Racial Profiling, Bad Cops, and Police Shootings

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Outline

- Do police target black drivers?
- Are there individual officers that appear to target minorities?
- Which officers are most likely to shoot?

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Racial Profiling Continues to Be a Concern

- I-95 “turnpike” studies in the mid-1990s raised public concern about racial profiling
- Public concern has led to state and local-level action
- Events periodically renew interest
  - Questionable police shootings
  - Arrest of Henry Louis Gates and the “beer summit” of July 2009

Unfortunately, the Quality of the Analysis Using Collected Data Is Weak

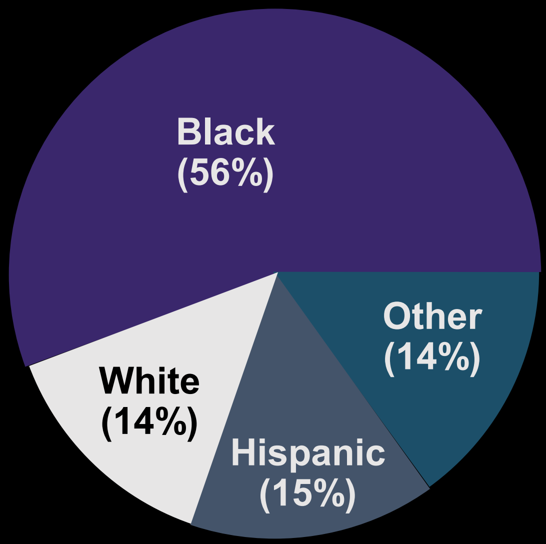
- A large number of studies claim racial profiling
  - Texas: Concluded that “75% of agencies stop more black and Latino drivers than white drivers”
- And some studies hastily conclude no profiling
  - Sacramento: The percentage of black drivers stopped matched the percentage of blacks among crime suspect descriptions

Why Is Testing for Racial Profiling So Hard?

Racial Distribution of People Stopped

Racial Distribution of People at Risk of Being Stopped

Difference Between



And

?

= Racial Profiling

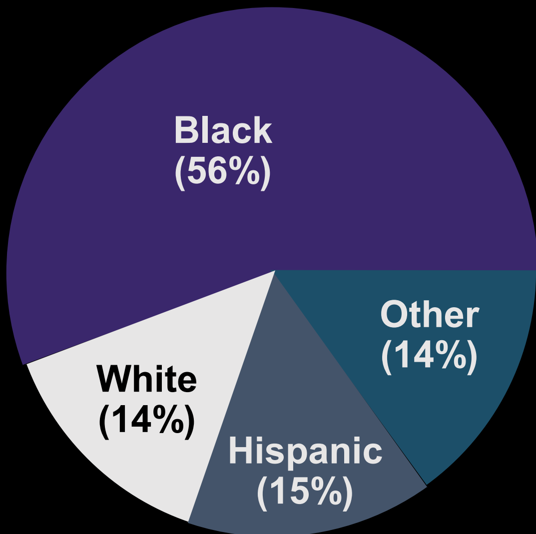
Source: Oakland Police Department, 2003

Why Is Testing for Racial Profiling So Hard?

Racial Distribution of People Stopped

Racial Distribution of Residents According to the Census

Difference Between



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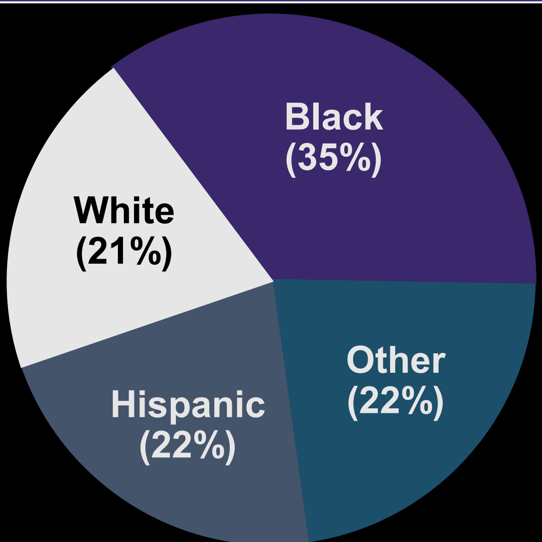


= 1.6

Source: Oakland Police Department, 2003

Source: U.S. Census, 2000

- The 1.6 disparity between the racial distributions may result from:
  - A race bias
  - Driving behavior: car ownership, time on the road, and care
  - Exposure to police by area of city, neighborhood characteristics, etc.

