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UNIVERSITY of PENNSYLVANIA

Statistics of Police Shootings and Racial Profiling

Greg Ridgeway
Department of Criminology
Department of Statistics

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Outline

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

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Confounding Chronically Hindered Connecting Officer Features and Risk

"the overrepresentation of minority officers among police shooters [is] closely associated with racially varying pattern of assignment, socialization, and residence"

Fyfe (1981)

Confounding Chronically Hindered Connecting Officer Features and Risk

"it is quite possible that other factors, such as the extent to which college-educated officers versus non-college-educated officers encounter resistant suspects, may account for why education appears to matter"

Paoline and Terrill (2007)

Confounding Chronically Hindered Connecting Officer Features and Risk

"based on an officer's rank, time on the job, age, and gender, he or she may have been less active, assigned to areas with lower crime rates, or working in a position that did not have frequent contact with citizens"

McElvain and Kposowa (2008)

Officer Van Dyke Fired 16 Rounds
Officer Walsh Holstered His Firearm

Model the Chance of Shooting

- Probability of shooting for an officer with features **x** in an environment with features **z**

$$\log \frac{P(\mathbf{x},\mathbf{z})}{1-P(\mathbf{x},\mathbf{z})} = h(\mathbf{z}) + \beta'\mathbf{x}$$

- **z** includes suspect features, time, place, …
- $h(\mathbf{z})$ is a large negative number for almost all environments
- **x** includes officer age, race, sex, prior involvement in shootings, complaints, awards, assignment, …
- $\exp(\beta_j)$ indicates how much a unit change in x_j increases the odds of the officer shooting

Model the Number of Rounds Fired

- Probability of shooting *r* rounds for an officer with features **x** in an environment with features **z**

$$\log P(R = r) = r(h(\mathbf{z}) + \beta'\mathbf{x}) - e^{h(\mathbf{z})+\beta'\mathbf{x}} - \log r!$$

- Poisson regression with shooting rate $e^{h(\mathbf{z})+\beta'\mathbf{x}}$
- $\exp(\beta_j)$ indicates how much a unit change in x_j multiplies the expected rounds discharged

Traditional Logistic Regression Model Requires Complex Data Collection

- Collect data at random point in time for randomly selected officers
  - Record $\mathbf{x}_i$, the officer's features
  - Record $\mathbf{z}_i$, the environment features
  - Record $r_i = 1$ if officer *i* shot and 0 otherwise

Rounds	Years on job	Sex	Race	Prior OIS #	…	Time	Lighting	Armed suspect	…
0	4	Male	White	0		8pm	Sunny	No	
0	4	Male	White	0		3am	Sunny	No	
0	9	Female	Black	1		11am	Dark	No	
0	5	Male	Hispanic	0		10am	Dark	No	
0	1	Male	White	0		7pm	Inside	No	
…									
1	3	Female	White	1		6pm	Dark	No	
…									

r_i $\mathbf{x}_i$ $\mathbf{z}_i$

Nuisance Parameter $h(\mathbf{z})$ Complicates Traditional Likelihood Analysis

- Collect data at random point in time for randomly selected officers
  - Record $\mathbf{x}_i$, the officer's features
  - Record $\mathbf{z}_i$, the environment features
  - Record $r_i = 1$ if officer *i* shot and 0 otherwise
- Traditional logistic regression would find β to maximize

$$P(R_1 = r_1, \dots, R_n = r_n | \mathbf{x}_1, \dots, \mathbf{x}_n, h(\mathbf{z}_1), \dots, h(\mathbf{z}_n), \beta)$$

1. A random sample would likely capture no shootings
2. Hard to completely document **z**
3. $h(\mathbf{z})$ difficult to model

Condition on a Sufficient Statistic for Nuisance Parameter

- Consider one moment in time, one place in space
- Condition on the number of shooters

$$P(R_1 = r_1, \dots, R_n = r_n | R_1 + \cdots + R_n = r_1 + \cdots + r_n, \mathbf{x}_1, \dots, \mathbf{x}_n, h(\mathbf{z}), \beta)$$

$$= \frac{e^{r_1 \beta' \mathbf{x}_1} \dots e^{r_n \beta' \mathbf{x}_n}}{\sum_{\rho_i \in \{0,1\}, \sum \rho_i = \sum r_i} e^{\rho_1 \beta' \mathbf{x}_1} \dots e^{\rho_n \beta' \mathbf{x}_n}}$$

- Knowing or not knowing $h(\mathbf{z})$ produces the same $\hat{\beta}$
- Still yields consistent estimates for β (Manski & Lerman, 1977; Prentice & Pyke, 1979)

The only times and places that provide information about β through the conditional likelihood are multi-officer shootings

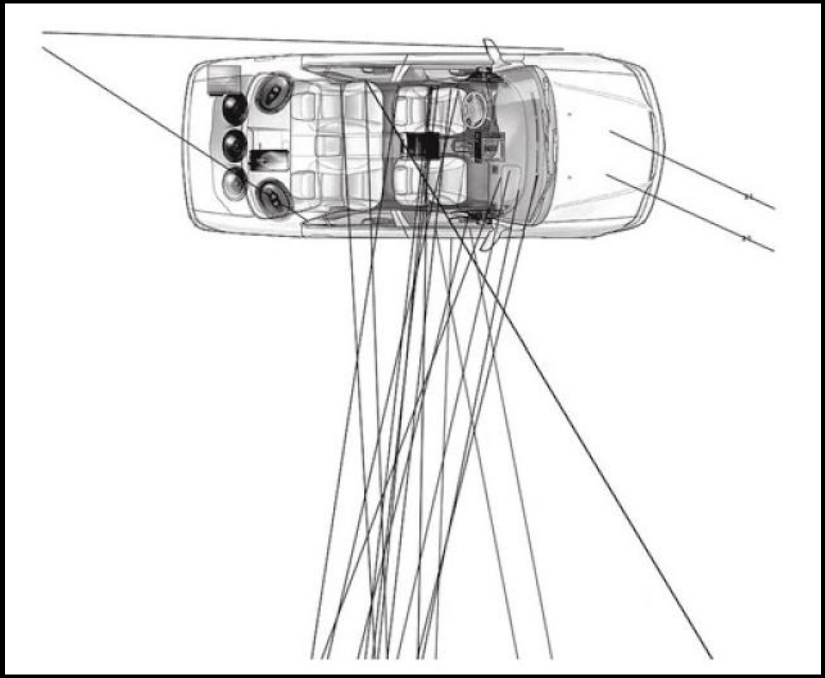
Conditional Likelihood Also Applies to the Number of Rounds

- For the number of round fired, the contribution of a shooting to the conditional likelihood is

$$\frac{e^{r_1\beta'\mathbf{x}_1}\dots e^{r_n\beta'\mathbf{x}_n}}{\sum_{\sum\rho_i=\sum r_i}\frac{1}{\rho_1!\cdots\rho_n!}e^{\rho_1\beta'\mathbf{x}_1}\dots e^{\rho_n\beta'\mathbf{x}_n}}$$

The only times and places that provide information about β through the conditional likelihood are multi-officer shootings

Five Officers Discharged 50 Rounds, Killing Sean Bell in 2006



- Detective Oliver, age 35, white, 31 rounds
- Detective Isnora, age 28, black, 11 rounds
- Detective Cooper, age 39, black, 4 rounds
- Officer Carey, age 26, white, 3 rounds
- Detective Headley, age 35, black, 1 round

Major Cities Chiefs (MCCA) and Police Foundation Standardized Collection

- 56 agencies from MCCA in the U.S. and Canada contributed to this data collection effort
- Full dataset describes 2,574 officers involved in 1,600 shootings between 2010-2018
- Analysis used all 317 multi-officer shootings, 849 officers, 5,026 rounds
- Only included data on officers who discharged their firearm

G. Ridgeway, B. Cave, and J. Grieco (under review). "A Conditional Likelihood Model of the Relationship Between Officer Features and Rounds Discharged in Police Shootings."

