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Certified Class and Subclasses

UNITED STATES DISTRICT COURT

SOUTHERN DISTRICT OF CALIFORNIA

DARRYL DUNSMORE, ANDREE ANDRADE, ERNEST ARCHULETA, JAMES CLARK, ANTHONY EDWARDS, REANNA LEVY, JOSUE LOPEZ, CHRISTOPHER NORWOOD, JESSE OLIVARES, GUSTAVO SEPULVEDA, MICHAEL TAYLOR, and LAURA ZOERNER, on behalf of themselves and all others similarly situated,

Plaintiffs,

v.

SAN DIEGO COUNTY SHERIFF'S DEPARTMENT, COUNTY OF SAN DIEGO, SAN DIEGO COUNTY PROBATION DEPARTMENT, and DOES 1 to 20, inclusive,

Defendants.

Case No. 3:20-cv-00406-AJB-DDL

EXPERT REPORT OF MATTHEW B. ROSS, PH.D.

Judge: Hon. Anthony J. Battaglia
Magistrate: Hon. David D. Leshner

Trial Date: None Set

I, Matthew B. Ross, Ph.D., declare:

1. A true and correct copy of my expert report is attached hereto as **Exhibit A**.

PROFESSIONAL BACKGROUND AND QUALIFICATIONS

2. I am an Associate Professor of Economics and Public Policy at Northeastern University and serve as an independent consultant for the U.S. Department of Justice Civil Rights Division and the New Jersey Office of the Attorney General. I also work as an independent consultant and subject matter expert for both the U.S. Department of Justice Civil Rights Division and the New Jersey Office of the Attorney General. I am recognized as a national expert in analyzing policing data for discrimination. I developed the "Connecticut Model" for identifying and mitigating racial and ethnic disparities in police traffic stops. This model has been adopted by numerous states and endorsed by national advocacy organizations. The U.S. Department of Justice has integrated my framework into its enforcement activities and has invited me to serve as a subject matter expert. My scholarly work on testing for discrimination in policing data has been published in highly ranked academic journals. My research has been funded by the National Science Foundation, the Russell Sage Foundation, Arnold Ventures, and the U.S. Department of Transportation. A true and correct copy of my *curriculum vitae* is attached hereto as **Exhibit B**.

3. I authored or co-authored the following publications that have been published in journals, conference proceedings, or books over the past ten years:

- Yu, H., Marschke, G., Ross, M.B. et al. Publish or Perish: Selective Attrition as a Unifying Explanation for Patterns in Innovation over the Career. *Journal of Human Resources* 59-1 (2024)
- Kalinowski, J.J., Ross, S.L., Ross, M.B. Endogenous Driving Behavior in Tests of Racial Profiling. *Journal of Human Resources* 59-2 (2023).
- Ross, M.B., Glennon, B.M., Murciano-Goroff, R. et al. Women are credited less in science than men. *Nature* 608, 135–145 (2022).
- Ross, M.B., Kalinowski, J.J., Barone, K. Testing for Disparities in Traffic

Stops: Best Practices from the Connecticut Model. *Criminology & Public Policy* 19-4 (2020).

- Chevalier, G. Chomienne, C. Jeanrenaud, N.G., Lane, J.I., Ross, M.B. A New Approach for Estimating Research Impact: An Application to French Cancer Research. *Quantitative Science Studies* 1-4 (2020).
- Ross, M.B. The Effect of Intensive Margin Changes to Task Content on Employment Dynamics over the Business Cycle. *Industrial and Labor Relations Review* 74-4 (2020).
- Kalinowski, J.J., Ross, S.L., Ross, M.B. Now You See Me, Now You Don't: The Geography of Police Stops. *American Economic Review Papers and* Proceedings 109 (2019).
- Couch, K.A., Ross, M.B., Vavrek, J. Career Pathways and Integrated Instruction: A National program Review of I-Best Implementations. *Journal of Labor Research* 39 (2018).
- Kehoe, A.K., Vetle, T.I., Ross, M.B., Smalheiser, N.R. Predicting MeSH Beyond MEDLINE. Association of Computing Machinery (ACM): *Proceedings of Workshop on Scholarly Web Mining* (2018).
- Ross, M.B. Routine-Biased Technical Change: Panel Evidence of Task Orientation and Wage Effects. *Labour Economics* 48 (2017).
- Ross, M.B. Ikudo, A., Lane, J.I. The Food Safety Research Workforce and Economic Outcomes. *Measuring the Economic Value of Research: The Case of Food Safety*, c. 6 pp. 100- 112, Cambridge University Press (2017)**.**
- King, J.L. Johnson, S.R., Ross, M.B. Assessing the Effects of Food Safety Research on Early Career Outcomes. *Measuring the Economic Value of Research: The Case of Food Safety*, c. 8 pp. 100- 112, Cambridge University Press (2017).

4. In the past four years, I have testified in one case: *NOPD Consent Decree, USA v. City of New Orleans*, Case No. 12-cv-1024 (E.D. La.) (June 5, 2024 testimony).

5. I am being compensated at a rate of $160 per hour for work on this expert report, and $200 per hour for depositions and trial testimony.

SCOPE OF EXPERT REPORT

6. The plaintiffs in the case Dunsmore v. State of California et al. (Case No. 3:20-cv-00406-AJB-DDL) allege that the San Diego County Sheriff's Department disproportionately targets and incarcerates members of Black and Latino(a) communities using state funds. They cite a 2021 study by the Center for

Policing Equity, which reports that in 2020, 16% of all arrestees and 11% of non-traffic stop subjects were Black/AA, despite Black/AA residents comprising only 5% of San Diego County's population. A 2022 study by Catalyst California and the ACLU of Southern California indicates that Black/AA residents were 2.2 times more likely than White residents to be stopped by the San Diego County Sheriff's Department.

7. This expert report evaluates these and other claims in Plaintiffs' Third Amended Complaint using the Sheriff's Department administrative data obtained during discovery, as well as public and unreleased traffic stop data, employing advanced empirical techniques to confirm that the data reveal significant disparities affecting Black/AA and Latino(a) individuals consistent with disparate treatment.

8. This report addresses two core questions from the plaintiffs' complaint: (1) Does the data support the claim that the San Diego County Sheriff's Department disproportionately targets Black/AA and Hispanic/Latino(a) communities with discretionary stops? (2) Does the data support the claim that these communities are disproportionately more likely to be detained and arrested?

DATA SUMMARY

9. The analysis in this report is based on two distinct datasets: computer-aided dispatch (CAD) records, which are linked to arrest and other administrative records, and data from the Racial and Identity Profiling Act (RIPA) on stops reported to the State of California by the San Diego County Sheriff's Department. The CAD dataset comprises 1,970,623 events from 2021 to 2023, with 1,460,946 involving an officer responding on the scene and 184,187 categorized as traffic or subject stops. Under California law, one would expect the RIPA dataset to reflect a similar number of stops. However, the RIPA data documented only 67,658 stops during the same period. Notably, stops recorded in the CAD system but absent from the RIPA dataset are disproportionately likely to have occurred in predominantly Black/African American or Hispanic/Latino(a) neighborhoods. While the CAD data

appears to encompass the full scope of stops, it lacks race or ethnicity information for the individuals involved. Consequently, this analysis conducts separate evaluations for each dataset, though it is significantly constrained by the limitations inherent in both sources. While I cannot definitively conclude that the Sheriff's department has intentionally underreported data to RIPA or that it has strategically chosen not to collect race/ethnicity in CAD, these two factors have resulted in a significant barrier to obtaining estimates of the full extent of disparate treatment within the agency.

10. The information and opinions contained in this report are based on evidence, documentation, and/or observations available to me. The Sheriff's Department administrative data analyzed in this report and other materials I have reviewed in connection with this report are identified in the index attached hereto as **Exhibit C**. I reserve the right to modify or expand these opinions should additional information become available to me.

ANALYTICAL METHODS

11. This report employs advanced econometric techniques and quasi-experimental tests to analyze the data. Multivariate regression analysis is used to control for various circumstantial factors influencing stops and arrests. Despite the limitations of the Sheriff's Department data and the conservative nature of my analytical approach, the findings consistently show significant disparities in the likelihood of stops and arrests for Black/AA and Hispanic/Latino(a) individuals compared to their White counterparts.

SUMMARY OF OPINIONS

12. The findings from this expert report provide compelling evidence that the San Diego County Sheriff's Department engages in practices that disproportionately target and arrest Black/AA and Hispanic/Latino(a) individuals. My key opinions, formed from my analysis of the Sheriff's Department data include:

I. Opinion One: The Sheriff's Department Systematically Underreports Stops, Particularly in Black and Hispanic Neighborhoods

13. The CAD data shows 163,012 stops, but only 67,658 are reported in RIPA, with pronounced underreporting in Black/AA and Hispanic/Latino(a) neighborhoods. This discrepancy indicates systemic issues in data reporting, leading to potential sample selection bias and undermining efforts to assess racial profiling.

II. Opinion Two: The Sheriff's Department Stops Black People Nearly 30% More than White People in Daylight

14. RIPA data shows stops of Black/AA individuals are 29.2% more likely in daylight when race is more visible as compared to White non-Hispanic motorists.

III. Opinion Three: The Sheriff's Department Is Less Likely to Stop People in White, Non-Hispanic Neighborhoods and More Likely to Stop People in Hispanic Neighborhoods in Daylight

15. CAD data indicates stops are less likely to occur in White non-Hispanic dominant neighborhoods during daylight relative to darkness, and more likely to occur in Hispanic/Latino(a) neighborhoods during daylight hours.

IV. Opinion Four: Hispanic Individuals Are Nearly 30% More Likely to Be Arrested After a Stop by the Sheriff's Department than White, Non-Hispanic Individuals

16. Hispanic/Latino(a) stops are 28.6% more likely to end in arrest, and stops in their neighborhoods are 32.9% more likely to result in arrest.

V. Opinion Five: Hispanic Individuals Are Nearly 20% More Likely to Be Asked to Exit Their Vehicle After a Stop by the Sheriff's Department than White, Non-Hispanic Individuals

17. Hispanic/Latino(a) motorists are 19.6% more likely to be asked to exit their vehicle and 30.5% more likely to be searched. Black/AA motorists show similar trends, though only marginally statistically significant.

VI. Opinion Six: The Data Show a Pattern of Disparate Treatment by the Sheriff's Department Towards Black and Hispanic People

18. Collectively, the results demonstrate a pattern of disparate treatment

towards Black/AA and Hispanic/Latino(a) individuals in the enforcement practices of the San Diego County Sheriff's Department. The evidence suggests that these communities are not only more likely to be stopped but also face higher probabilities of subsequent searches and arrests, indicative of systemic bias. While I find similar evidence of disparate treatment in both the RIPA and CAD datasets, it is my conjecture that these estimates likely underestimate the extent of the disparities due to the aforementioned limitations of each dataset. The findings in this report underscore the necessity for comprehensive policy reforms and enhanced oversight to ensure equitable treatment in law enforcement practices, and to address the deeply rooted disparities identified in this analysis.

19. The information contained in this report and the accompanying exhibits are a fair and accurate representation of the subject of my anticipated testimony in this case.