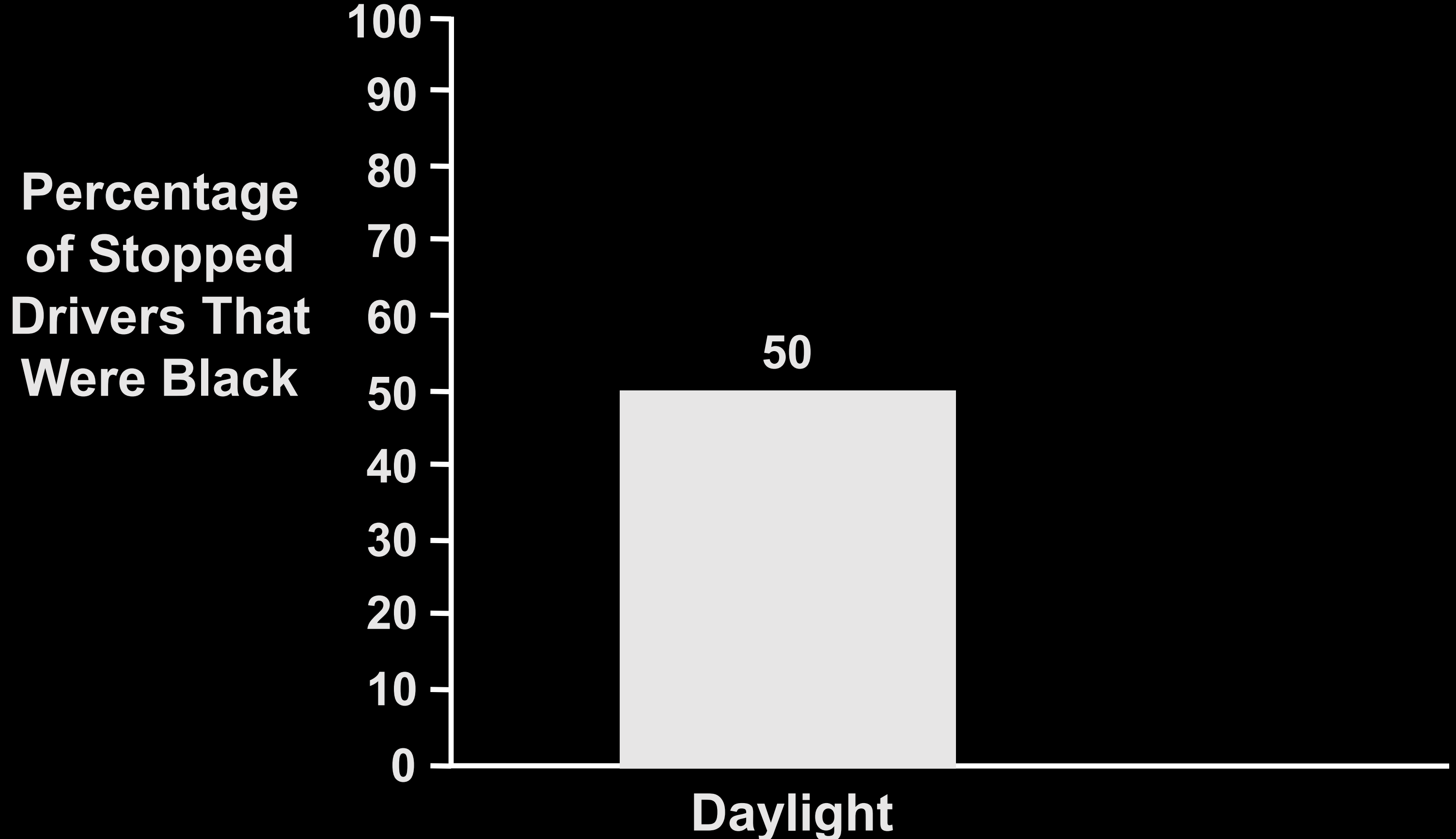
Does the Ability to See the Driver Influence Which Drivers Are Stopped?

- The ability to discriminate requires officers to identify the race in advance
- The ability to identify race in advance of the stop decreases as it becomes dark

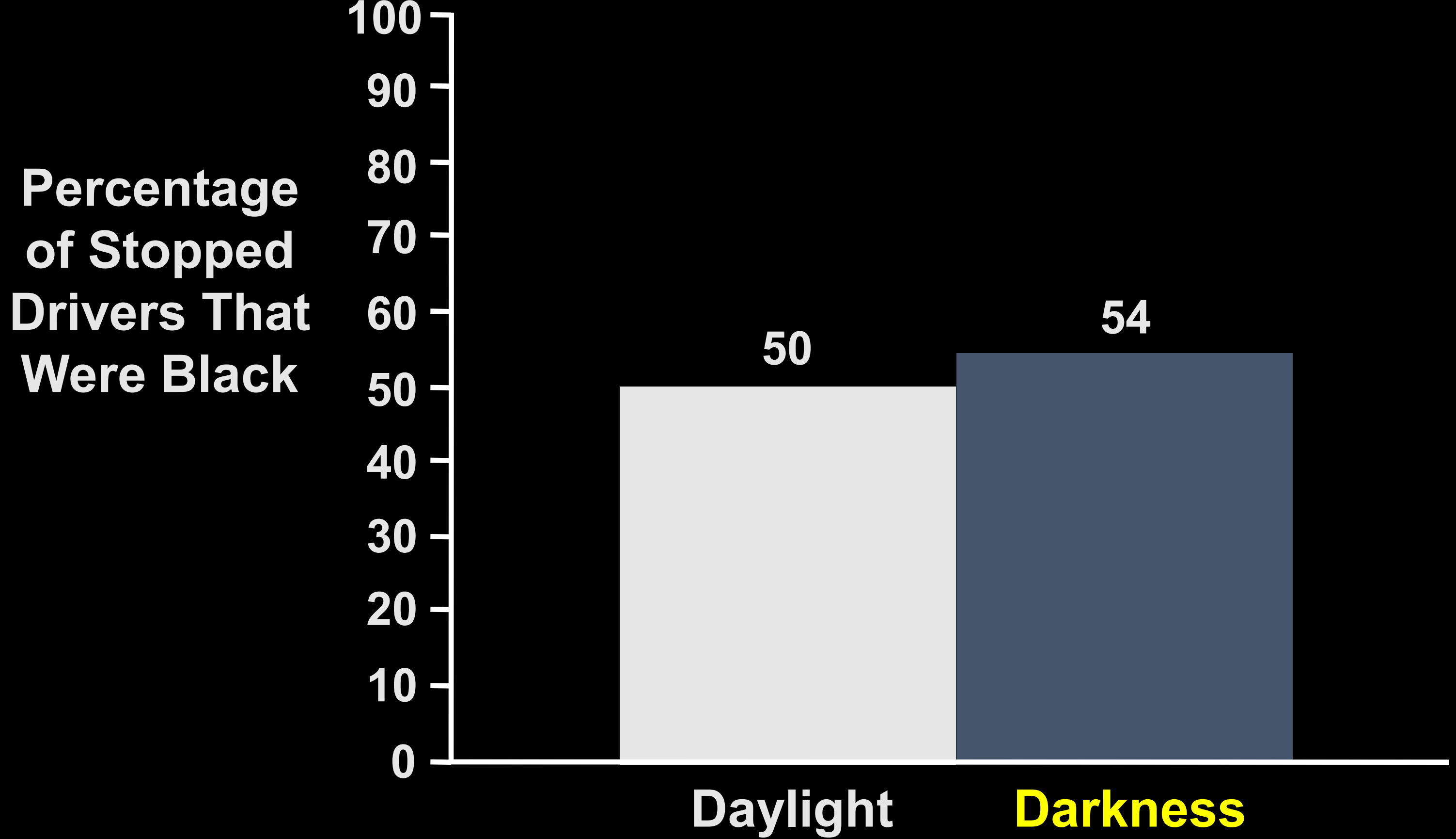
Grogger & Ridgeway (2006). "Testing for Racial Profiling in Traffic Stops from Behind a Veil of Darkness," JASA 101(475):878-887