Conditional Likelihood Truncated at $r_i > 0$ is Complex

$$-\sum_{s=1}^{S} \log\left(\sum_{\sum \rho_i = \sum r_{si}, \rho_i > 0} \prod_{i=1}^{n_s} \frac{1}{\rho_i!} \exp((\rho_i - r_{si})\beta' \mathbf{x}_{si})\right)$$

Shootings

Rounds

Officers

- Inner sum has $\binom{(\sum r_{si}) - 1}{n_s - 1}$ terms
- Recursive algorithm feasible up to 10^8 terms
- Can also be computed as

$$p_i \propto \exp(\beta' \mathbf{x}_{si})$$
$$\boldsymbol{\rho} \sim \text{Multinomial}(n_r - n_s, \boldsymbol{p})$$
$$E\left(\frac{1}{(\rho_1 + 1) \cdots (\rho_{n_s} + 1)}\right)$$

No Effect of Age

Officer features	Rate ratio	Permutation 95% CI	Permutation p-value
Age at recruitment	1.01	(0.99, 1.02)	0.25
Years of experience	1.00	(0.98, 1.01)	0.62

No Effect of Sex or Race

Officer features	Rate ratio	Permutation 95% CI	Permutation p-value
Age at recruitment	1.01	(0.99, 1.02)	0.25
Years of experience	1.00	(0.98, 1.01)	0.62
Female	0.86	(0.63, 1.16)	0.31
Race (relative to white)			
Black	1.05	(0.86, 1.28)	0.62
Hispanic	1.09	(0.87, 1.36)	0.46
Other	0.76	(0.56, 1.03)	0.07

No Effect of Prior OIS or Complaints

Officer features	Rate ratio	Permutation 95% CI	Permutation p-value
Age at recruitment	1.01	(0.99, 1.02)	0.25
Years of experience	1.00	(0.98, 1.01)	0.62
Female	0.86	(0.63, 1.16)	0.31
Race (relative to white)			
Black	1.05	(0.86, 1.28)	0.62
Hispanic	1.09	(0.87, 1.36)	0.46
Other	0.76	(0.56, 1.03)	0.07
Prior OIS (relative to 0)			
1 or more	1.02	(0.77, 1.35)	0.90
2 or more	1.23	(0.88, 1.73)	0.21
Prior force complaint	1.25	(0.95, 1.64)	0.10

No Effect of Rank or Assignment

Officer features	Rate ratio	Permutation 95% CI	Permutation p-value
Age at recruitment	1.01	(0.99, 1.02)	0.25
Years of experience	1.00	(0.98, 1.01)	0.62
Female	0.86	(0.63, 1.16)	0.31
Race (relative to white)			
Black	1.05	(0.86, 1.28)	0.62
Hispanic	1.09	(0.87, 1.36)	0.46
Other	0.76	(0.56, 1.03)	0.07
Prior OIS (relative to 0)			
1 or more	1.02	(0.77, 1.35)	0.90
2 or more	1.23	(0.88, 1.73)	0.21
Prior force complaint	1.25	(0.95, 1.64)	0.10
Role			
Detective	1.09	(0.72, 1.64)	0.68
Sergeant or more senior	1.03	(0.82, 1.30)	0.81
Other	0.66	(0.34, 1.31)	0.23
Special assignment	1.28	(0.95, 1.72)	0.10

No Effect of Firearm Type

Officer features	Rate ratio	Permutation 95% CI	Permutation p-value
Age at recruitment	1.01	(0.99, 1.02)	0.25
Years of experience	1.00	(0.98, 1.01)	0.62
Female	0.86	(0.63, 1.16)	0.31
Race (relative to white)			
Black	1.05	(0.86, 1.28)	0.62
Hispanic	1.09	(0.87, 1.36)	0.46
Other	0.76	(0.56, 1.03)	0.07
Prior OIS (relative to 0)			
1 or more	1.02	(0.77, 1.35)	0.90
2 or more	1.23	(0.88, 1.73)	0.21
Prior force complaint	1.25	(0.95, 1.64)	0.10
Role			
Detective	1.09	(0.72, 1.64)	0.68
Sergeant or more senior	1.03	(0.82, 1.30)	0.81
Other	0.66	(0.34, 1.31)	0.23
Special assignment	1.28	(0.95, 1.72)	0.10
Long gun (relative to pistol)	1.01	(0.78, 1.30)	0.97

Few Incidents Provide Information

Officer features	Rate ratio	Permutation 95% CI	Permutation p-value	Shootings with info
Age at recruitment	1.01	(0.99, 1.02)	0.25	272
Years of experience	1.00	(0.98, 1.01)	0.62	277
Female	0.86	(0.63, 1.16)	0.31	36
Race (relative to white)				
Black	1.05	(0.86, 1.28)	0.62	49
Hispanic	1.09	(0.87, 1.36)	0.46	73
Other	0.76	(0.56, 1.03)	0.07	35
Prior OIS (relative to 0)				
1 or more	1.02	(0.77, 1.35)	0.90	86
2 or more	1.23	(0.88, 1.73)	0.21	30
Prior force complaint	1.25	(0.95, 1.64)	0.10	40
Role				
Detective	1.09	(0.72, 1.64)	0.68	21
Sergeant or more senior	1.03	(0.82, 1.30)	0.81	67
Other	0.66	(0.34, 1.31)	0.23	9
Special assignment	1.28	(0.95, 1.72)	0.10	40
Long gun (relative to pistol)	1.01	(0.78, 1.30)	0.97	54

Analysis of NYPD Shootings Found Differences

Variable	Risk difference
Years at NYPD	
Age when recruited	-11%
Education	
Special assignment	
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

G. Ridgeway (2016). "Officer Risk Factors Associated with Police Shootings: A Matched Case-Control Study," *Statistics and Public Policy* 3(1):1-6.

