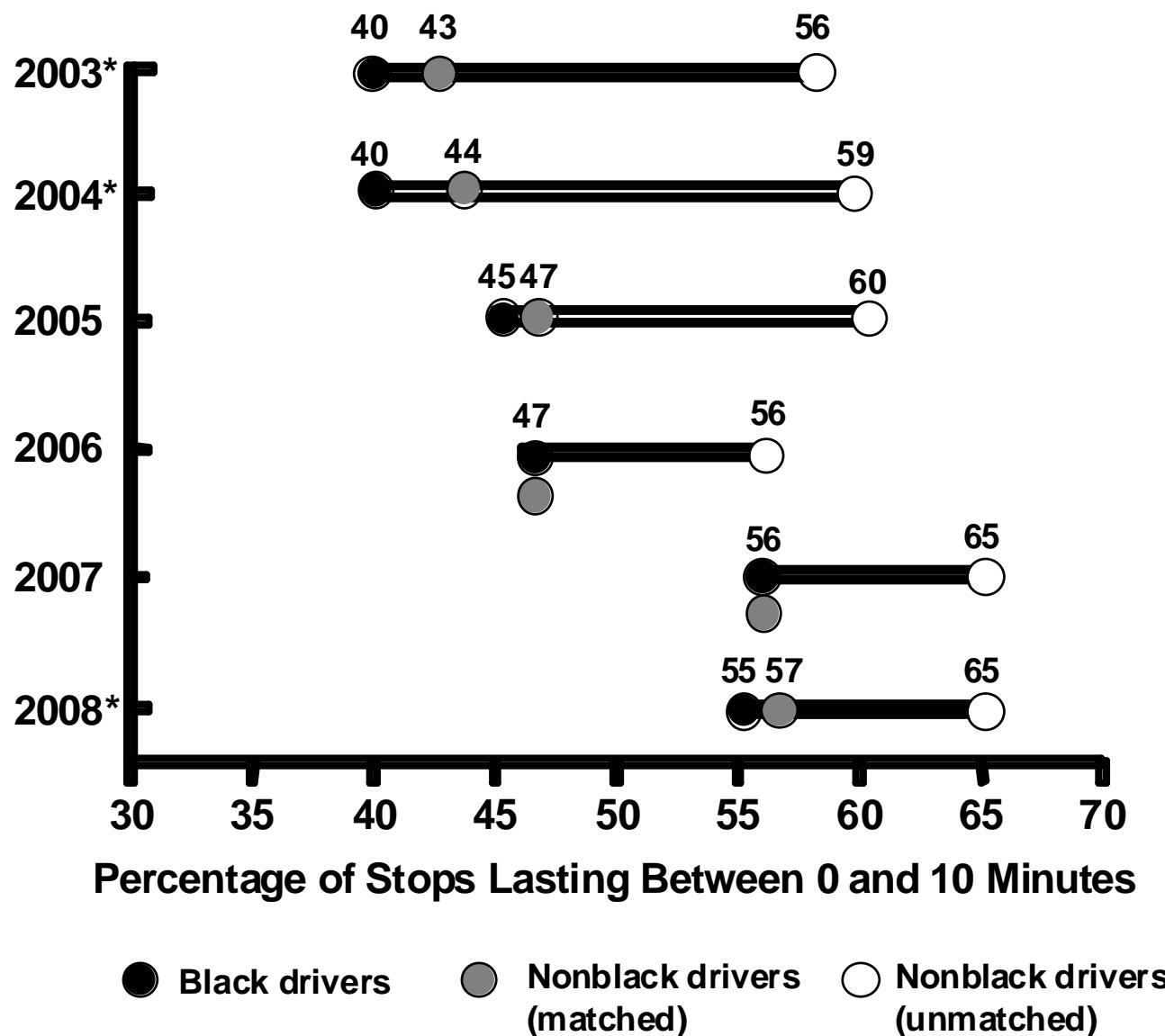
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❖ Results: Search rates in Cincinnati

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Results: Search rates in Cincinnati