2007 ASA Outstanding Statistical Application award

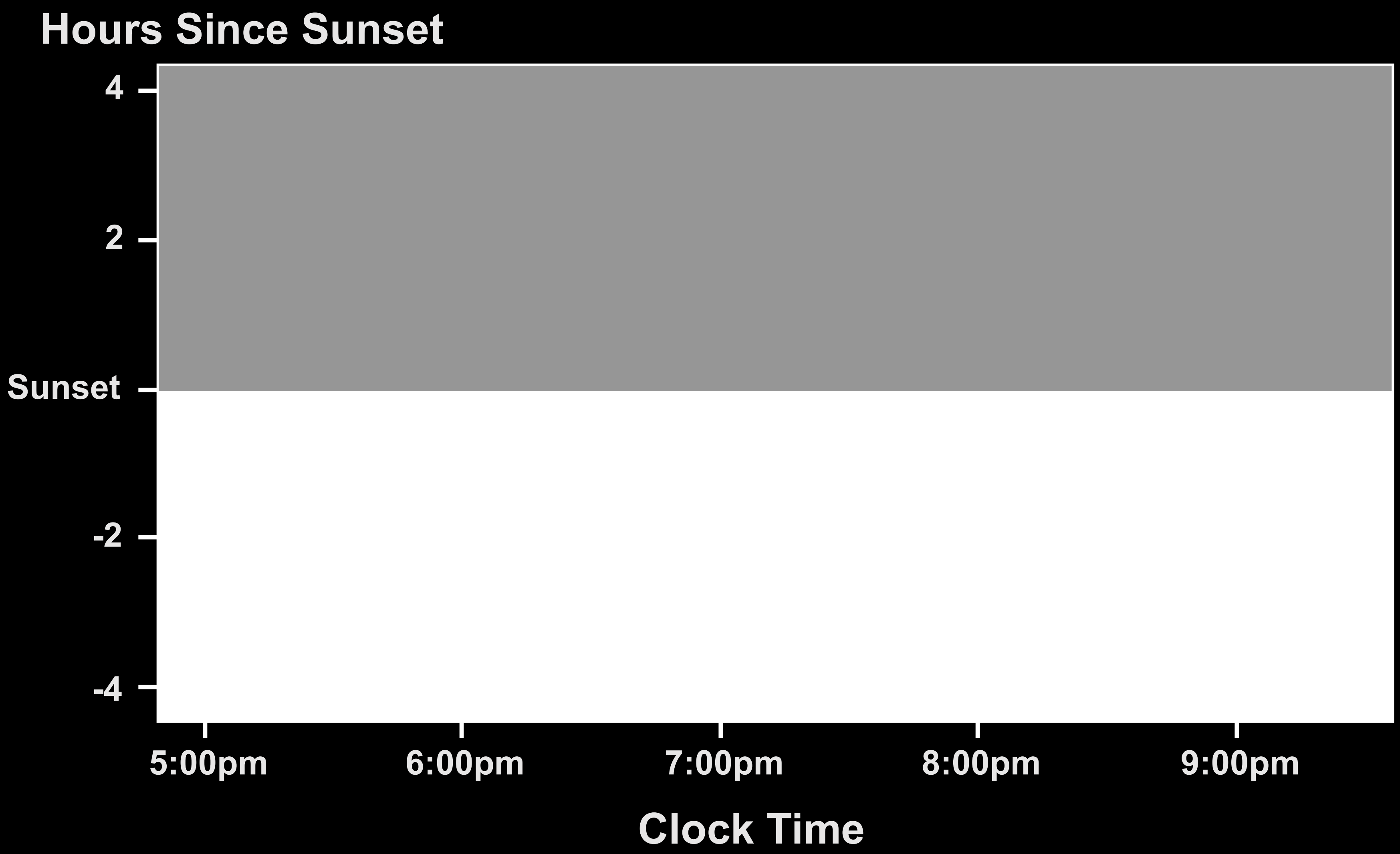
Simple "Veil of Darkness" Test Shows No Evidence of Racial Bias