Outline

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

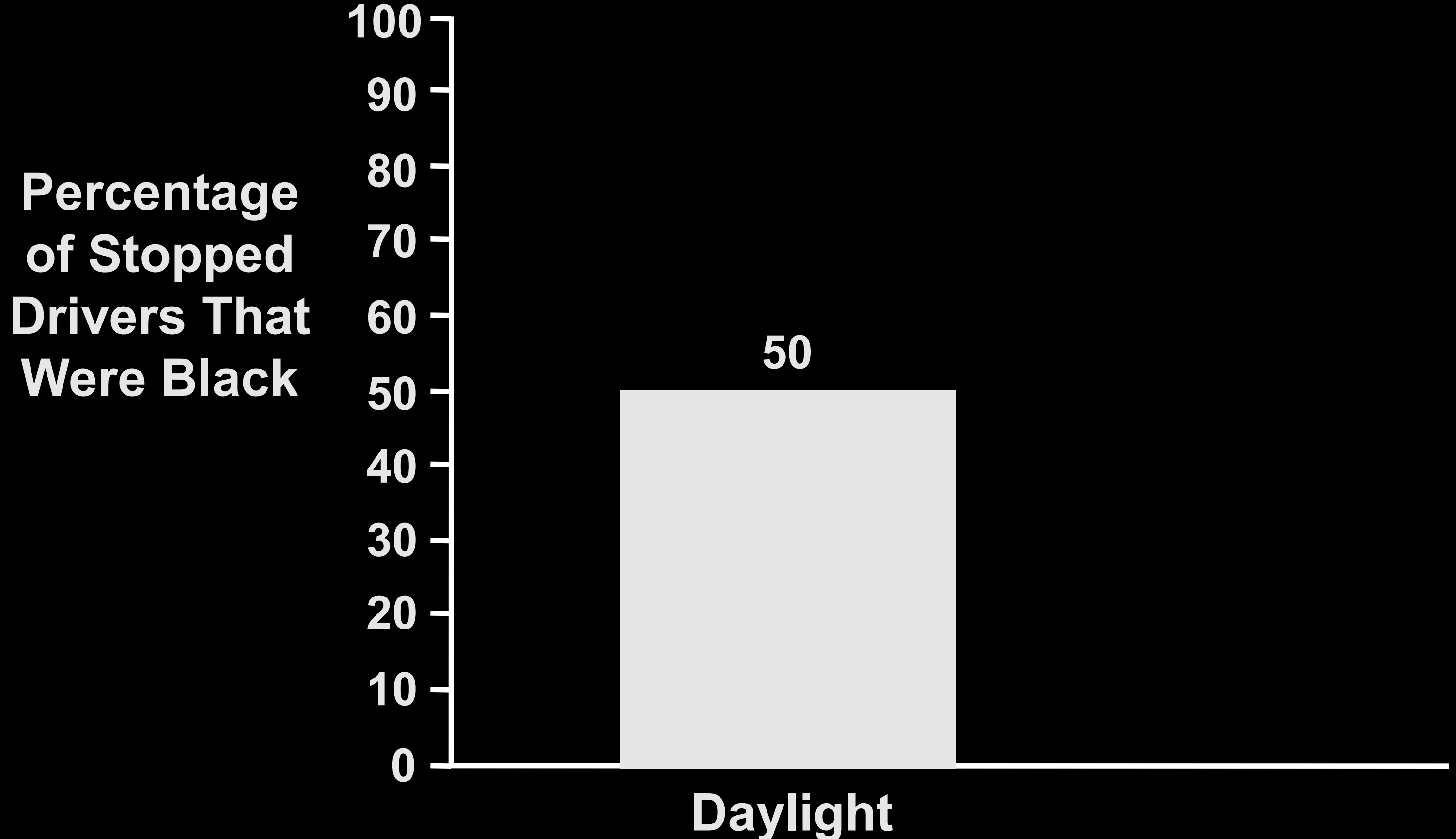
Does the Ability to See the Driver Influence Which Drivers Are Stopped?

- 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

J. Grogger & G. Ridgeway (2006). "Testing for Racial Profiling in Traffic Stops from Behind a Veil of Darkness," *Journal of the American Statistical Association* 101(475):878-887