Dated: August 21, 2024

Matthew B. Ross

Matthew B. Ross, Ph.D.

Exhibit A

Expert Witness Report

Title: Expert Report of Matthew B. Ross, Ph.D.

Date: August 21, 2024

Pursuant to: Dunsmore v. State of California et al. (Case No. 3:20-cv-00406-AJB-DDL)

Prepared for: Rosen Bien Galvan & Grunfeld LLP

Prepared by: Matthew B. Ross, PhD as CEO and Owner of Matthew B. Ross LLC.

Matthew B. Ross LLC is a limited liability corporation providing technical analysis and expert witness services. The company was formed in the State of Delaware and is currently registered and operating in the States of Massachusetts and New Jersey.

Expert Witness Report

1. Introduction and Background

In the complaint filed by plaintiffs in Dunsmore v. State of California et al. (Case No. 3:20-cv-00406-AJB-DDL), the plaintiffs allege that the San Diego County Sheriff's Department disproportionately targets and incarcerates members of Black and Latino(a) communities. Citing a 2021 study by the Center for Policing Equity, the plaintiffs report that in 2020, 16% of all arrestees and 11% of all individuals stopped in non-traffic stops were Black/AA, despite Black/AA residents comprising only 5% of San Diego County's population. Additionally, a 2022 study by Catalyst California and the ACLU of Southern California indicates that Black/AA residents of San Diego County were 2.2 times more likely than White residents to be stopped by the San Diego County Sheriff's Department. Using administrative data obtained during discovery, along with public and unreleased traffic stop data, this expert report evaluates plaintiffs' claim that the San Diego County Sheriff's Department disproportionately targets and incarcerates Black/AA and Latino(a) individuals. While the statistics cited in the plaintiffs' complaint are troubling, they are primarily descriptive and lack the rigorous analysis needed to confirm a pattern or practice of discrimination. In this expert report, I analyze a more comprehensive and detailed dataset using advanced empirical techniques. Ultimately, I confirm that the data from the San Diego County Sheriff's Department reveal statistically significant disparities affecting Black/AA and Latino(a) individuals, which are substantial in magnitude and consistent with disparate treatment towards racial and ethnic minorities.

This expert report is authored by me, Dr. Matthew B. Ross, in my role as an expert witness for Rosen Bien Galvan & Grunfeld LLP in the case of *Dunsmore v. State of California et al.* (Case No. 3:20-cv-00406-AJB-DDL). I am compensated for my work on this report at a rate of $160 per hour. In my primary professional capacity, I am an academic scholar and serve as an Associate Professor of Economics and Public Policy at Northeastern University. Additionally, I work as an independent consultant and subject matter expert for both the U.S. Department of Justice Civil Rights Division and the New Jersey Office of the Attorney General. I am nationally recognized as an expert in the analysis of administrative policing data for evidence of discrimination, a reputation that I have earned through extensive scholarly research and the execution of numerous public-facing disparity studies. Over the past decade, I have analyzed data from hundreds of policing agencies and authored more than a dozen multi-agency disparity studies for jurisdictions across Connecticut, Massachusetts, New Jersey, Rhode Island, and Washington D.C. Notably, my colleagues and I provided testimony and technical assistance during the passage and implementation of California's Racial and Identity Profiling Act (RIPA). My scholarly contributions on discrimination and public policy have been published in leading academic journals, including *Nature*, the *Journal of Human Resources*, *Criminology & Public Policy*, and the *Industrial & Labor Relations Review*. My research has been supported by funding from the National Science Foundation, the Russell Sage Foundation, Arnold Ventures, and the U.S. Department of Transportation.

I am particularly well-known for developing the technical framework of the "Connecticut Model," a pioneering approach designed to identify and mitigate racial and ethnic disparities in police traffic stops. This model has been adopted by multiple states, endorsed by advocacy organizations, and is widely recognized as a national best practice. The influence of the Connecticut Model extends far beyond Connecticut's borders, significantly shaping the national discourse on police reform. As early as 2015, my collaborators and I offered detailed guidance to states interested in enacting data collection laws, conducting analyses, and implementing similar interventions. To date, we have provided guidance and technical assistance to states including Alabama, California, Colorado, the District of Columbia, Maine, Maryland, Minnesota, Nevada, New Jersey, New York, Oregon, Ohio, and Rhode Island. In 2021, my collaborator testified before Congress regarding this initiative (Barone 2021), which was subsequently promoted as a model for state reforms by two major national traffic safety organizations: Mothers Against Drunk Driving (MADD) (Hawkins 2021; MADD 2021) and the Governors Highway Safety Association (Sprattler and Statz 2021). Recently, the Arnold Foundation funded the Justice Center at the Council of State Governments to provide technical assistance to Nevada and two other states in crafting legislation inspired by Connecticut's program. If funded, the second-round proposal at Arnold would expand this effort to provide technical assistance to up to 10 states through the entire process from initial legislation to program implementation. Additionally, the U.S. Department of Justice (DOJ) has integrated my framework into its enforcement activities and has invited me to serve as a subject matter expert.

In this expert report, I focus my analysis on providing salient answers to two questions that are core to the plaintiff's complaint:

> *(1) Does the data support the claim that the San Diego County Sheriff's Department engages in enforcement policies whereby members of Black/AA and Hispanic/Latino(a) communities are disproportionately the target of discretionary officer-initiated stops?*
> *(2) Does the data support the claim that the San Diego County Sheriff's Department engages in enforcement policies whereby Black/AA and Hispanic/Latino(a) communities are disproportionately more likely to be detained and arrested?*

My analysis relies solely on two distinct analytical datasets that I have constructed by combining various administrative records provided by defendants during discovery. The first of these datasets is based primarily on computer-aided dispatch (CAD) records linked to arrest records and associated features of subsequent criminal investigations. These CAD data consist of 1,970,623 events which occurred from January 1st, 2021 to December 31st, 2023 of which 1,460,946 involve an officer responding on the scene. The second of these datasets is based primarily on public and soon-to-be public RIPA stop data. These RIPA data consist of 67,658 unique stops which occurred from January 1st, 2021 to December 31st, 2023 which were reported by the San Diego County Sheriff's Department to the State of California pursuant AB 953, i.e. "The Racial and Identity Profiling Act of 2015".

Of particular note, neither of the datasets are ideal in terms of coverage and data elements. While the RIPA data should contain most of the necessary information for my analysis, there appears to be systematic and widespread underreporting of stops by the Sheriff's Department in the state's anti-profiling data system. In a subsequent section, I document the extent of this underreporting, but I note here that there are 163,012 events in CAD associated with a stop, yet only 67,658 unique stops in RIPA. Even when allowing an extreme amount of leniency in terms of the match between two databases, I am still unable to match a large portion of the stops in the Sheriff's administrative CAD data to the stops reported to RIPA. As such, I conduct two separate analyses: one relies on the RIPA data, where I definitively know the officer's perception of a motorist's race and ethnicity but have a potentially biased sample of stops, and the other relies on the CAD events, where I do not know the race of the individual involved but have the universe of stops and a rich set of circumstantial control variables. In my experience analyzing administrative data from hundreds of agencies across the country, the fact that the Sheriff's Department does not collect race and ethnicity information associated with stops in their CAD system is extremely unusual. This, combined with the strong evidence suggesting systemic underreporting into RIPA, is particularly telling regarding the Sheriff Department's commitment to identify and eliminate disparate treatment in their enforcement activity.

As a final introductory note, I want to emphasize that the analysis in this expert report relies on advanced econometric techniques and quasi-experimental tests of disparity. The goal of this report is to create an apples-to-apples comparison to assess whether officers are disproportionately more likely to stop and arrest racial and ethnic minorities relative to their majority peers. To effectively conduct such an analysis, I utilize the richness of the administrative data to develop a granular set of controls that account for the circumstantial factors influencing an officer's decision to make a stop or an arrest. While the main body of the report features graphical figures that are relatively easy to read, all estimates are generated using multivariate regression analysis on datasets containing tens-of-thousands to hundreds-of-thousands of observations. The appendix to this report includes supporting tables with the associated coefficient estimates, numerous robustness checks on model specification, and technical details on the underlying tests. Despite the limitations of both datasets and the conservative nature of my analytical approach, I find persistent disparities in both the decision to stop and the decision to arrest which are consistent with disparate treatment towards racial and ethnic minorities.

2. Data and Descriptive Statistics

The administrative CAD and RIPA data, provided by the Sheriff's Department during discovery, covers January 2021 to December 2023 and offers a comprehensive record of enforcement activities, with detailed variables describing each event. The raw CAD data comprises 1,970,623 events, with 1,460,946 involving an officer's response on the scene. While the Sheriff's Department indicated during a meet & confer meeting that the analysis should focus exclusively on the 496,358 CAD events labeled as "Deputy Initiated Activity" (DIA), I identified an additional 19,735 events that appear to be discretionary stops which aren't labeled as DIA events. However, only 184,187 of these stops can be truly categorized as discretionary enforcement actions. Among these, 145,440 DIA events are explicitly labeled as subject or traffic stops, with an additional 17,572 events labeled as "Other" but with similar descriptions (see Column 1). These 163,012 stops are the primary sample used for the analysis of the CAD data. As shown in Column 2 of Table 1, the RIPA data only includes 67,658 stops, 2,725 of which resulted in arrests. Additional more detailed descriptive statistics are contained in Appendix Table A.1.

Table 1: Descriptive Statistics for Stops in CAD and RIPA

Period: 2021-23		(1)	(2)
	Dataset:	CAD	RIPA
	Sample:	Stops	
	N=	163,012	67,658
Neighborhood or Motorist*	White	0.501	0.498
		(0.227)	(0.5)
	Hispanic/Latino(a)	0.338	0.346
		(0.223)	(0.476)
	Black/AA	0.042	0.063
		(0.066)	(0.244)
	Sample:	Discretionary Arrests**	
	N=	6,862	2,725
	P(Arrest | Stop)	0.042	0.040
Motorist	White	0.464	0.421
		(0.499)	(0.494)
	Hispanic/Latino(a)	0.41	0.449
		(0.492)	(0.498)
	Black/AA	0.086	0.091
		(0.28)	(0.287)

*Demographics in CAD are from location of traffic stops (i.e. Census Block) using residential population from the 2020 Census. **Discretionary arrests in CAD include only misdemeanor arrests. Discretionary arrests in RIPA include custodial arrests without a warrant, i.e. arrests not coded as cite and release, custodial arrests pursuant to a warrant, or psychiatric holds.