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❖ Central question

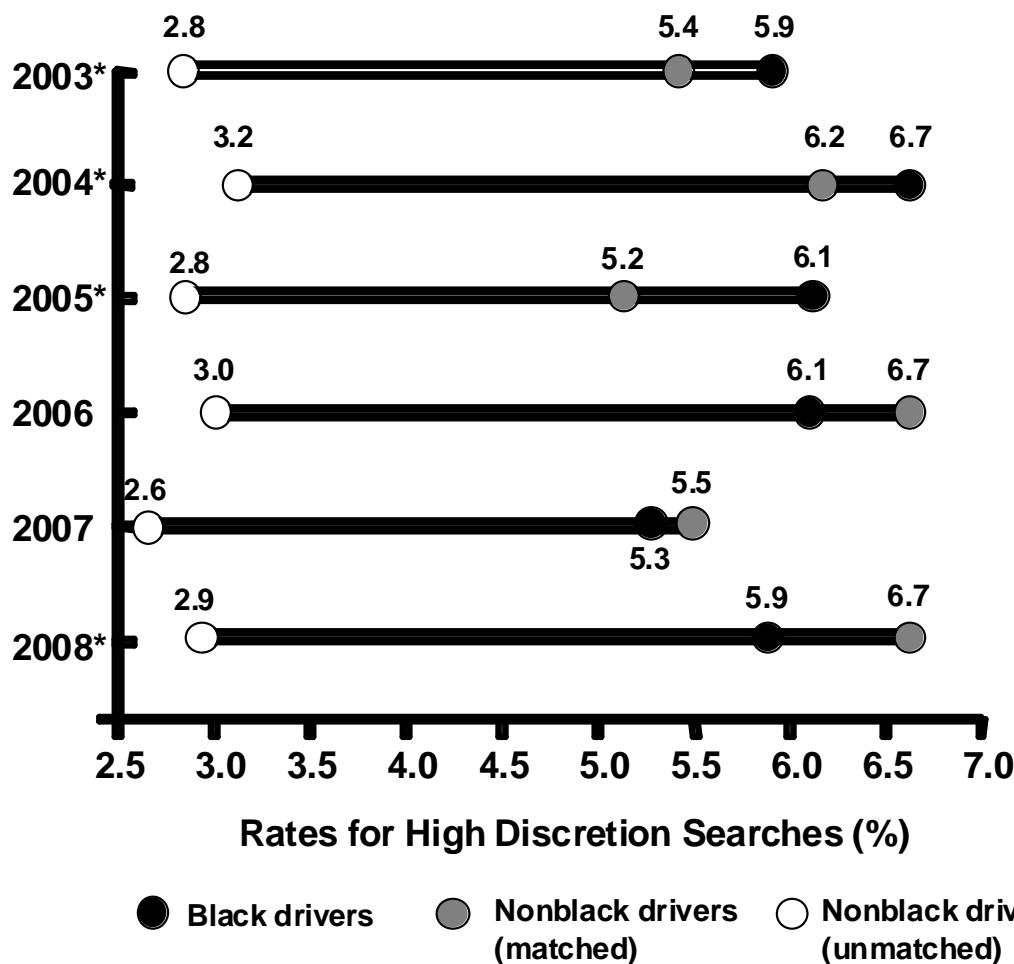
❖ Reweighting balances the group

❖ Results: Stop durations in Cincinnati

❖ Results: Search rates in Cincinnati

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- Hit rates for black and white drivers are about 23% for high discretion searches

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❖ Summary

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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
- Complete reports and papers are available at www.rand.org

Results: VoD estimates of bias, all months

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❖ Results

Year	$K(t)$	95% interval	N
2003	1.04	(0.90,1.20)	3,899
2004	0.99	(0.87,1.14)	4,346
2005	1.06	(0.94,1.20)	5,193
2006	0.90	(0.79,1.02)	4,644
2007	0.94	(0.83,1.05)	6,028
2008	0.84	(0.74,0.95)	4,817
Combined	0.95	(0.90,1.00)	28,927

- Includes all stops during the evening intertwilight period