2007 ASA Outstanding Statistical Application award

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



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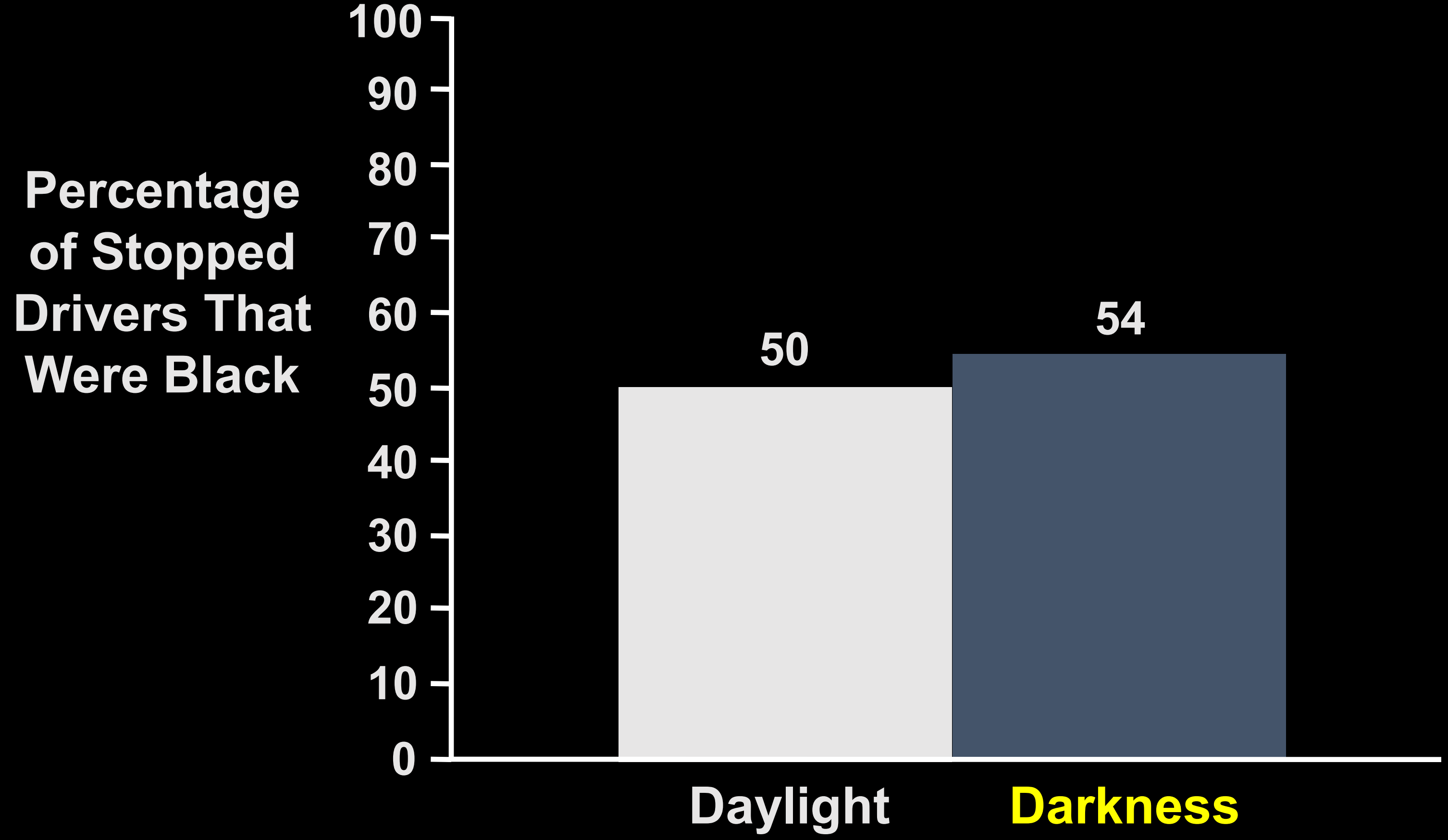
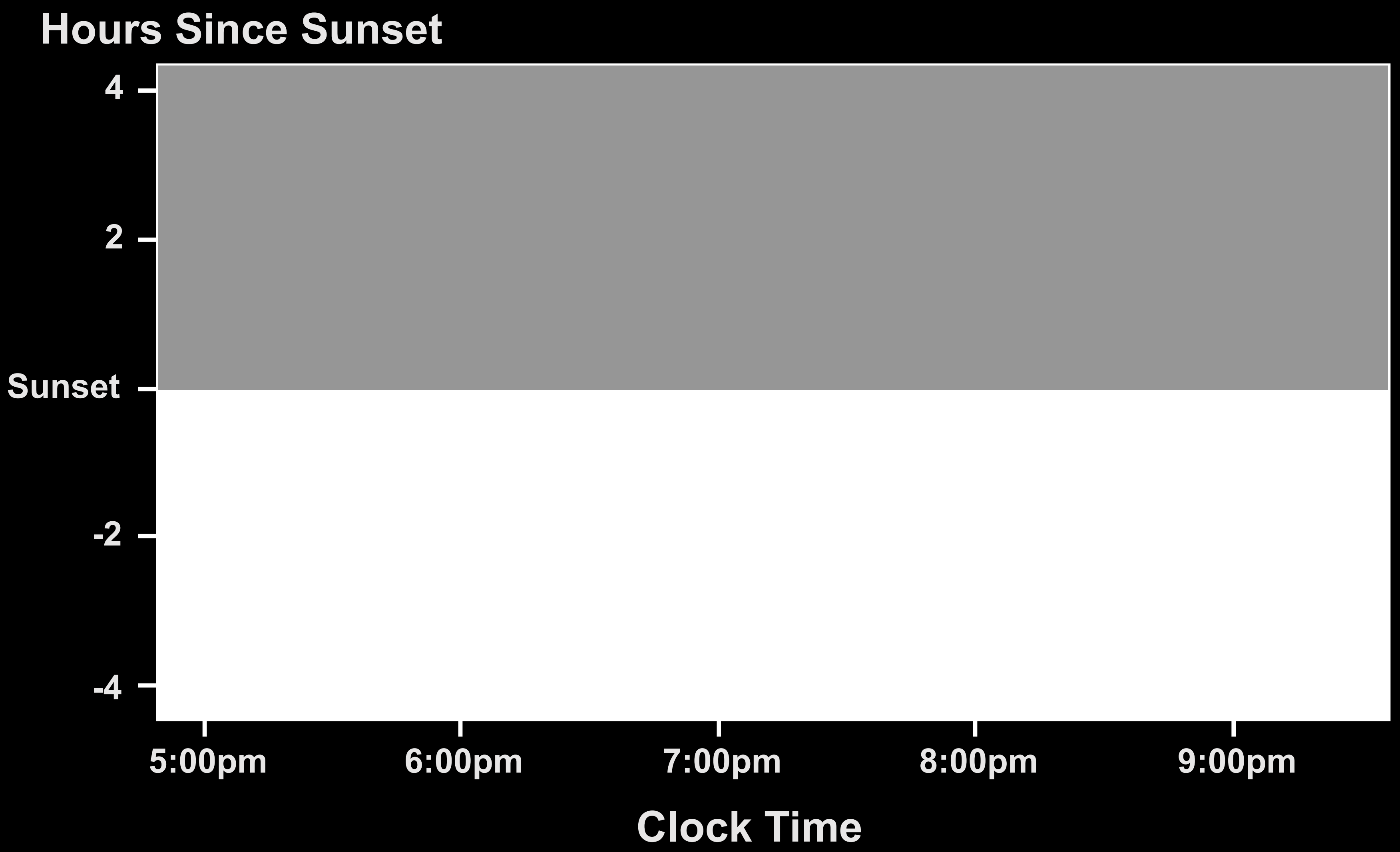
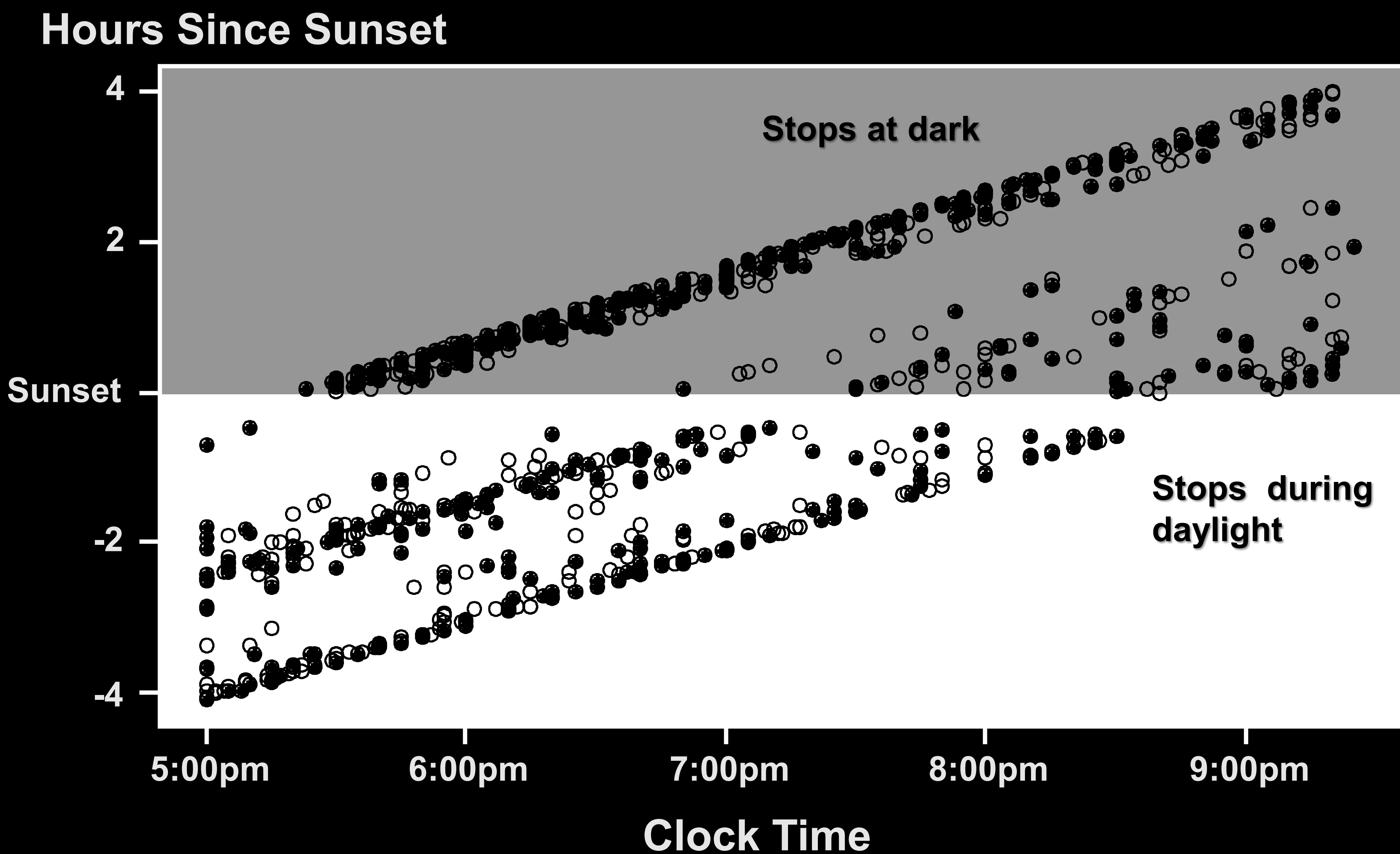