The discrepancy between the number of stops in the CAD (Column 1) and RIPA (Column 2) data suggests significant underreporting into the RIPA database. Specifically, while the CAD data indicates 163,012 stop-related events, there are only 67,658 unique stops in RIPA. This raises concerns about using RIPA data exclusively, as it may represent a select and biased sample. In the technical appendix, I present evidence that stops in predominantly Black/AA and Hispanic/Latino(a) neighborhoods are less likely to be recorded in RIPA, suggesting that any analysis of disparate treatment using RIPA data alone may underestimate the extent of disparity.[1] On the other hand, while the CAD data likely captures the full universe of stops, it lacks information on the race or ethnicity of individuals involved. To address this, I linked each CAD event's geographic location to Census Block-level residential demographics, providing neighborhood demographic data. However, this approach uses neighborhood composition as a proxy for individual race/ethnicity, which introduces potential measurement error and likely attenuates the resulting estimates. As such, I proceed with conducting separate analyses on each dataset which the necessary caveat that both have significant limitations which warrant both scrutiny and concern. In general, it is extremely concerning that there is such a significant discrepancy between the CAD and RIPA systems, that the San Diego Sheriff's

[1] Figure A.1 in the Technical Appendix shows a matching exercise where stops in predominantly Black/AA or Hispanic/Latino(a) neighborhoods are more likely to be unreported in RIPA

Department does not have a direct link between these datasets, and that the Sheriff's Department does not collect race/ethnicity for all CAD events.

3. Analysis of RIPA Data

Figure 1 below presents estimates of the racial composition of stopped motorists in daylight relative to darkness within a window of time when sunset varies through the year. These estimates are estimated using the so-called "Veil of Darkness" test which assesses racial profiling in traffic stops by comparing the racial composition of motorists stopped during daylight to those stopped during darkness (Grogger and Ridgeway in 2006; Horace and Rohlin 2016; Kalinowski et al. 2023, 2019a; 2019b). The test is predicated on the assumption that racially biased enforcement is more likely to occur during daylight when race is more easily observed by police prior to making a stop. The test isolates the effect of daylight on the composition of stopped motorists from changes in the underlying motorists on the roadway by focusing on a narrow window of time throughout the year when the timing of sunset varies. Since a subset of stops like lighting violations might be correlated with daylight and race/ethnicity via socioeconomic status, the test is typically run on a subsample of stops that excludes equipment violations as well as seatbelt and cellphone infractions. Over the last decade and a half since the test's inception, subsequent research has validated its effectiveness by expanding the application and refining the methodology. The Veil of Darkness remains the most reliable and rigorous test of disparate treatment in the decision to stop a motorist.[2]

The estimates in Figure 1 were generated using an ordinary least squares regression that includes a number of controls that hold fixed potential variation in the underlying driving population.[3]

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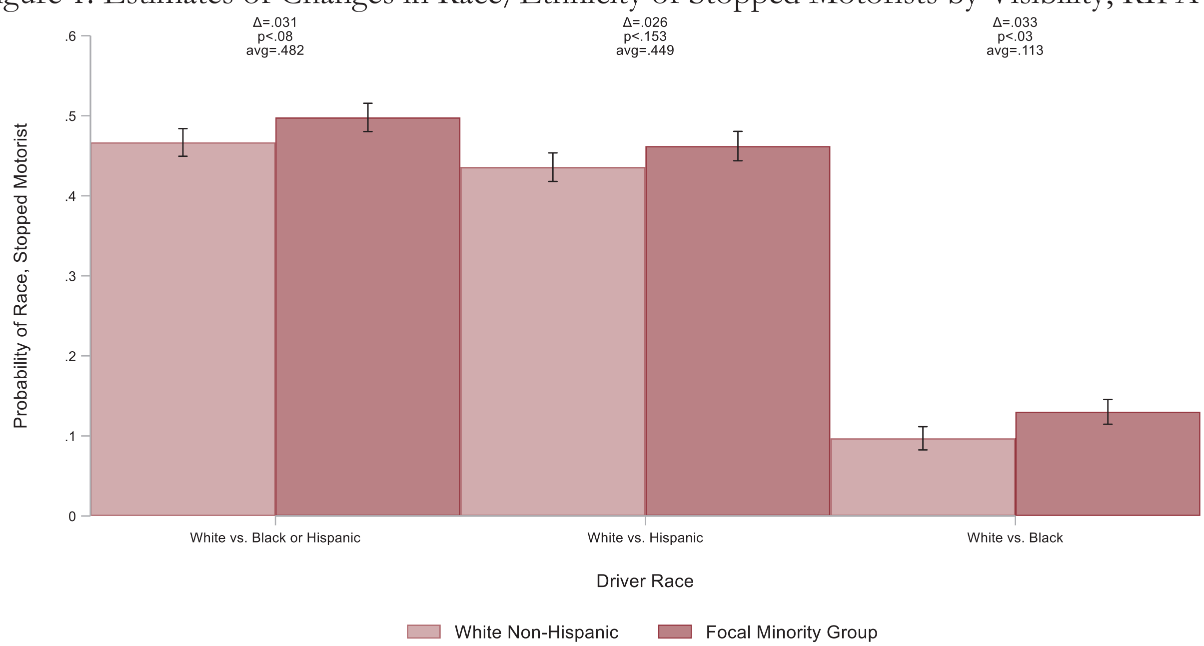
[2] Scholarly critiques of Veil of Darkness have largely found it is a very conservative and strict test (see Horace and Rohlin 2016; Kalinowski et al. 2023, 2019a; 2019b) A recent national application of Veil of Darkness on 100 million traffic stops from 21 state patrol agencies and 35 municipal police departments was published in Nature Human Behavior (Pierson et al. 2020). Statewide multi-agency studies relying on the VOD include Connecticut (Ross et al. 2015, 2016, 2017a, 2017b, 2018, 2019a, 2019b, 2020, 2021, 2022), Rhode Island (Ross et al. 2019, 2020, 2021), California (Sanchagrin et al. 2019, 2020, 2021), Oregon (Oregon DOJ dashboard), and Massachusetts (Salem State 2020, 2022, Ross 2023). Agency-specific studies relying on the VOD include in Oakland, CA (Grogger and Ridgeway 2006); Cincinnati, OH (Ridgeway 2009); Minneapolis, MN (Ritter and Bael 2009 and Ritter 2017); Syracuse, NY (Worden, McLean, and Wheeler 2010, 2012; Horace and Rohlin 2016); Portland, OR (Renauer, Henning, and Covelli 2009); Durham Greensboro, Raleigh, and Fayetteville, North Carolina (Taniguchi et al. 2016a, 2016b, 2016c, 2016d); New Orleans, LA (Asher 2016); San Diego, CA (Chanin et al. 2016); Corvallis PD (Criminal Justice Policy Research Institute 2017); Columbia, MO (Milyo 2017); San Jose, CA (Smith et al. 2017); Maricopa, AZ (Wallace et al. 2017); Portland, ME (McDevitt et al. 2023), Douglas Co, KS (McDevitt et al. 2023); Tennessee State Police (Kalinowski et al. 2023); Texas Highway Patrol (Kalinowski et al. 2023, Mello et al. 2024); Massachusetts State Police (Kalinowski et al. 2023); New Jersey State Police (Ross 2023); and DC Metro (Forthcoming).

[3] To generate Figure 5, I estimate a model of the form $1[minority_i] = \gamma + \beta\ 1[daylight_i] + \sum \lambda_j + \mu_i$ where $1[minority_i]$ is a is a dichotomous indicator variable equal to one if a stop is made of a racial/ethnic minority and zero otherwise. The underlying sample of stops is limited to the so-called "inter-twilight window" occurring between the earliest sunset and the latest end to civil twilight within a given year. The variable of interest $1[daylight_i]$ is a dichotomous indicator variable equal to one if a stop during daylight and zero otherwise. The regression includes a constant term (γ) and an idiosyncratic error term (μ_i). In Figure 5, the vector of fixed effects ($\sum \lambda_j$) includes indicators for day of week by year and time of day (15-minute increments) by year. In the figure, the levels and standard errors are predicted by holding all variables, except for the variable of interest, at their sample mean and multiplying by the coefficient estimates obtained from the regression model. Standard errors are clustered on time by year.

As shown below, stops were 3.1 percentage points ("pp") (6.4% relative to a mean of 48.2%, significance of p<0.08) more likely to involve a Hispanic/Latino(a) or Black/AA motorist during daylight relative to darkness and compared to White non-Hispanic motorists. Another way of saying this is that Sheriff's Department stops were 6.4% more likely to involve a Hispanic/Latino(a) or Black/AA motorist during daylight (relative to night) than a White non-Hispanic motorist. Stops were 2.6pp (5.8% relative to a mean of 44.9%, significance of p<0.153) more likely to involve a Hispanic/Latino(a) motorist during daylight relative to darkness and compared to White non-Hispanic motorists. Stops were 3.3pp (29.2% relative to a mean of 11.3%, significance of p<0.03) more likely to involve a Black/AA motorist during daylight relative to darkness and compared to White non-Hispanic motorists. This means that Sheriff's Department stops were 29.2% more likely to involve a Black/AA motorist during daylight (relative to night) than a White non-Hispanic motorist. These estimates are consistent with disparate treatment towards racial/ethnic minorities, particularly Black/AA motorists, by the San Diego County Sherrif in the decision to make a stop. These results are qualitatively similar and statistically robust to including alternative controls (see Appendix Table A.2) and expanding the sample to include all stops (see Appendix Table A.3). As mentioned, these estimates are likely an underestimate of the extent of the disparity due to selection bias in the underlying sample of stops reported to RIPA.

Figure 1: Estimates of Changes in Race/Ethnicity of Stopped Motorists by Visibility, RIPA Stops



Notes: The estimates represented by each pair of bars were obtained from an ordinary least squares regression of the racial/ethnic perception of motorists on an indicator for daylight and conditional on the factors impacting the composition of the driving population. In each of the three pairs of bars, the leftmost bar (light maroon) represents a White non-Hispanic motorist, and the rightmost bar (dark maroon) represents the focal minority group. The focal minority group is labeled on the X-axis. The estimated difference between the two bars is annotated along the top of the figure by use of a triangle, along with the associated p-value and sample mean. As an example, the estimated difference shown in the first pair of bars is .031, equal to 3.1 percentage points. Given that the mean is .482, or 48.2%, the first pair of bars show that Sheriff's Department stops were 6.4% (3.1 percentage points divided by 48.2%) more likely to involve a Hispanic/Latino(a) or Black/AA motorist during daylight than a White non-Hispanic motorist.

Conditional outcome tests aim to assess whether different groups receive equitable treatment by examining outcomes conditioned on observable characteristics and legal justification. Economists and econometricians have developed sophisticated models to control confounding variables that might otherwise obscure true disparities. One common approach is regression analysis, which allows researchers to isolate the effect of race or ethnicity on an outcome like arrest by holding constant other relevant factors (Kotchel et al. 2011; Novak and Chamlin 2012). By adjusting for these confounders, these models strive to produce unbiased estimates of the effect of race or ethnicity, which are crucial for identifying and addressing potential discrimination. These estimates help to reveal whether disparities exist beyond what would be expected based on observable characteristics alone. Such analyses are essential for informing policy and intervention strategies aimed at promoting fairness and equity in various sectors, particularly in law enforcement and the criminal justice system. By accurately measuring disparities, conditional outcome tests provide a robust foundation for efforts to mitigate discrimination and ensure equitable treatment across different populations.