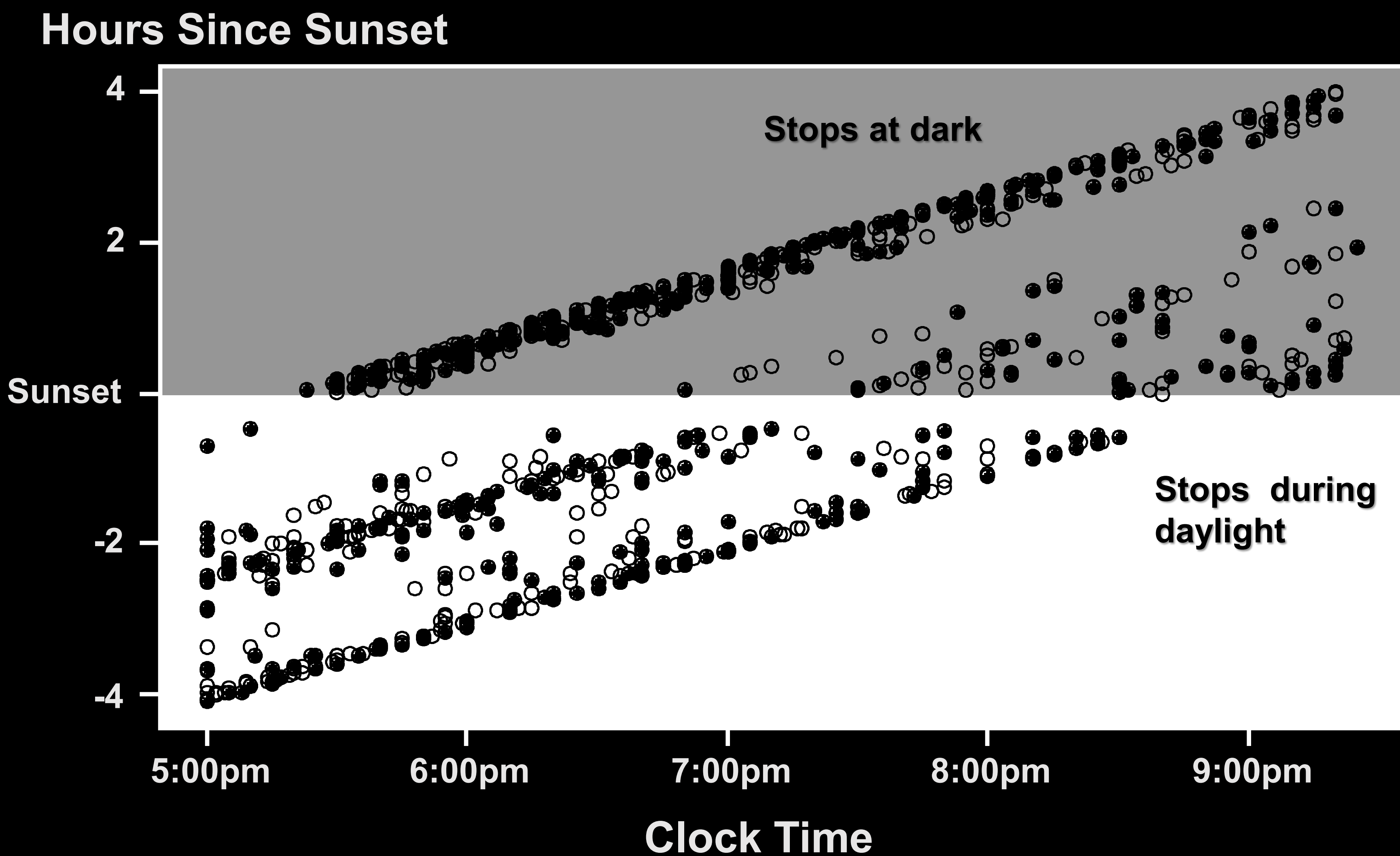
Simple "Veil of Darkness" Test Shows No Evidence of Racial Bias



An Approach That Involved Adjusting for "Clock Time"



Compare Stops During Daylight with Stops in Darkness



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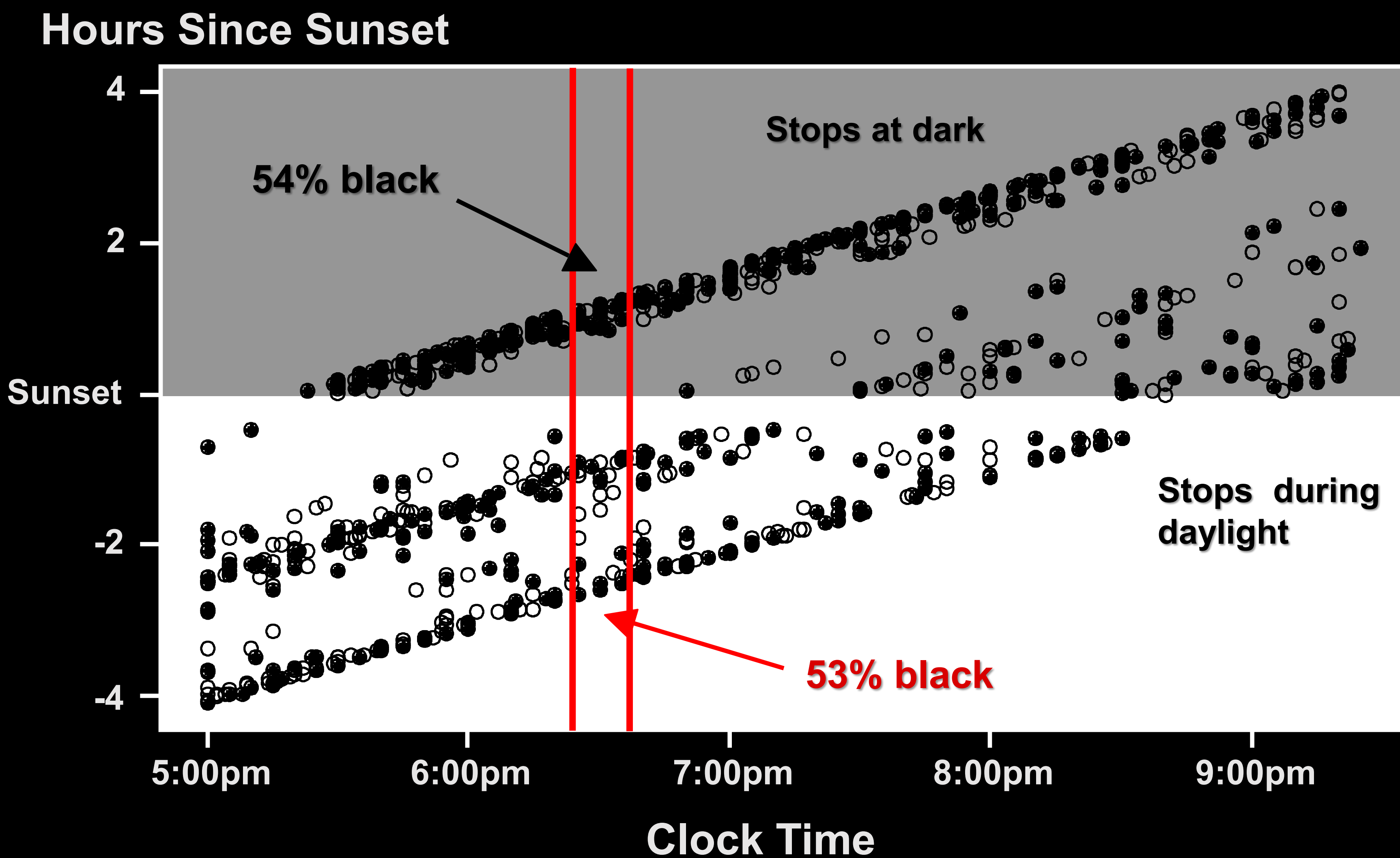
There Is No Difference in the Rate that Black Drivers Are Stopped