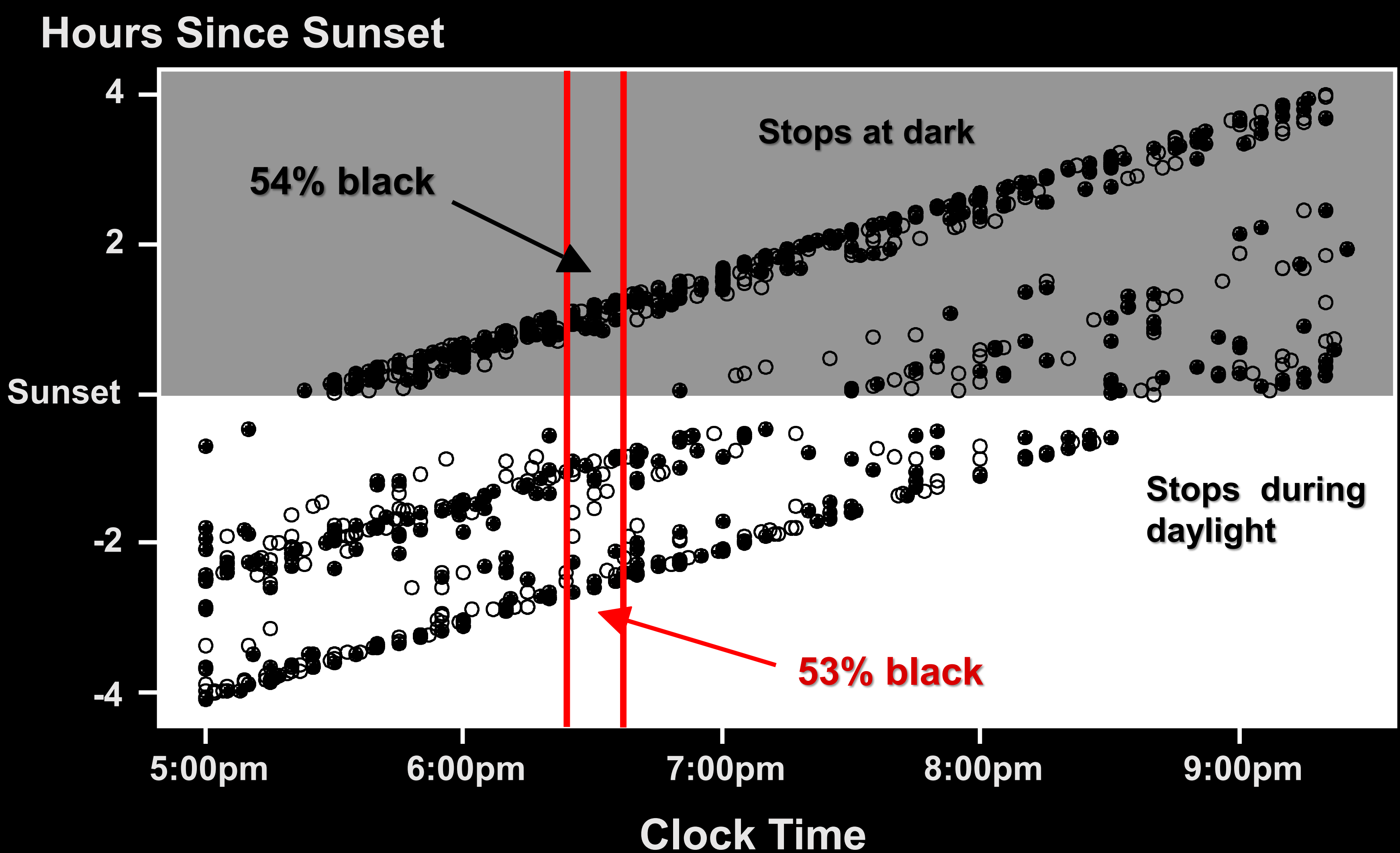
An Approach That Involved Adjusting for "Clock Time"



Compare Stops During Daylight with Stops in Darkness



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



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

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

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

- 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
- Columbia, MO
- 21 state, 29 city

A large-scale analysis of racial disparities in police stops across the United States

Emma Pierson*, Camelia Simoiu*, Jan Overgoor*, Sam Corbett-Davies*, Daniel Jenson*, Amy Shoemaker*, Vignesh Ramachandran, Phoebe Barghouty*, Cheryl Phillips*, Ravi Shroff† and Sharad Goel*‡

Stanford Computational Policy Lab
March 13, 2019

EXECUTIVE SUMMARY

To assess racial disparities in police interactions with the public, we compiled and analyzed a dataset detailing nearly 100 million municipal and state patrol traffic stops conducted in dozens of jurisdictions across the country—the largest such effort to date. We analyze these records in three steps. First, we measure potential bias in stop decisions by examining whether black drivers are less likely to be stopped after sunset, when a "veil of darkness" masks one's race. After adjusting for time of day—and leveraging variation in sunset times across the year—we find evidence of bias against black drivers both in highway patrol and in municipal police stops. Second, we investigate potential bias in decisions to search stopped drivers. Examining both the rate at which drivers are searched and the likelihood that searches turn up contraband, we find evidence that the bar for searching black and Hispanic drivers is lower than for searching whites. Finally, we examine the effects of legalizing recreational marijuana on policing in Colorado and Washington state. We find evidence that legalization reduced the total number of searches conducted for both white and minority

report having been recently stopped by the police. In addition to such survey data, some local and state agencies have released periodic reports on traffic stops in their jurisdictions, and have also made their data available to outside researchers for analysis [2, 3, 7, 14, 21–28]. While useful, these datasets provide only a partial picture. For example, there is concern that the PPCS, like nearly all surveys, suffers from selection bias and recall errors. Data released directly by police departments are potentially more complete, but are available only for select agencies, are typically limited in what is reported, and are inconsistent across jurisdictions.