Estimates of the conditional likelihood that a stop results in a discretionary arrest in the RIPA dataset are presented in Figure 2 for White non-Hispanic motorists compared to Black/AA or Hispanic/Latino motorists. These estimates were generated using an ordinary least squares regression that includes a number of controls that hold fixed the circumstances of the stop.[4] For the purpose of this analysis, I define a discretionary arrest as those coded in the data as custodial arrests without a warrant, i.e. arrests not coded as cite and release, custodial arrests pursuant to a warrant, or psychiatric holds.[5] As shown below, the combined group of Black/AA and Hispanic/Latino motorists were 1.1pp (26.2% relative to a mean of 4.2%, significance of $p<0.001$) more likely to be arrested relative to White non-Hispanic motorists and conditional on the circumstances of the stop. This means that Black/AA and Hispanic/Latino motorists were 26.2% more likely to be arrested relative to White non-Hispanic motorists, controlling for the circumstances of the stop. Hispanic/Latino(a) motorists were 1.2pp (28.6% relative to a mean of 4.2%, significance of $p<0.001$) more likely to be arrested. Black/AA motorists were 0.6pp (16.2% relative to a mean of 3.7%, significance of $p<0.097$) more likely to be arrested. The estimates for Hispanic/Latino(a) and Black/AA motorists are consistent with disparate treatment by the San Diego County Sherrif in the decision to make an arrest. However, the results for Black/AA motorists were only marginally significant. These results are qualitatively similar and statistically robust to including alternative controls (see Appendix Table A.4, A.5, and A.6) and using a more inclusive definition of arrest (see Appendix Table A.7, A.8, and A.9). As mentioned, these estimates are likely an underestimate of the extent of the disparity due to selection bias in the underlying sample of stops reported to RIPA.

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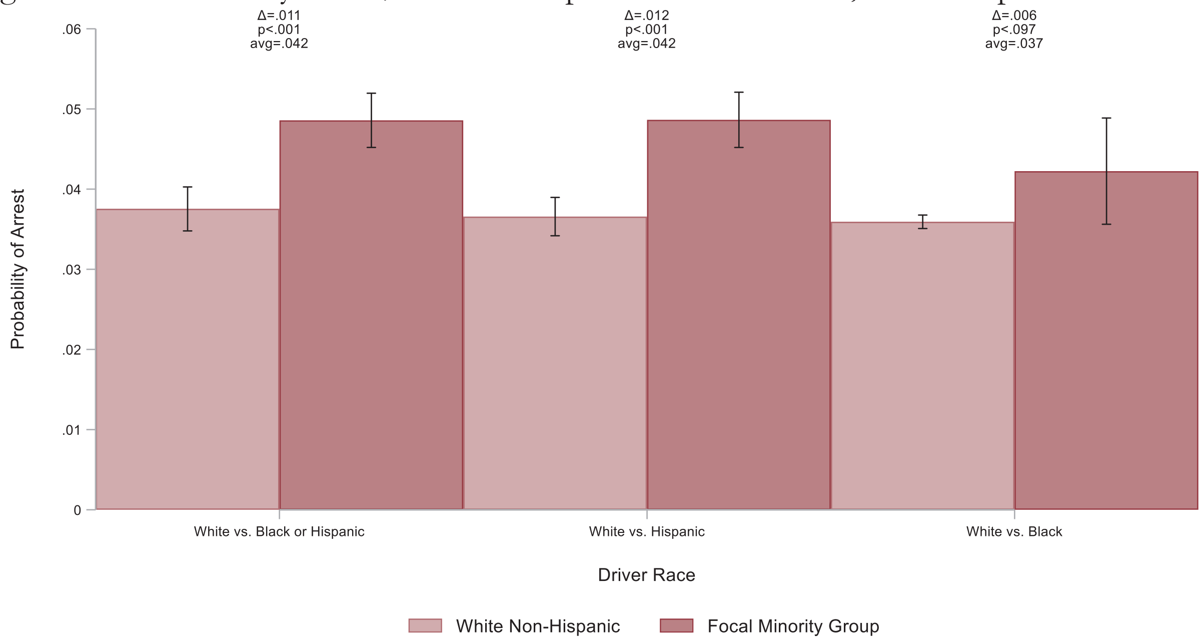
[4] To generate Figure 2, I estimate a model of the form $1[arrest_i] = \gamma + \beta\, 1[minority_i] + \sum \lambda_j + \mu_i$ where $1[arrest_i]$ is a dichotomous indicator variable equal to one if a stop yielded a custodial arrest without a warrant and zero otherwise. The variable of interest ($1[minority_i]$) is a dichotomous indicator variable equal to one if the motorist involved in the stop was a racial or ethnic minority and zero if the motorist was White non-Hispanic. The regression includes a constant term (γ) and an idiosyncratic error term (μ_i). In Figure 2, the vector of fixed effects ($\sum \lambda_j$) includes indicators for month by year (36), day of week by hour (168), reason (8), and city (56). In the figure, the levels and standard errors are predicted by holding all variables, except for the variable of interest, at their sample mean and multiplying by the coefficient estimates obtained from the regression model. Standard errors are clustered on city.

[5] Note that the estimates are robust to a more inclusive definition of arrests. The results are contained in Appendix Table A.7, A.8, and A.9.

Figure 2: Arrest Rate by Racial/Ethnic Composition of Motorists, RIPA Stops



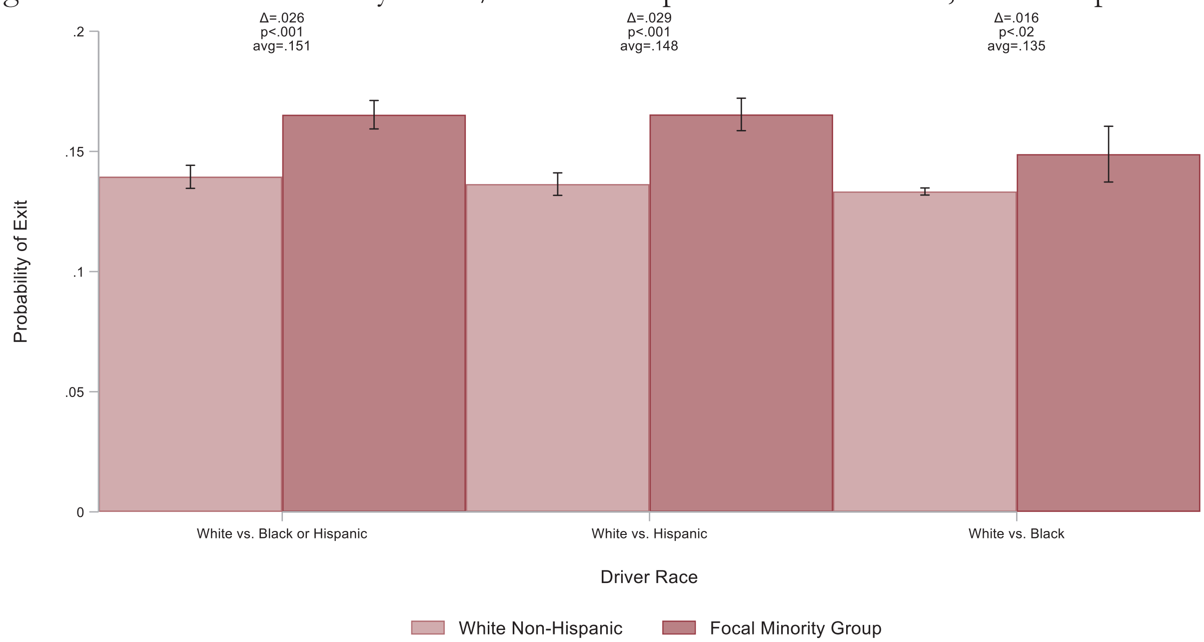
Notes: The estimates represented by each pair of bars were obtained from an ordinary least squares regression of an indicator for a stop involving a discretionary arrest on an indicator for a racial/ethnic minority and conditional on the circumstances of the stop. In each of the three pairs of bars, the leftmost bar (light maroon) represents the reference group (White non-Hispanics) and the rightmost bar (dark maroon) represents the focal minority group which is labeled on the X-axis. The estimated difference between the two bars is annotated along the top of the figure along with the associated p-value and sample mean.

Asking a motorist to exit their vehicle is a discretionary action that is also a key precursor to making an arrest. Estimates of the likelihood that a stop results in a deputy asking a motorist to exit their vehicle are presented in Figure 3 for White non-Hispanic motorists compared to Black/AA or Hispanic/Latino(a) motorists. These estimates were generated using an ordinary least squares regression that includes a number of controls that hold fixed the circumstances of the stop.[6] As shown below, the combined group of Black/AA and Hispanic/Latino(a) motorists were 2.6pp (17.2% relative to a mean of 15.1%, significance of p<0.001) more likely to be asked to exit their vehicle relative to White non-Hispanic motorists and conditional on the circumstances of the stop. Hispanic/Latino(a) motorists were 2.9pp (19.6% relative to a mean of 14.8%, significance of p<0.001) more likely to be asked to exit their vehicle. Black/AA motorists were 1.6pp (11.9% relative to a mean of 13.5%, significance of p<0.02) more likely but the results are only marginally significant. The estimates for Hispanic/Latino(a) and Black/AA motorists are consistent with disparate treatment by the San Diego County Sherrif in the decision to ask a motorist to exit their vehicle.

[6] To generate Figure 3, I estimate a model of the form $1[exit_i] = \gamma + \beta\ 1[minority_i] + \sum \lambda_j + \mu_i$ where $1[exit_i]$ is a dichotomous indicator variable equal to one if a stop resulted in a vehicle exit and zero otherwise. The variable of interest ($1[minority_i]$) is a dichotomous indicator variable equal to one if the motorist involved in the stop was a racial or ethnic minority and zero if the motorist was White non-Hispanic. The regression includes a constant term (γ) and an idiosyncratic error term (μ_i). In Figure 3, the vector of fixed effects ($\sum \lambda_j$) includes indicators for month by year (36), day of week by hour (168), reason (8), and city (56). In the figure, the levels and standard errors are predicted by holding all variables, except for the variable of interest, at their sample mean and multiplying by the coefficient estimates obtained from the regression model. Standard errors are clustered on city.

These results are qualitatively similar and statistically robust to including alternative controls (see Appendix Table A.10, A.11, and A.12). As mentioned, these estimates are likely an underestimate of the extent of the disparity due to selection bias in the underlying sample of stops reported to RIPA.

Figure 3: Vehicle Exit Rates by Racial/Ethnic Composition of Motorists, RIPA Stops



Notes: The estimates represented by each pair of bars were obtained from an ordinary least squares regression of an indicator for a stop involving a vehicle exit on an indicator for a racial/ethnic minority and conditional on the circumstances of the stop. In each of the three pairs of bars, the leftmost bar (light maroon) represents the reference group (White non-Hispanics) and the rightmost bar (dark maroon) represents the focal minority group which is labeled on the X-axis. The estimated difference between the two bars is annotated along the top of the figure along with the associated p-value and sample mean.