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K Measures Racial Bias

$$\frac{P(S|B,V)}{P(S|\bar{B},V)} = K_{\text{ideal}} \frac{P(S|B,\bar{V})}{P(S|\bar{B},\bar{V})}$$

- S – Stop
- B – Black driver
- V – Race is visible

- $K_{\text{ideal}} > 1$ suggests officers are more likely to stop black drivers when their race is visible

Derivation of the VoD Estimator

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

$$1 < K \leq K_{\mathrm{ideal}}$$

- S – Stop
- B – Black driver
- t – Clock time
- d – Darkness

- $K > 1$ suggests officers are more likely to stop black drivers when their race is visible

Decomposition of the VoD Estimator

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

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

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

VoD is Easily Implemented

- For each stop record race of driver, darkness indicator, and clock time
- Subset dataset to dates near the switch to/from Daylight Savings Time
- Logistic regression, predict race from darkness and clock time
- Report VoD estimate as $K = \exp(-\beta_1)$

Oakland 2003: K = 0.88
Cincinnati 2003-2008: K = 0.96

VoD Has Become Widely Used

- Connecticut
- San Diego
- Syracuse
- Urbana
- Minneapolis
- Raleigh-Durham

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Next wave of police departments face racial disparity analysis

By: JAKE KARA | November 10, 2017 — View as "Clean Read"

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JAKE KARA / CTMIRROR.ORG

Kenneth Barone, beneath the screen, a project manager at Central Connecticut State University's Institute for Municipal and Regional Policy Research describes the latest traffic stop analysis.

Central Connecticut State University researchers released their third annual statewide report Thursday that identified seven Connecticut police departments for further study because of racial or ethnic disparities in their traffic stop patterns.

The departments are Berlin, Monroe, Newtown, Norwich, Ridgefield, Darien and State Police Troop B in North Canaan.

In these jurisdictions, minority drivers were more likely to be stopped during daylight hours than at night. The assumption is that it's generally easier to see a driver to determine their apparent race or ethnicity during the daytime. Applying this so-called "Veil of Darkness" analysis to Ridgefield, for example, researchers found Hispanic drivers were 2.5 times more likely to be stopped in daylight than at night.

Outline

- Do police target black drivers?
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Is an Officer Who Stops 86% Black Pedestrians Unusual?

Stop Characteristic	Example Officer (%) n = 392	
% black pedestrians stopped	86%	

- Combine three statistical techniques to answer this question
  - Propensity score weighting
  - Doubly robust estimation
  - False discovery rate

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

We Know a Lot About the Environment of this Officer's Stops

Stop Characteristic		Example Officer (%) n = 392	
% black pedestrians stopped		86%	
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	

We Also Know the Exact Location of This Officer's Stops

Example Officer

Idea: Reweight Stops Made By Other Officers to Resemble This Officer's Stops

Example Officer

- Align their distributions

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

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

$$w(\mathbf{x}) \propto \frac{P(t=1|\mathbf{x})}{1-P(t=1|\mathbf{x})}$$

- Estimate $P(t=1|\mathbf{x})$ using boosted logistic regression as implemented in `gbm`

Reweighting Aligns the Distribution of Stop Locations

Example Officer

Matched Stops

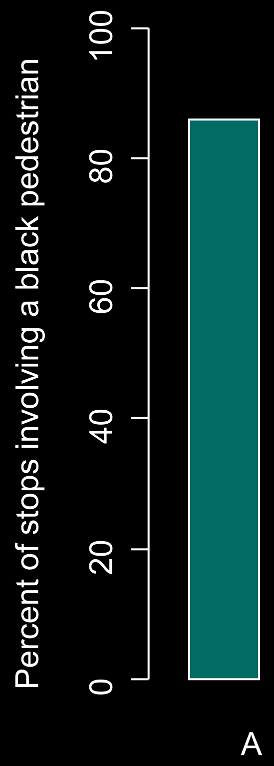
Reweighting Also Aligns the Distribution of All Other Stop Features

Stop Characteristic		Example Officer (%) n = 392	Internal Benchmark (%) ESS = 3,676
% black pedestrians stopped		86%	
Month	January	3	3
	February	4	4
	March	8	9
Day of the week	Monday	13	13
	Tuesday	11	10
	Wednesday	14	15
Time of day	(4-6 p.m.]	9	10
	(6-8 p.m.]	8	8
	(8-10 p.m.]	23	23
	(10 p.m. -12 a.m.]	17	17
Patrol borough	Brooklyn North	100	100
Precinct	B	98	98
	C	1	1
Outside		96	94
In uniform	Yes	99	97
Radio run	Yes	1	3

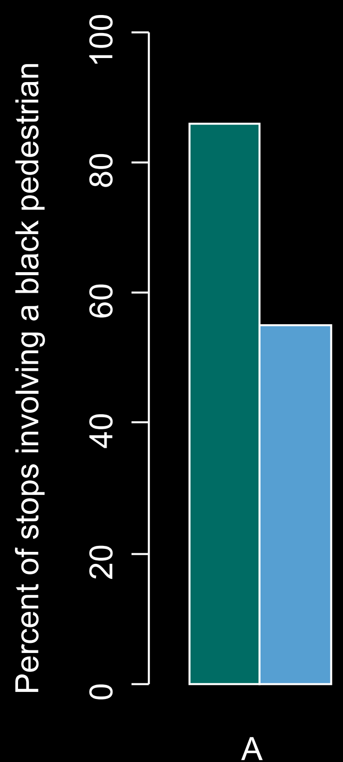
Colleagues at the Same Time, Place, and Context Stop 55% Black Pedestrians