To address these challenges, we compiled and analyzed a unique dataset detailing nearly 100 million traffic stops carried out by 21 state patrol agencies and 29 municipal police departments over almost a decade. This dataset was built through a series of public records requests filed in all 50 states. To facilitate future analysis, we are redistributing these records in a standardized form. To our knowledge, this is the most comprehensive public release and analysis of U.S. traffic stop records to date.[1]

Our statistical analysis of these records proceeds in three steps. First, we assess potential bias in stop decisions by applying the "veil of darkness" test developed by Grogger and Ridgeway [13]. The test is based on a sim-

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- Which officers are most likely to shoot?
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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," *Journal of the American Statistical Association* 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

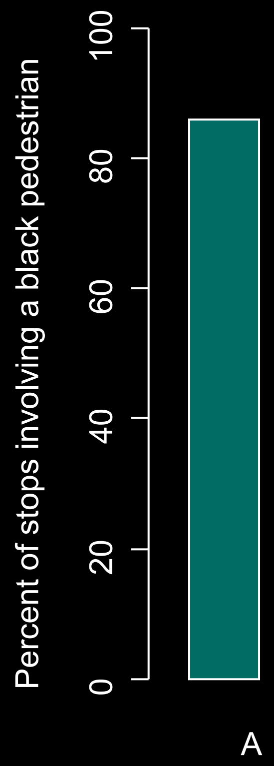
Reweighting Also Aligns the Distribution of All Other Stop Features

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

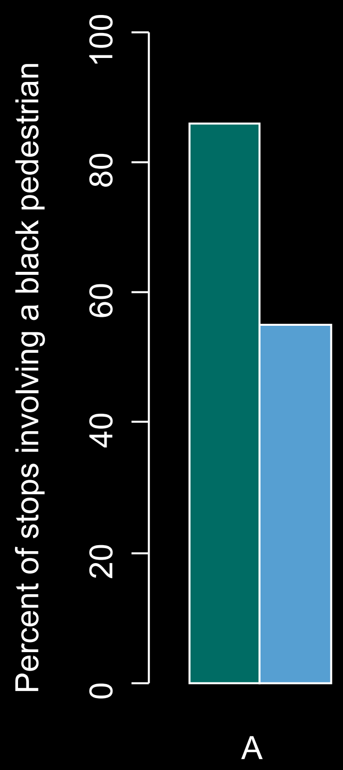
Colleagues at the Same Time, Place, and Context Stop 55% Black Pedestrians

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



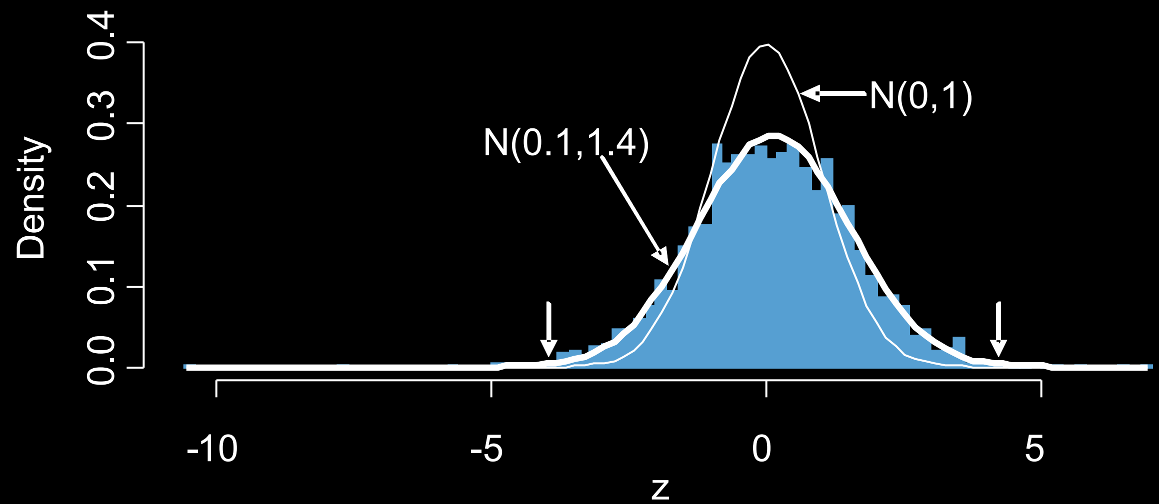
- Doubly robust benchmark estimate obtainable from weighted logistic regression

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

- Disparity computed as

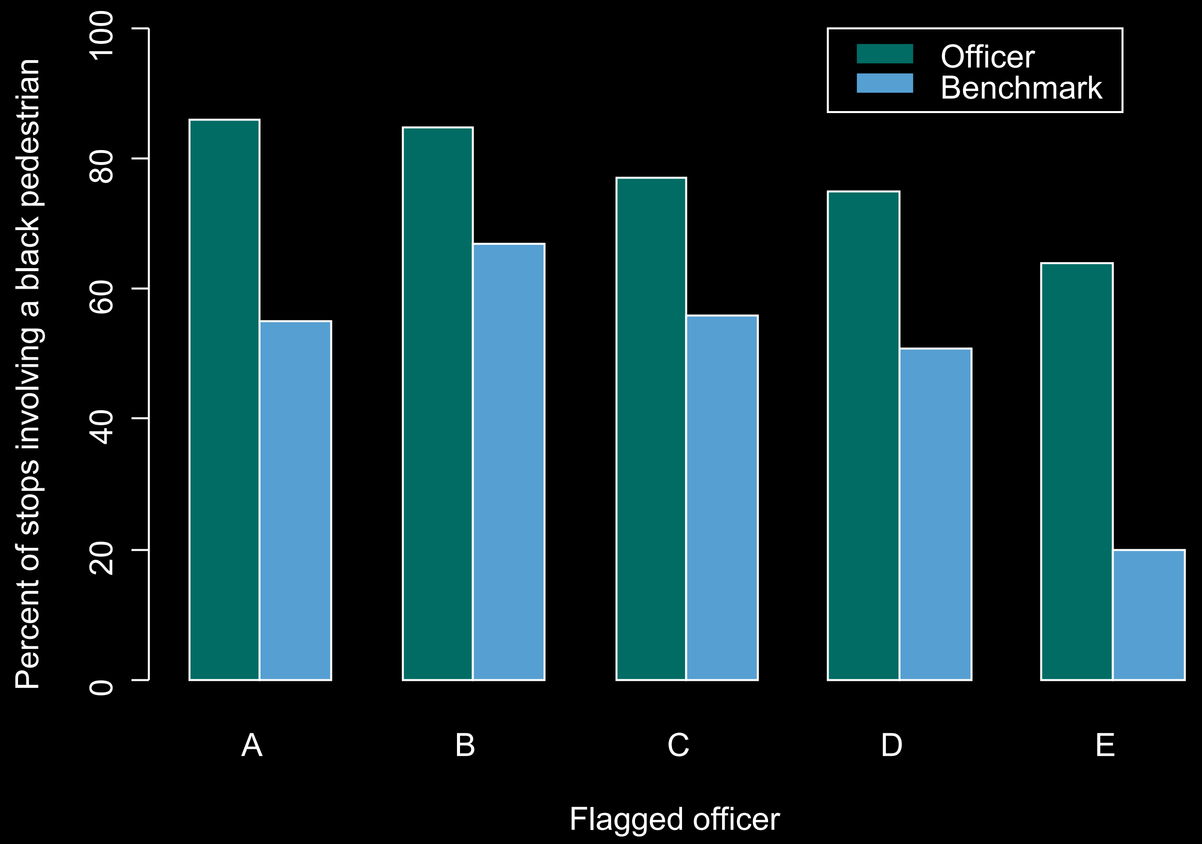
$$\hat{\theta}_A^{DR} = \sum_{i=1}^{n} t_i \left(\frac{1}{1 + \exp\left(-s(1, \mathbf{x}_i | \hat{\boldsymbol{\beta}})\right)} - \frac{1}{1 + \exp\left(-s(0, \mathbf{x}_i | \hat{\boldsymbol{\beta}})\right)} \right)$$