Conducting a discretionary search is another key precursor to making an arrest. Estimates of the likelihood that a stop results in a deputy conducting a discretionary search are presented in Figure 4 for White non-Hispanic motorists as compared to Black/AA or Hispanic/Latino(a) motorists. These estimates were generated using an ordinary least squares regression that includes a number of controls that hold fixed the circumstances of the stop.[7] For the purpose of this analysis, I define a discretionary search as those coded in the data as a consent search, precautionary safety search, suspected weapons, or exigent circumstances as well as odor of contraband and plain view contraband searches.[8] As shown below, the combined group of Black/AA and Hispanic/Latino(a) motorists were

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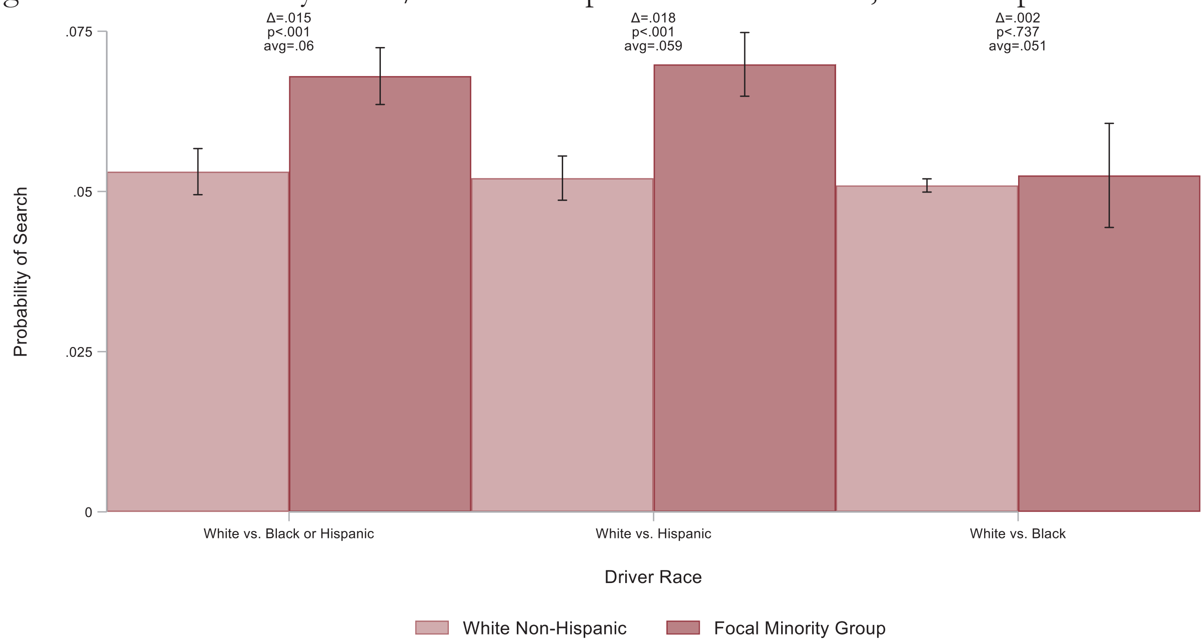
[7] To generate Figure 4, I estimate a model of the form $1[search_i] = \gamma + \beta\, 1[minority_i] + \sum \lambda_j + \mu_i$ where $1[search_i]$ is a dichotomous indicator variable equal to one if a stop resulted in a discretionary search and zero otherwise. The variable of interest ($1[minority_i]$) is a dichotomous indicator variable equal to one if the motorist involved in the stop was a racial or ethnic minority and zero if the motorist was White non-Hispanic. The regression includes a constant term (γ) and an idiosyncratic error term (μ_i). In Figure 4, the vector of fixed effects ($\sum \lambda_j$) includes indicators for month by year (36), day of week by hour (168), reason (8), and city (56). In the figure, the levels and standard errors are predicted by holding all variables, except for the variable of interest, at their sample mean and multiplying by the coefficient estimates obtained from the regression model. Standard errors are clustered on city.

[8] The findings are generally robust to excluding odor of contraband and plain view contraband searches.

1.5pp (25% relative to a mean of 6%, significance of $p<0.001$) more likely to experience a discretionary search relative to White non-Hispanic motorists and conditional on the circumstances of the stop. Hispanic/Latino(a) motorists were 1.8pp (30.5% relative to a mean of 5.9%, significance of $p<0.001$) more likely to be searched. Black/AA motorists were 0.2pp (3.9% relative to a mean of 5.1%, significance of $p<0.737$) more likely to be searched but the results were not statistically significant at conventional levels. The estimates for Hispanic/Latino(a) motorists are consistent with disparate treatment by the San Diego County Sherrif in the decision to search. These results are qualitatively similar and statistically robust to including alternative controls (see Appendix Table A.13, A.14, and A.15). As mentioned, these estimates are likely an underestimate of the extent of the disparity due to selection bias in the underlying sample of stops reported to RIPA.

Figure 4: Search Rates by Racial/Ethnic Composition of Motorists, RIPA Stops



Notes: The estimates represented by each pair of bars were obtained from an ordinary least squares regression of an indicator for a stop involving a discretionary search on an indicator for a racial/ethnic minority and conditional on the circumstances of the stop. In each of the three pairs of bars, the leftmost bar (light maroon) represents the reference group (White non-Hispanics) and the rightmost bar (dark maroon) represents the focal minority group which is labeled on the X-axis. The estimated difference between the two bars is annotated along the top of the figure along with the associated p-value and sample mean.

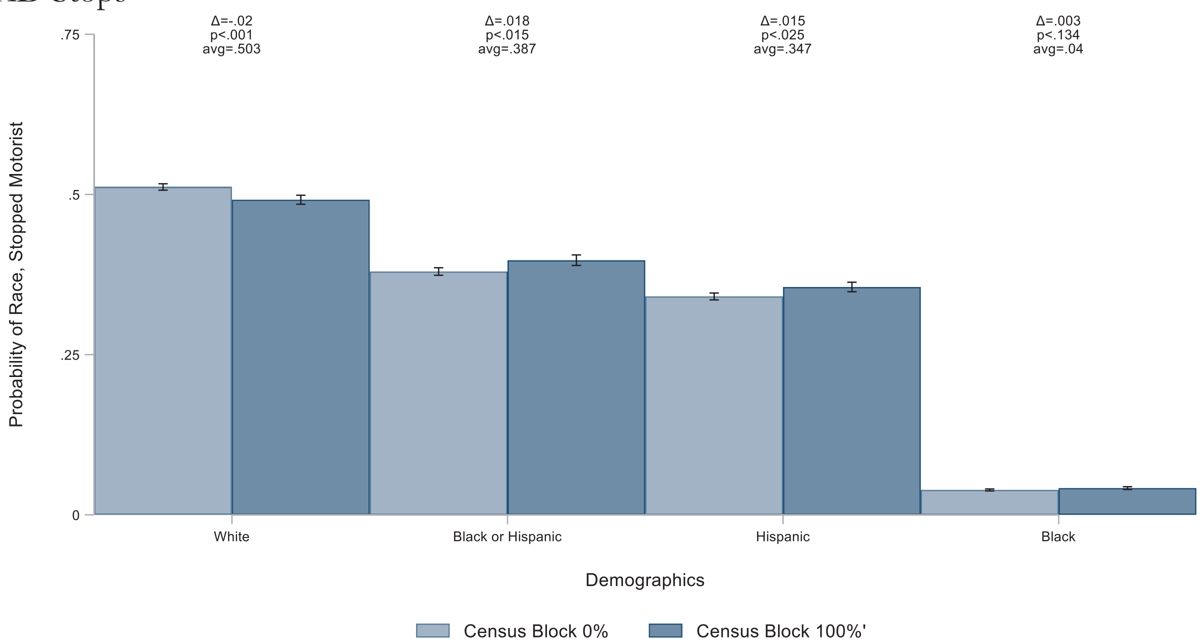
4. Analysis of CAD Data

Figure 5 presents estimates of the racial composition of the neighborhood where a stop occurred in daylight relative to darkness within a window of time when sunset varies through the year. These estimates were generated using an ordinary least squares regression that includes a number of controls that hold fixed potential variation in the underlying driving population.[9] As noted above, the sample

[9] To generate Figure 5, I estimate a model of the form $minority_i = \gamma + \beta\ 1[daylight_i] + \sum \lambda_j + \mu_i$ where $minority_i$ is a continuous variable ranging from zero to one representing the neighborhood racial/ethnic minorities as a share of the resident population. The underlying sample of stops is limited to the so-called "inter-twilight window" occurring between the earliest sunset and the latest end to civil twilight within a given year. The variable of interest

includes CAD events coded explicitly as traffic or pedestrian stops as well as those likely to be discretionary events.[10] As shown below, stops were -2pp (-4% relative to a mean of 50.3%, significance of $p<0.001$) less likely to have occurred in White non-Hispanic dominant neighborhoods during daylight relative to darkness. This means that Sheriff's Department stops were 4% less likely to occur in White non-Hispanic dominant neighborhoods during daylight (relative to night) as compared to Hispanic/Latino(a) or Black/AA dominant neighborhoods. In contrast, stops were 1.8pp (4.7% relative to a mean of 38.7%, significance of $p<0.015$) more likely to have occurred in Hispanic/Latino(a) or Black/AA dominant neighborhoods during daylight relative to darkness. Stops were 1.4pp (4.3% relative to a mean of 34.7%, significance of $p<0.025$) more likely to have occurred in Hispanic/Latino(a) dominant neighborhoods during daylight relative to darkness. Stops were 0.3pp (0.8% relative to a mean of 4%, significance of $p<0.134$) more likely to have occurred in Black/AA dominated neighborhoods but the results were not statistically significant at conventional levels. These estimates are consistent with disparate treatment towards racial/ethnic minorities, particularly Hispanic/Latino(a) motorists, by the San Diego County Sherrif in the decision to make a stop. These results (see Appendix Table A.16) are qualitatively similar and statistically robust to expanding the sample to include all possible stops (see Appendix Table A.17). As mentioned, these estimates are likely an underestimate of the extent of the disparity due to attenuation bias from measurement error because there is no direct measure of race/ethnicity in the CAD data.

Figure 5: Estimates of Changes to Neighborhood Racial/Ethnic Composition of Stops by Visibility, CAD Stops



$1[daylight_i]$ is a dichotomous indicator variable equal to one if a stop during daylight and zero otherwise. The regression includes a constant term (γ) and an idiosyncratic error term (μ_i). In Figure 5, the vector of fixed effects ($\sum \lambda_j$) includes indicators for day of week by year and time of day (15-minute increments) by year. The levels and standard errors are predicted by holding all variables, except for the variable of interest, at their sample mean and multiplying by the coefficient estimates obtained from the regression model. Standard errors are clustered on time by year.

[10] Note that the estimates are robust to alternative samples that either expand the present criteria to include stops and likely stops. The results are contained in Appendix Table A.17.

Notes: The estimates represented by each pair of bars were obtained from an ordinary least squares regression of the neighborhood racial/ethnic minorities as a share of the resident population on an indicator for daylight and conditional on the factors impacting the composition of the driving population. In each of the three pairs of bars, the leftmost bar (light navy) represents a minority-absent neighborhood (i.e. estimates at 0% of the focal demographic) and the rightmost bar (dark navy) represents a minority-dominant neighborhood (i.e. estimates at 100% of the focal demographic). The focal minority group is labeled on the X-axis. The estimated difference between the two bars is annotated along the top of the figure along with the associated p-value and sample mean.