Stop Characteristic		Example Officer (%) n = 392	Internal Benchmark (%) ESS = 3,676
	% black pedestrians stopped	**86%**	**55%**
Month	January	3	3
	February	4	4
	March	8	9
Day of the week	Monday	13	13
	Tuesday	11	10
	Wednesday	14	15
Time of day	(4-6 p.m.]	9	10
	(6-8 p.m.]	8	8
	(8-10 p.m.]	23	23
	(10 p.m. -12 a.m.]	17	17
Patrol borough	Brooklyn North	100	100
Precinct	B	98	98
	C	1	1
Outside		96	94
In uniform	Yes	99	97
Radio run	Yes	1	3

86% of the Officer’s Stops Were Black…



…Compared with 55% for the Benchmark



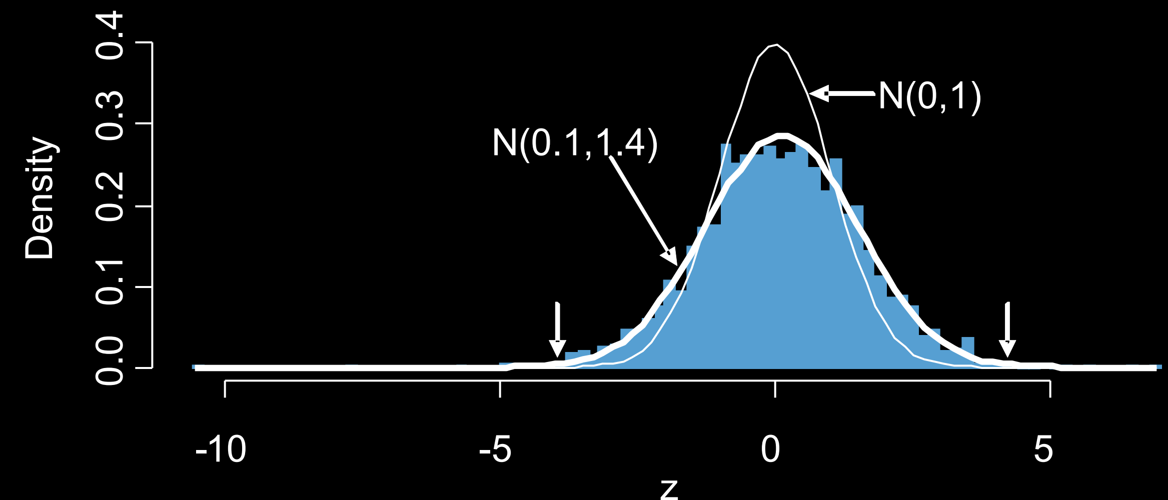
- Doubly robust benchmark estimate obtainable from weighted logistic regression

$$\ell(\boldsymbol{\beta}) = \sum_{i=1}^{n} w_i \left(y_i s(t_i, \mathbf{x}_i | \boldsymbol{\beta}) - \log\left(1 + e^{s(t_i, \mathbf{x}_i|\boldsymbol{\beta})}\right)\right)$$

- Disparity computed as

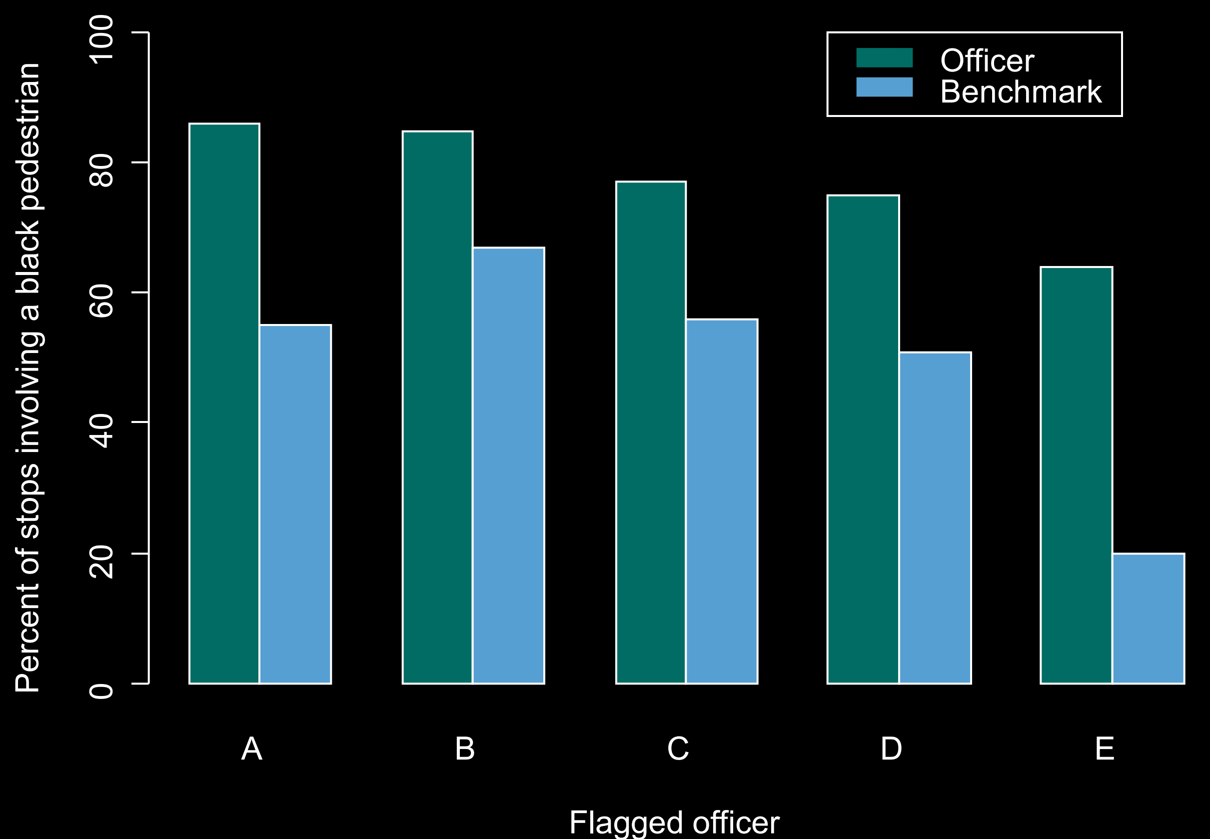
$$\hat{\theta}_A^{DR} = \sum_{i=1}^{n} t_i \left(\frac{1}{1 + \exp\left(-s\left(1, \mathbf{x}_i \middle| \hat{\boldsymbol{\beta}}\right)\right)} - \frac{1}{1 + \exp\left(-s\left(0, \mathbf{x}_i \middle| \hat{\boldsymbol{\beta}}\right)\right)} \right)$$