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

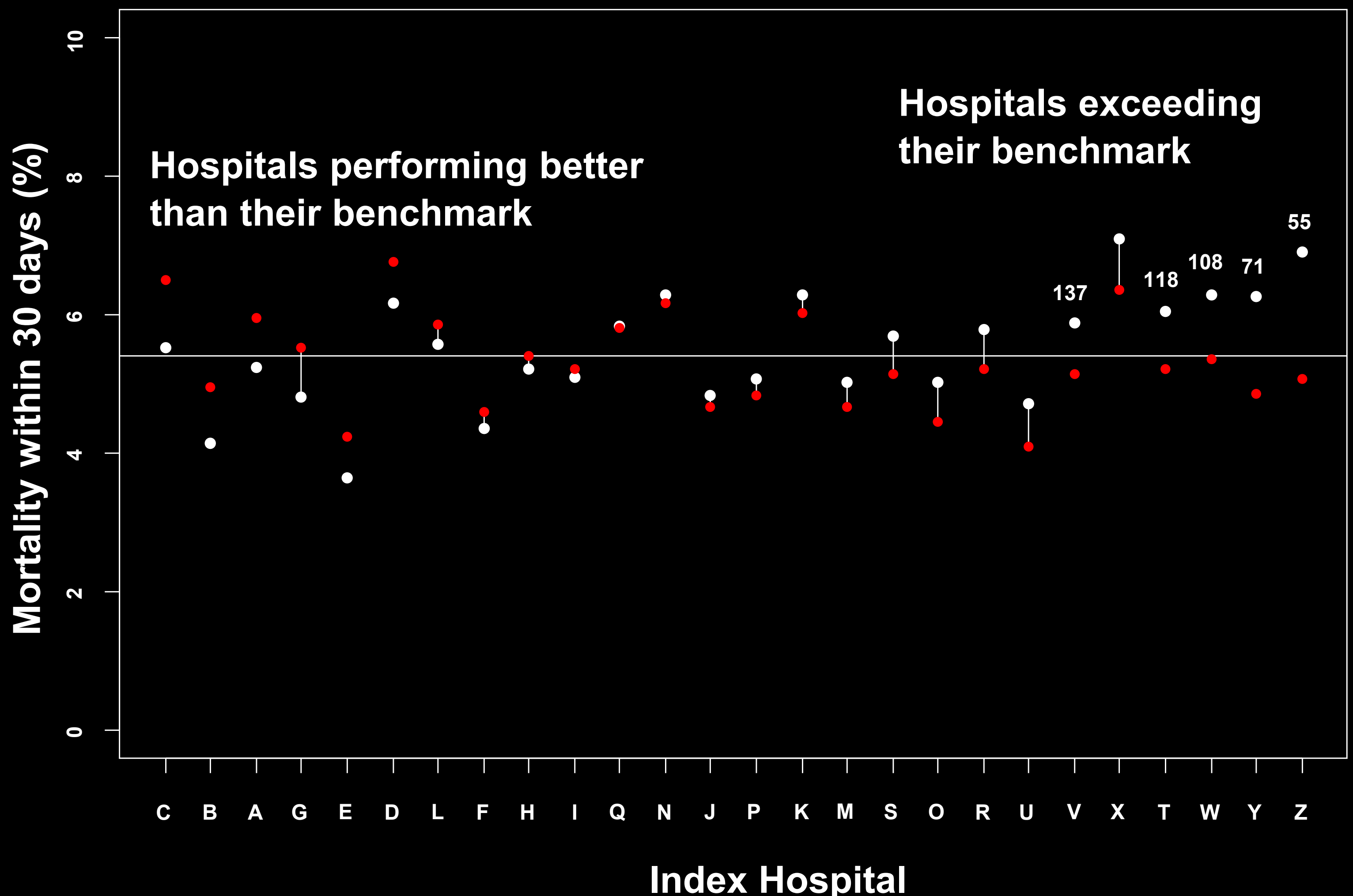


- $P(\text{problem}|z) = 1 - \dfrac{f(z|\text{no problem})f(\text{no problem})}{f(z)}$
$$\geq 1 - \frac{f_0(z)}{f(z)}$$
- Right tail consists of 5 officers with "problem officer" probabilities in excess of 50%
- Standard cutoff of z > 2.0 flags 242 officers, 90% of which have fdr estimated to be greater than 0.999

Analysis in NYPD Flagged Five Officers



Benchmarking Can Also Flag Hospitals



G. Ridgeway, M. Nørgaard, T.B. Rasmussen, W.D. Finkle, L. Pedersen, H.E. Bøtker, and H.T. Sørensen (2019). “Benchmarking Danish Hospitals on Mortality and Readmission Rates After Cardiovascular Admission,” *Clinical Epidemiology* 11:67-80

Statistics of Police Shootings and Racial Profiling

Greg Ridgeway

Department of Criminology

Department of Statistics

NYU Apr 2019

Two Nearly Identical Officers

OIS ID	Rounds	Recruit age	Years on job	Sex	Race	Prior OIS #	Force complaints	Rank	Assign	Gun type	Caliber
2	3	24	4	Male	White	0	0	Off	Special	Pistol	9 mm
2	4	25	4	Male	White	0	0	Off	Special	Pistol	9 mm