Estimates of the likelihood that a stop results in a discretionary misdemeanor arrest are presented in Figure 6 for the majority/minority White non-Hispanic, Black/AA, or Hispanic/Latino(a) neighborhoods. These estimates were generated using an ordinary least squares regression that includes a number of controls that hold fixed the circumstances of the stop.[11] As noted above, the sample includes CAD events coded explicitly as traffic or pedestrian stops as well as those likely to be discretionary events.[12] While this sample restriction is likely to preclude the need to specifically identify arrests resulting from a warrant, I focus on those identified in the data as resulting from a misdemeanor.[13] As shown below, stops in White non-Hispanic dominant neighborhoods are -1.8pp (42.9% relative to a mean of 4.2%, significance of $p<0.016$) less likely to end in an arrest. In contrast, stops in combined Black/AA and Hispanic/Latino(a) dominant neighborhoods are 2.2pp (52.4% relative to a mean of 4.2%, significance of $p<0.003$) more likely to end in an arrest but the results were only marginally significant. Stops in Hispanic/Latino(a) dominated neighborhoods were 2.4pp (57.1% relative to a mean of 4.2%, significance of $p<0.003$) more likely to be arrested. Stops in Black/AA dominated neighborhoods were 1.3pp (31% relative to a mean of 4.2%, significance of $p<0.557$) more likely to be arrested but the results were not statistically significant at conventional levels. These estimates are consistent with disparate treatment towards racial/ethnic minorities, particularly Hispanic/Latino(a) motorists, by the San Diego County Sherrif in the decision to make an arrest. These results are qualitatively similar and statistically robust to including alternative controls (see Appendix Table A.18, A.19, A.20, A.21), expanding the sample to include all possible stops (see Appendix Table A.22, A.23, A.24, A.25), using a less restrictive definition of a discretionary arrest (see Appendix Table A.26, A.27, A.28, A.29), and using both an expanded sample of possible stops as well as a less restrictive definition of arrest (see Appendix Table A.30, A.31, A.32, A.33).As mentioned, these estimates are likely an underestimate of the extent of the

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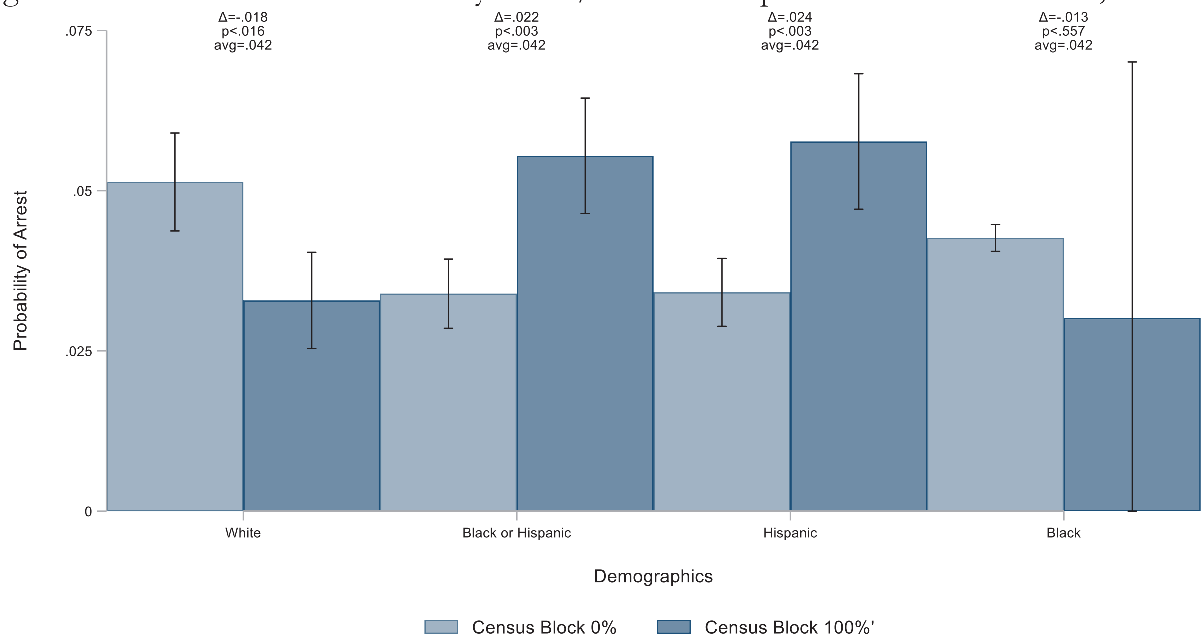
[11] To generate Figure 6, I estimate a model of the form $1[arrest_i] = \gamma + \beta\ minority_i + \sum \lambda_j + \mu_i$ where $1[arrest_i]$ is a dichotomous indicator variable equal to one if a stop yielded a misdemeanor arrest and zero otherwise. The variable of interest ($minority_i$) is a continuous variable ranging from zero to one representing the neighborhood racial/ethnic minorities as a share of the resident population. The regression includes a constant term (γ) and an idiosyncratic error term (μ_i). In Figure 6, the vector of fixed effects ($\sum \lambda_j$) includes indicators for month by year (36), day of week by hour (168), priority by reason (34), Census Tract (603) as well as indicators for the presence of witnesses and use of force. I also include indicators from a keyword search of the case narratives for a field sobriety test, search, or a temporary detention. In the figure, the levels and standard errors are predicted by holding all variables, except for the variable of interest, at their sample mean and multiplying by the coefficient estimates obtained from the regression model. Standard errors are clustered on Census block group.

[12] Note that the estimates are robust to alternative samples that either expand the present criteria to include all deputy-initiated activities or restrict the sample to only traffic and pedestrian stops. The results are contained in Appendix Table A.26, A.27, A.28, A.29 as well as Appendix Table A.30, A.31, A.32, A.33.

[13] Note that the estimates are robust to a more inclusive definition of arrests. The results are contained in Appendix Table A.30, A.31, A.32, A.33

disparity due to attenuation bias from measurement error because there is no direct measure of race/ethnicity in the CAD data.

Figure 6: Misdemeanor Arrest Rate by Racial/Ethnic Composition of Census Block, CAD Stops



Notes: The estimates represented by each pair of bars were obtained from an ordinary least squares regression of an indicator for a stop involving a misdemeanor arrest on neighborhood racial/ethnic minorities as a share of the resident population and conditional on the circumstances of the stop. In each of the three pairs of bars, the leftmost bar (light navy) represents a minority-absent neighborhood (i.e. estimates at 0% of the focal demographic) and the rightmost bar (dark navy) represents a minority-dominant neighborhood (i.e. estimates at 100% of the focal demographic). The focal minority group is labeled on the X-axis. The estimated difference between the two bars is annotated along the top of the figure along with the associated p-value and sample mean.

5. Conclusion

Collectively, the results demonstrate a pattern of disparate treatment towards Black/AA and Hispanic/Latino(a) individuals in the enforcement practices of the San Diego County Sheriff's Department. The evidence suggests that these communities are not only more likely to be stopped but also face higher probabilities of subsequent searches and arrests, indicative of systemic bias. While I find similar evidence of disparate treatment in both the RIPA and CAD datasets, it is my conjecture that these estimates likely underestimate the extent of the disparities due to the aforementioned limitations of each dataset. The findings in this report underscore the necessity for comprehensive policy reforms and enhanced oversight to ensure equitable treatment in law enforcement practices, and to address the deeply rooted disparities identified in this analysis.

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Technical Appendix: Additional Tables and Figures

Table A.1: Descriptive Statistics for All Stops in CAD and RIPA

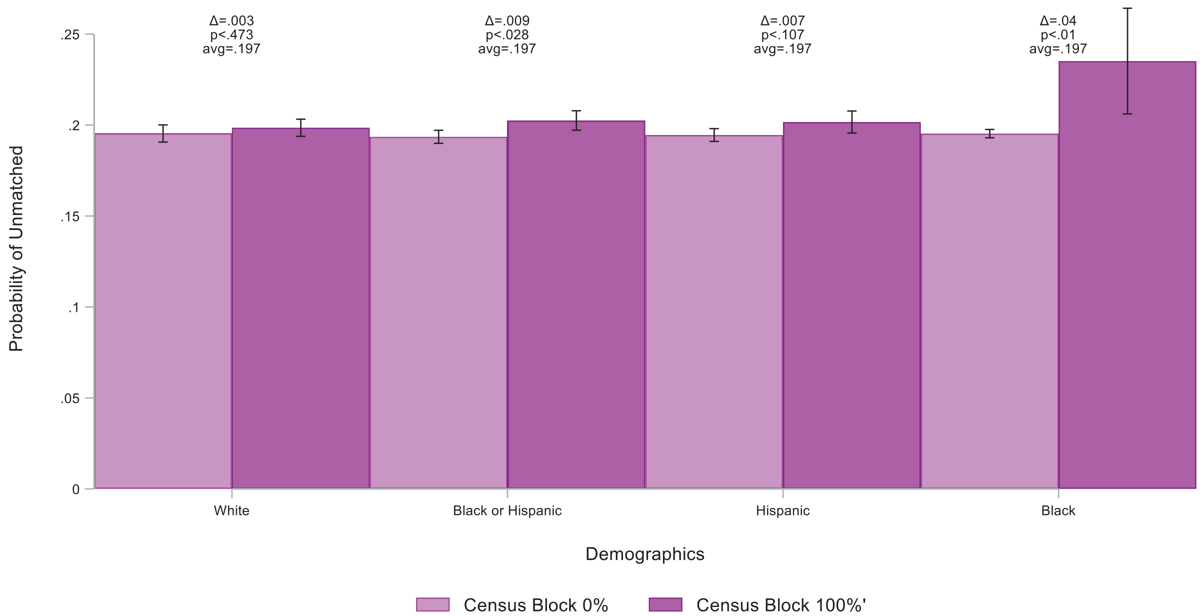
Period: 2021-23		(1)	(2)	(3)	(4)
	Dataset:	CAD			RIPA
	Sample:	Stops & All DIA	Stops & Likely Stops	Stops	Stops
	N=	516,093	184,187	163,012	67,658
Neighborhood or Motorist*	White	0.52 (0.228)	0.501 (0.226)	0.501 (0.227)	0.498 (0.5)
	Hispanic/Latino(a)	0.317 (0.219)	0.339 (0.222)	0.338 (0.223)	0.346 (0.476)
	Black/AA	0.039 (0.061)	0.041 (0.065)	0.042 (0.066)	0.063 (0.244)
	Sample:	Arrests**			
	N=	19,483	15,018	13,108	5,201
	P(Arrest | Stop)	0.038	0.082	0.080	0.077
Motorist	White	0.455 (0.498)	0.456 (0.498)	0.456 (0.498)	0.452 (0.498)
	Hispanic/Latino(a)	0.402 (0.49)	0.408 (0.491)	0.409 (0.492)	0.411 (0.492)
	Black/AA*	0.094 (0.292)	0.09 (0.287)	0.089 (0.285)	0.092 (0.289)
	Sample:	Discretionary Arrests***			
	N=	9,236	7,840	6,862	2,725
	P(Arrest | Stop)	0.018	0.043	0.042	0.040
Motorist	White	0.462 (0.499)	0.467 (0.499)	0.464 (0.499)	0.421 (0.494)
	Hispanic/Latino(a)	0.413 (0.492)	0.404 (0.491)	0.41 (0.492)	0.449 (0.498)
	Black/AA	0.086 (0.28)	0.089 (0.285)	0.086 (0.28)	0.091 (0.287)

*Demographics in CAD are from location of traffic stops (i.e. Census Block) using residential population from the 2020 Census.