Repeat for Nearly 3,000 NYPD Officers Actively Involved in Stops



- $P(\text{problem}|z) = 1 - \dfrac{f(z|\text{no problem})f(\text{no problem})}{f(z)}$
  $$\geq 1 - \frac{f_0(z)}{f(z)}$$
- 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

Analysis in NYPD Flagged Five Officers



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Police Use of Lethal Force Sparks Unrest

- 2001 Cincinnati PD shooting of Timothy Thomas resulted in 4 days of riots and $3.6M in damage

- 2006 NYPD shooting of Sean Bell, 50 shots fired. Officers found not guilty at trial, but fired or resigned

- 2014 Chicago PD shooting of Laquan McDonald. 16 bullets fired by one officer, no other officer fired

McElvain and Kposowa (2008) Compared Shooters to Non-Shooters

- Riverside County Sheriff Department
  - 186 shooting incidents involving 314 deputies
  - Control group consisted of 334 deputies with no involvement in shooting incidents
  - Data for shooters collected at time of shooting, controls collected in 2004
- Shooters were more likely to be male, Hispanic, no college, younger, and in lower ranks
- Unmeasured confounding is a major concern in such a study design

Fyfe (1989) states that "there is virtually no empirical support for assertions that individual officer characteristics are measurably related to any type of performance in office"

NYPD Sought a Comprehensive Review of Firearm Practices

- Prompted by controversy surrounding an officer-involved shooting, NYPD Police Commissioner sought a review of:
  - Initial firearms training provided to new recruits
  - In-service firearms training
  - Firearms Discharge Review Board functions and processes
  - The phenomenon of reflexive shooting

“The characteristics of officers involved in discharge incidents will be examined for patterns in training, experience, supervision, and other factors that may help predict, and thus reduce, firearms discharges generally and inappropriate discharges in particular”

Assessing Officer Risk Factors Requires Controlled Comparison

- Officers that discharge their weapons often look different from other officers in obvious ways, such as
  - In the field
  - In particular neighborhoods
  - Conducting higher risk operations
  - Not at a desk
- Idea: Compare shooting officer to other non-shooting officers on the scene
  - Does not judge shooting justification
  - But if there is a consistent pattern it could inform training or assignments

Each Shooting Is an Experiment

1. Multiple officers on the scene
2. Each officer has a latent risk of shooting
3. Before the shooting, each officer on the scene could have been the shooter
4. Test whether there are officer features that affect the risk of shooting

G. Ridgeway (2016). “Officer Risk Factors Associated with Police Shootings: A Matched Case-Control Study,” *Statistics and Public Policy*

Learn the Factors Affecting the Probability of Shooting

$$\log \frac{P(S = 1|\mathbf{x}, \mathbf{z})}{1 - P(S = 1|\mathbf{x}, \mathbf{z})} = h(\mathrm{z}) + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_d x_d$$

- S indicates that the officer shoots
- **x** are the officer's features
- **z** are the features of a particular scenario (kinds of suspects involved, location, and lighting)

Collected data do not quite match this framework

Utilized Data on a Review of Three Years of OIS Records

- Gathered data on all officer-involved shootings adjudicated in 2004, 2005, and 2006
- For each shooting I recorded
    - department ID numbers for shooters in the incident
    - department ID numbers for non-shooting officers that were witnesses or in the immediate vicinity of the shooting
- 106 incidents involving 150 shooting officers and 141 non-shooting officers
- Collected data on age, experience, education, training, and past performance

Consider the Likelihood of a Shooting Involving Two Officers

$$P(S_A = 1, S_B = 0 | S_A + S_B = 1, \mathbf{x}_A, \mathbf{x}_B, \mathbf{z}) =$$

$$\frac{\boxed{}\boxed{}}{\boxed{}} =$$

$$\frac{\boxed{}}{\boxed{}}$$

Substituting Simplifies the Model

$$\frac{P(S_A = 1|\mathbf{x}_A, \mathbf{z}) \qquad P(S_B = 0|\mathbf{x}_B, \mathbf{z})}{\qquad} =$$

$$=$$

Who Is More Likely to Shoot?

Variable	Risk difference
Rank	
Police officer (reference)	
Detective	
Sergeant	
Lieutenant	
Captain	

- If an OIS occurs and an officer at each of these ranks is on the scene, who is most likely to be the shooter?

Supervisors and Management Ranks Are Less Likely to Shoot

Variable	Risk difference
Rank	
Police officer (reference)	
Detective	No difference
Sergeant	-74%
Lieutenant	-95%
Captain	-96%

Who Is More Likely to Shoot?

Variable	Risk difference
Rank	
Police officer (reference)	
Detective	No difference
Sergeant	-74%
Lieutenant	-95%
Captain	-96%
Male	
Race	
White (reference)	
Black	
Hispanic	

Black Officers More Likely to Shoot

Variable	Risk difference
Rank	
Police officer (reference)	
Detective	No difference
Sergeant	-74%
Lieutenant	-95%
Captain	-96%
Male	No difference
Race	
White (reference)	
Black	+226%
Hispanic	No difference

Each Additional Year of Recruiting Age Decreases Risk by 11%

Variable	Risk difference
Rank	
Police officer (reference)	
Detective	No difference
Sergeant	-74%
Lieutenant	-95%
Captain	-96%
Male	No difference
Race	
White (reference)	
Black	+226%
Hispanic	No difference
Years at NYPD	No difference
Age when recruited	-11%
Education	No difference
Special assignment	No difference

Tracked Annual Activity

Variable	Risk difference
Average annual	
Evaluation score < 3.5	
Range score < 86	
Complaints > 0.6	
Medal count > 3.8	
CPI points > 3.1	
Gun arrests > 2.4	
Felony arrests > 9.3	
Misdemeanor arrests > 10.0	
Days of leave	