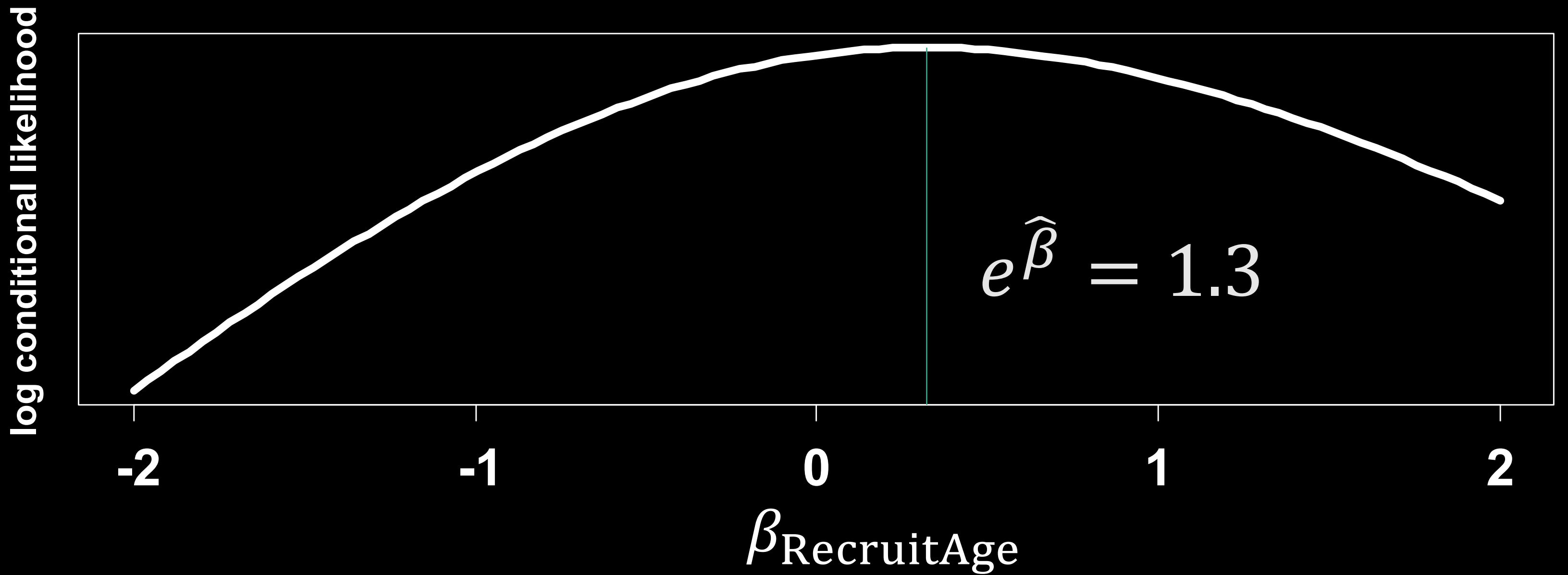
- Identical on all features except recruit age
- Older officer shot 1.3 times more than the younger officer

Only data on officers firing one or more rounds were available

Example Shooting Only Has Information on Recruit Age

- Conditional likelihood simplifies to

$$\frac{1}{\sum_{\rho_2=1}^{6} \frac{1}{(7-\rho_2)!\,\rho_2!} \exp\left((\rho_2 - 4)\beta_{\text{RecruitAge}}\right)}$$



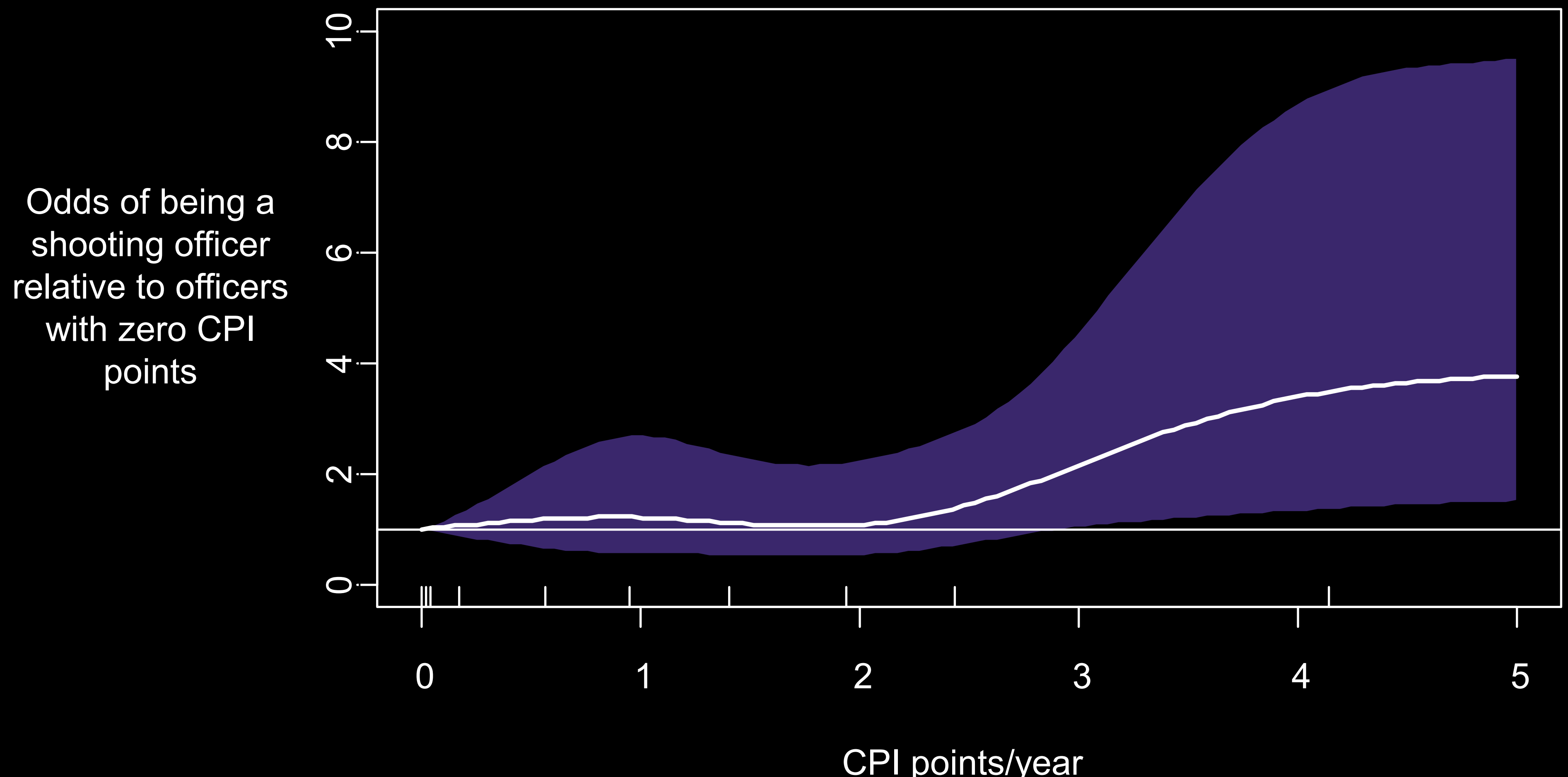
Central Personnel Index Assign Points to Problematic Incidents

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
```

Exceeding 3.1 CPI/year Strongly Associated with Shooting Risk



NYU Apr 2019

Utilized Three Years of NYPD Data, Decision to Shoot

- All officer-involved shootings adjudicated in 2004, 2005, and 2006
- 106 incidents involving 150 shooting officers and 141 non-shooting officers
- Collected data on age, experience, education, training, and past performance

G. Ridgeway (2016). "Officer Risk Factors Associated with Police Shootings: A Matched Case-Control Study," *Statistics and Public Policy* 3(1):1-6.

Officer Race and Age at Recruitment Appear to Affect Shooting Risk

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

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	No difference
CPI points > 3.1	+212%
Gun arrests > 2.4	No difference
Felony arrests > 9.3	No difference
Misdemeanor arrests > 10.0	-80%
Days of leave	No difference

8% of NYPD officers
15% of shooting scene officers