**Arrests in CAD include all arrests except warrant arrests. Arrests in RIPA include custodial arrests without a warrant, cite and release, or psychiatric holds.

***Discretionary arrests in CAD include only misdemeanor arrests. Discretionary arrests in RIPA include custodial arrests without a warrant, i.e. arrests not coded as cite and release, custodial arrests pursuant to a warrant, or psychiatric holds.

Figure A.1: Probability of Stops in CAD Unmatched to RIPA by Racial/Ethnic Composition of Census Block



Notes: Focusing on the most conservative sample of 163,012 CAD events labeled explicitly as deputy-initiated patrol or traffic stops, I attempt to match records in RIPA with events in CAD. I allow for many-to-one matches between CAD and RIPA, i.e. only one record from RIPA can be matched to CAD but more than one CAD record can be matched to a given RIPA record. I do not put any restrictions on the number of CAD events matching a single RIPA record. The only requirements I imposed on the match were that the date matches and the timestamp from RIPA is within the arrival and clearance time reported in CAD, plus or minus thirty minutes. To be as conservative as possible, I allow for discrepancies between the two datasets in terms of numerous different variables, e.g. location, whether an arrest was made, time, duration etc. Similarly, I also allow for an unrealistic number of CAD events to match to a single RIPA stop, i.e. nearly 25% of the RIPA stops match to 5 or more CAD events. Even with this extremely generous matching criterion, I am only able to match 80.31% of CAD stop events to a corresponding record in RIPA. Given the generosity of the match criteria and considering there are tens of thousands of additional events that might actually be related to stops, this match rate is likely a dramatic underestimate of potential reporting issues by the San Diego County Sherrif to the RIPA system. In Figure 1, I present additional evidence that the unreported stops in CAD are disproportionately more likely to occur in predominantly Black/AA or Hispanic/Latino(a) neighborhoods. I obtain this evidence from regressing an indicator for whether a record from CAD was matched to RIPA on the demographic composition of the Census Block where the event occurred. The evidence presented in this figure suggests systematic under-reporting into the State of California's data collection program aimed at identifying racial and ethnic profiling.

Table A.2: Estimates of Changes to Race/Ethnicity of Stopped Motorists by Visibility, Moving Violations in RIPA

	(1)	(2)	(3)
	1[Black or Hispanic]	1[Hispanic]	1[Black]
1[Daylight]	0.0313 (0.0178)	0.0264 (0.0185)	0.0330** (0.0152)
N=	3667	3445	2141
Y Mean=	0.482	0.449	0.113
Time x Year FE	Y	Y	Y
Day of Week x Year FE	Y	Y	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.3: Estimates of Changes to Race/Ethnicity of Stopped Motorists by Visibility, All RIPA Stops

	(1)	(2)	(3)
	1[Black or Hispanic]	1[Hispanic]	1[Black]
1[Daylight]	0.0162	0.00839	0.0314**
	(0.0116)	(0.0126)	(0.0144)
N=	7536	7030	4261
Y Mean=	0.507	0.471	0.127
Time x Year FE	Y	Y	Y
Day of Week x Year FE	Y	Y	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.4: Discretionary Arrest Rate by Racial/Ethnic Composition of Motorists, RIPA Stops of Black and Hispanic Motorists

	(1)	(2)	(3)
1[Black or Hispanic]	0.0138*** (0.00291)	0.0117*** (0.00329)	0.0111*** (0.00313)
N=	61066	61066	61066
Y Mean=	0.0425	0.0425	0.0425
Month x Year FE	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y
Reason for Stop	N	Y	Y
City	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.5: Discretionary Arrest Rate by Racial/Ethnic Composition of Motorists, RIPA Stops of Black Motorists

	(1)	(2)	(3)
1[Black]	0.0170***	0.00692*	0.00632
	(0.00408)	(0.00405)	(0.00381)
N=	37997	37997	37997
Y Mean=	0.0366	0.0366	0.0366
Month x Year FE	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y
Reason for Stop	N	Y	Y
City	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.6: Discretionary Arrest Rate by Racial/Ethnic Composition of Motorists, RIPA Stops of Hispanic Motorists

	(1)	(2)	(3)
1[Hispanic]	0.0133*** (0.00340)	0.0125*** (0.00337)	0.0121*** (0.00298)
N=	57087	57087	57087
Y Mean=	0.0415	0.0415	0.0415
Month x Year FE	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y
Reason for Stop	N	Y	Y
City	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.7: Arrest Rate by Racial/Ethnic Composition of Motorists, RIPA Stops of Black and Hispanic Motorists

	(1)	(2)	(3)
1[Black or Hispanic]	0.0169***	0.0127***	0.00993***
	(0.00405)	(0.00333)	(0.00337)
N=	61067	61067	61067
Y Mean=	0.0806	0.0806	0.0806
Month x Year FE	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y
Reason for Stop	N	Y	Y
City	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.8: Arrest Rate by Racial/Ethnic Composition of Motorists, RIPA Stops of Black Motorists

	(1)	(2)	(3)
1[Black]	0.0304***	0.0120***	0.00965*
	(0.00736)	(0.00442)	(0.00501)
N=	37997	37997	37997
Y Mean=	0.0743	0.0743	0.0743
Month x Year FE	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y
Reason for Stop	N	Y	Y
City	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.9: Arrest Rate by Racial/Ethnic Composition of Motorists, RIPA Stops of Hispanic Motorists

	(1)	(2)	(3)
1[Hispanic]	0.0145***	0.0126***	0.00992***
	(0.00518)	(0.00379)	(0.00361)
N=	57088	57088	57088
Y Mean=	0.0786	0.0786	0.0786
Month x Year FE	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y
Reason for Stop	N	Y	Y
City	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.10: Vehicle Exit Rate by Racial/Ethnic Composition of Motorists, RIPA Stops of Black and Hispanic Motorists

	(1)	(2)	(3)
1[Black or Hispanic]	0.0420*** (0.00669)	0.0309*** (0.00516)	0.0258*** (0.00546)
N=	61066	61066	61066
Y Mean=	0.151	0.151	0.151
Month x Year FE	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y
Reason for Stop	N	Y	Y
City	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.11: Vehicle Exit Rate by Racial/Ethnic Composition of Motorists, RIPA Stops of Black Motorists

	(1)	(2)	(3)
1[Black]	0.0574***	0.0193***	0.0156**
	(0.0134)	(0.00613)	(0.00667)
N=	37997	37997	37997
Y Mean=	0.135	0.135	0.135
Month x Year FE	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y
Reason for Stop	N	Y	Y
City	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.12: Vehicle Exit Rate by Racial/Ethnic Composition of Motorists, RIPA Stops of Hispanic Motorists

	(1)	(2)	(3)
1[Hispanic]	0.0411*** (0.00819)	0.0339*** (0.00573)	0.0290*** (0.00583)
N=	57087	57087	57087
Y Mean=	0.148	0.148	0.148
Month x Year FE	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y
Reason for Stop	N	Y	Y
City	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.13: Discretionary Search Rate by Racial/Ethnic Composition of Motorists, RIPA Stops of Black and Hispanic Motorists

	(1)	(2)	(3)
1[Black or Hispanic]	0.0194*** (0.00403)	0.0175*** (0.00351)	0.0149*** (0.00410)
N=	61067	61067	61067
Y Mean=	0.0598	0.0598	0.0598
Month x Year FE	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y
Reason for Stop	N	Y	Y
City	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.14: Discretionary Search Rate by Racial/Ethnic Composition of Motorists, RIPA Stops of Black Motorists

	(1)	(2)	(3)
1[Black]	0.0127**	0.00322	0.00157
	(0.00595)	(0.00442)	(0.00467)
N=	37997	37997	37997
Y Mean=	0.0511	0.0511	0.0511
Month x Year FE	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y
Reason for Stop	N	Y	Y
City	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.15: Discretionary Search Rate by Racial/Ethnic Composition of Motorists, RIPA Stops of Hispanic Motorists

	(1)	(2)	(3)
1[Hispanic]	0.0209*** (0.00436)	0.0202*** (0.00386)	0.0178*** (0.00429)
N=	57088	57088	57088
Y Mean=	0.0593	0.0593	0.0593
Month x Year FE	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y
Reason for Stop	N	Y	Y
City	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.16: Estimates of Changes to Neighborhood Racial/Ethnic Composition of Stops by Visibility, CAD Stops

	(1)	(2)	(3)	(4)
	% White	% Black & Hispanic	% Hispanic	% Black
1[Daylight]	-0.0199*** (0.00612)	0.0176** (0.00722)	0.0147** (0.00656)	0.00288 (0.00192)
N=	22358	22358	22358	22358
Y Mean=	0.503	0.387	0.347	0.0401
Time x Year FE	Y	Y	Y	Y
Day of Week x Year FE	Y	Y	Y	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.17: Estimates of Changes to Neighborhood Racial/Ethnic Composition of Stops by Visibility, CAD Stops and Possible Stops