Rapid Accumulation of Negative Marks Signals Elevated Shooting Risk

Variable	**Risk difference**
Average annual	
Evaluation score < 3.5	
Range score < 86	
Complaints > 0.6	
Medal count > 3.8	
CPI points > 3.1	+212%
Gun arrests > 2.4	
Felony arrests > 9.3	
Misdemeanor arrests > 10.0	-80%
Days of leave	

8% of NYPD officers
15% of shooting scene officers

Central Personnel Index Assign Points to Problematic Incidents

Event	Point value
Suspension	8
Loss of firearm	6
Negative evaluation - A	5
Fail to safeguard weapon	5
Chronic sick – B	4
Loss of shield	4
Negative evaluation – B	3
Chronic sick – A	2
Firearm discharge	1
Dept. auto accident	1

```
NEGATIVE EVALUAT. - B        10 MONTH EVAL - 3.0
DATE       : 04/30/2005      (1) LOW - BEHAV DIMENS
CONTROL #: 003
SERIAL  #: XXXX

FIREARMS DISCHARGE           NO VIOLATION
DATE       : 06/09/2006      NO CORRECTIVE ACTION
CONTROL #: 004
SERIAL  #: 053506
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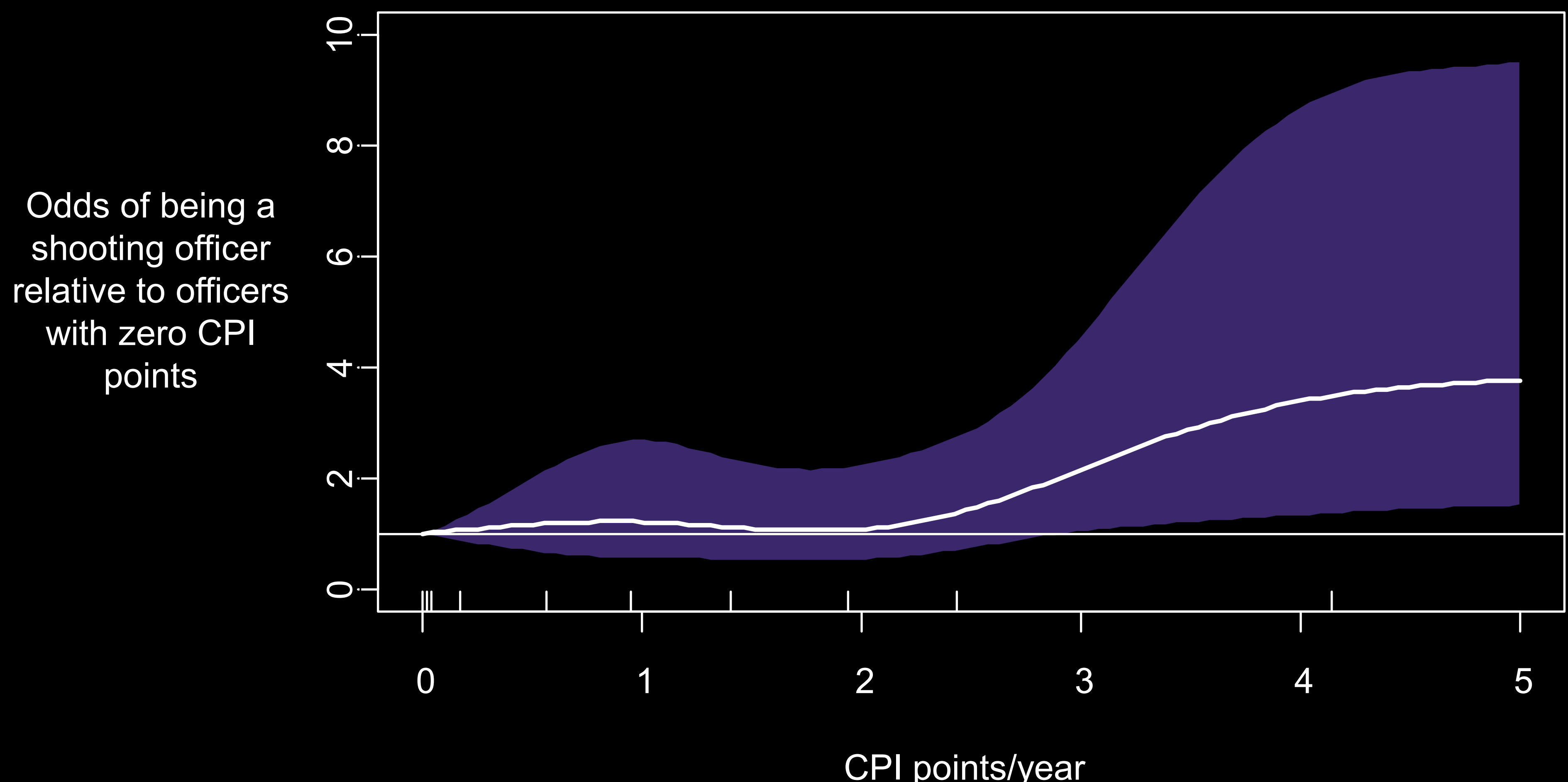
Exceeding 3.1 CPI/year Strongly Associated with Shooting Risk



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“Active” Officer May Be Key Factor

Variable	Risk difference
Average annual	
Evaluation score < 3.5	No difference
Range score < 86	No difference
Complaints > 0.6	+107%
Medal count > 3.8	+128%
CPI points > 3.1	+212%
Gun arrests > 2.4	No difference
Felony arrests > 9.3	+115%
Misdemeanor arrests > 10.0	-80%
Days of leave	No difference

Statistics Can Have a Prominent Role in Crime and Justice Policy

- Do police target black drivers?
- Are there individual officers that appear to target minorities?
- Which officers are most likely to shoot?

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Racial Profiling, Bad Cops, and Police Shootings

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Some current research…

- Average amount of marijuana in a joint
- Effect of gang injunctions on crime
- Effect of transit systems on crime
- Capture-recapture to estimate policing undercount
- Racial bias in New York state sentencing
- Graphical processing units in statistical computing
- Violence prevention in West Philadelphia