	(1)	(2)	(3)	(4)
	% White	% Black & Hispanic	% Hispanic	% Black
1[Daylight]	-0.0174*** (0.00581)	0.0160** (0.00682)	0.0138** (0.00626)	0.00217 (0.00162)
N=	24869	24869	24869	24869
Y Mean=	0.505	0.385	0.345	0.0397
Time x Year FE	Y	Y	Y	Y
Day of Week x Year FE	Y	Y	Y	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.18: Misdemeanor Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops in Black or Hispanic Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% Black & Hispanic	0.00358 (0.0125)	0.0161* (0.00896)	0.0111 (0.00832)	0.0112 (0.00832)	0.0215*** (0.00726)
N=	162950	162950	162950	162950	162950
Y Mean=	0.0421	0.0421	0.0421	0.0421	0.0421
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.19: Misdemeanor Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops in White Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% White	0.00132 (0.0148)	-0.00704 (0.00935)	-0.00209 (0.00883)	-0.00219 (0.00883)	-0.0185** (0.00764)
N=	162950	162950	162950	162950	162950
Y Mean=	0.0421	0.0421	0.0421	0.0421	0.0421
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.20: Misdemeanor Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops in Black Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% Black	-0.0528**	-0.0557***	-0.0634***	-0.0634***	-0.0125
	(0.0235)	(0.0194)	(0.0192)	(0.0195)	(0.0213)
N=	162950	162950	162950	162950	162950
Y Mean=	0.0421	0.0421	0.0421	0.0421	0.0421
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.21: Misdemeanor Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops in Hispanic Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% Hispanic	0.0117	0.0267***	0.0221**	0.0223**	0.0235***
	(0.0130)	(0.00955)	(0.00887)	(0.00890)	(0.00801)
N=	162950	162950	162950	162950	162950
Y Mean=	0.0421	0.0421	0.0421	0.0421	0.0421
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.22: Misdemeanor Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops and Possible Stops in Black or Hispanic Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% Black & Hispanic	0.00540 (0.0114)	0.0152* (0.00816)	0.0111 (0.00757)	0.0113 (0.00757)	0.0156** (0.00686)
N=	184122	184122	184122	184122	184122
Y Mean=	0.0426	0.0426	0.0426	0.0426	0.0426
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.23: Misdemeanor Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops and Possible Stops in White Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% White	-0.00275 (0.0132)	-0.00807 (0.00842)	-0.00382 (0.00792)	-0.00394 (0.00792)	-0.0138* (0.00709)
N=	184122	184122	184122	184122	184122
Y Mean=	0.0426	0.0426	0.0426	0.0426	0.0426
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.24: Misdemeanor Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops and Possible Stops in Black Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% Black	-0.0486**	-0.0481***	-0.0545***	-0.0542***	-0.0149
	(0.0212)	(0.0176)	(0.0174)	(0.0175)	(0.0198)
N=	184122	184122	184122	184122	184122
Y Mean=	0.0426	0.0426	0.0426	0.0426	0.0426
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.25: Misdemeanor Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops and Possible Stops in Hispanic Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% Hispanic	0.0132 (0.0120)	0.0245*** (0.00866)	0.0207*** (0.00804)	0.0209*** (0.00805)	0.0178** (0.00753)
N=	184122	184122	184122	184122	184122
Y Mean=	0.0426	0.0426	0.0426	0.0426	0.0426
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.26: Discretionary Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops in Black or Hispanic Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% Black & Hispanic	0.00863	0.0243	0.0169	0.0173	0.0297***
	(0.0194)	(0.0150)	(0.0124)	(0.0123)	(0.0107)
N=	162950	162950	162950	162950	162950
Y Mean=	0.0804	0.0804	0.0804	0.0804	0.0804
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.27: Discretionary Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops in White Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% White	-0.00402	-0.0148	-0.00667	-0.00688	-0.0251**
	(0.0204)	(0.0142)	(0.0123)	(0.0122)	(0.0109)
N=	162950	162950	162950	162950	162950
Y Mean=	0.0804	0.0804	0.0804	0.0804	0.0804
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.28: Discretionary Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops in Black Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% Black	-0.00927 (0.0376)	-0.0164 (0.0316)	-0.0360 (0.0304)	-0.0360 (0.0308)	-0.0155 (0.0319)
N=	162950	162950	162950	162950	162950
Y Mean=	0.0804	0.0804	0.0804	0.0804	0.0804
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.29: Discretionary Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops in Hispanic Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% Hispanic	0.0113	0.0304*	0.0248*	0.0252*	0.0322***
	(0.0217)	(0.0163)	(0.0130)	(0.0130)	(0.0113)
N=	162950	162950	162950	162950	162950
Y Mean=	0.0804	0.0804	0.0804	0.0804	0.0804
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.30: Discretionary Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops and Possible Stops in Black or Hispanic Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% Black & Hispanic	0.0136 (0.0179)	0.0233* (0.0138)	0.0170 (0.0115)	0.0174 (0.0114)	0.0250** (0.0100)
N=	184122	184122	184122	184122	184122
Y Mean=	0.0815	0.0815	0.0815	0.0815	0.0815
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.31: Discretionary Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops and Possible Stops in White Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% White	-0.0110 (0.0185)	-0.0160 (0.0130)	-0.00877 (0.0111)	-0.00904 (0.0111)	-0.0234** (0.0102)
N=	184122	184122	184122	184122	184122
Y Mean=	0.0815	0.0815	0.0815	0.0815	0.0815
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.32: Discretionary Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops and Possible Stops in Black Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% Black	-0.0106 (0.0345)	-0.0155 (0.0302)	-0.0315 (0.0289)	-0.0309 (0.0292)	-0.0114 (0.0302)
N=	184122	184122	184122	184122	184122
Y Mean=	0.0815	0.0815	0.0815	0.0815	0.0815
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Table A.33: Discretionary Arrest Rate by Racial/Ethnic Composition of Neighborhoods, CAD Stops and Possible Stops in Hispanic Majority Neighborhoods

	(1)	(2)	(3)	(4)	(5)
% Hispanic	0.0172 (0.0200)	0.0290* (0.0149)	0.0241** (0.0120)	0.0245** (0.0119)	0.0270** (0.0106)
N=	184122	184122	184122	184122	184122
Y Mean=	0.0815	0.0815	0.0815	0.0815	0.0815
Month x Year FE	Y	Y	Y	Y	Y
Day of Week x Hour FE	Y	Y	Y	Y	Y
Census Controls	Y	Y	Y	Y	Y
Priority x Reason FE	N	Y	Y	Y	Y
Officer Actions	N	N	Y	Y	Y
Witnesses Present	N	N	N	Y	Y
Tract FE	N	N	N	N	Y

Notes: Standard errors in parentheses, stars represent confidence levels where * p<.1, ** p<.05, and *** p<.01.

Exhibit B

Updated: August 2024

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Boston, MA

Primary Appointments

2022- Pres	Associate Professor, School of Public Policy & Urban Affairs and Department of Economics, Northeastern University
2024- Pres	Affiliated Faculty, Center for Race and Justice, School for Criminology & Criminal Justice, Northeastern University
2023-25	Policy Fellow, Community-to-Community Initiative, Northeastern University

External Appointments

2021-Pres	Subject Matter Expert, U.S. Department of Justice Civil Rights Division
2021-Pres	Subject Matter Expert, New Jersey Office of Attorney General
2024-Pres	Research Advisor, Justice Center at Council of State Governments
2023-Pres	Invited Research, J-PAL North American and the Science for Progress Initiative
2022-24	Visiting Scholar, Department of Public Policy, University of Connecticut

Education

2016	Ph.D. in Economics, University of Connecticut
2013	M.A. in Economics, University of Connecticut
2011	M.A. in Regional Economic & Community Development, University of Massachusetts Lowell
2010	B.A. in Economics, University of Massachusetts Lowell

Research Interests

Primary: labor economics, urban economics, and public policy
Secondary: discrimination, economics of crime, policing / public safety, labor market dynamics, training, skills and tasks, knowledge transfer

Previous Employment

2020-22	Assistant Professor, Department of Economic Sciences, Claremont Graduate University
2020-22	Visiting Scholar, Wagner School of Public Service, New York University
2018-20	Assistant Research Professor, Wagner School of Public Service and Center for Urban Science and Progress (CUSP), New York University
2016-18	Post-Doc, Ohio State University and National Bureau of Economic Research (NBER)

Scholarly Research

<u>Refereed Publications</u>

Yu, H., Marschke, G., Ross, M.B. et al. Publish or Perish: Selective Attrition as a Unifying Explanation for Patterns in Innovation over the Career. *Journal of Human Resources* 59-1 (2024).

Kalinowski, J.J., Ross, S.L., Ross, M.B. Endogenous Driving Behavior in Tests of Racial Profiling. *Journal of Human Resources* 59-2 (2023).

Ross, M.B., Glennon, B.M., Murciano-Goroff, R. et al. Women are credited less in science than men. *Nature* 608, 135–145 (2022).

Ross, M.B., Kalinowski, J.J., Barone, K. Testing for Disparities in Traffic Stops: Best Practices from the Connecticut Model. *Criminology & Public Policy* 19-4 (2020).

Chevalier, G. Chomienne, C. Jeanrenaud, N.G., Lane, J.I., Ross, M.B. A New Approach for Estimating Research Impact: An Application to French Cancer Research. *Quantitative Science Studies* 1-4 (2020).

Ross, M.B. The Effect of Intensive Margin Changes to Task Content on Employment Dynamics over the Business Cycle. *Industrial and Labor Relations Review* 74-4 (2020).

Couch, K.A., Ross, M.B., Vavrek, J. Career Pathways and Integrated Instruction: A National program Review of I-Best Implementations. *Journal of Labor Research* 39 (2018).

Ross, M.B. Routine-Biased Technical Change: Panel Evidence of Task Orientation and Wage Effects. *Labour Economics* 48 (2017).

Published Conference Proceedings

Kehoe, A.K., Vetle, T.I., Ross, M.B., Smalheiser, N.R. Predicting MeSH Beyond MEDLINE. Association of Computing Machinery (ACM): *Proceedings of Workshop on Scholarly Web Mining* (2018).

Kalinowski, J.J., Ross, S.L., Ross, M.B. Now You See Me, Now You Don't: The Geography of Police Stops. *American Economic Review Papers and* Proceedings 109 (2019).

Book Chapters

Ross, M.B. Ikudo, A., Lane, J.I. The Food Safety Research Workforce and Economic Outcomes. *Measuring the Economic Value of Research: The Case of Food Safety*, c. 6 pp. 100- 112, Cambridge University Press (2017)

King, J.L. Johnson, S.R., Ross, M.B. Assessing the Effects of Food Safety Research on Early Career Outcomes. *Measuring the Economic Value of Research: The Case of Food Safety*, c. 8 pp. 100- 112, Cambridge University Press (2017)

Working Papers

Adger, C. Ross, M.B., Sloan, C.W. The Effect of Field Training Officers on Police Use of Force. 2024. (Submitted).

Mello, S., Ross, M.B., Ross, S.L., Johnson, H. Diversity Training and Employee Behavior: Evidence from the Police. 2024. (Submitted).

Ross, M.B., Parker, S., Ross, S.L. Driving Change: Evaluating Connecticut's Collaborative Approach to Reducing Racial Disparities in Policing. 2024 (Preparing for Submission).

Kalinowski, J.J., Ross, S.L., Ross, M.B. Addressing Seasonality in Veil of Darkness Tests for Discrimination: A Regression Discontinuity Approach. (Resting)

Selected Works in Progress

Ross, M.B., Ross, S.L., Parker, S. Testing for Discrimination in Police Traffic Stops using Telemetric Mobility Data: New Methods and Findings. (Manuscript in Preparation).

Murciano-Goroff, R.M. Ross, M.B. Robots and Science: The Impact of Automation on the Scientific Research Teams. (Manuscript in Preparation).

Funk, R. Glennon, B., Murciano-Goroff, R.M. Ross, M.B. Connections and Credit: How Social Networks Shape the Gender Gap in Research Output. (Manuscript in Preparation).

Bollman, K.M., Gomez, A. Ross, M.B., Sloan, C.W. More with Less: The Impact of Excessive Overtime on Police Wellness, Productivity, and Bias. (Ongoing Analysis).

Ross, M.B. and Sloan, C.W. Estimating Police Value-Added Impacts on Criminal Investigations, Clearance Rates, Revictimization, and Recidivism. (Ongoing Analysis).

Ross, M.B., Ross, S.L., Parker, S. A Machine Learning Approach to Estimating Roadway Populations using Telemetric Mobility Data. (Preliminary Analysis).

Ross, M.B. Sloan, C.W. Understanding the Dynamics of Police Corruption: Evidence from Connecticut's Fake Ticket Scandal. (Preliminary Analysis)

Grants, Awards, and Honors

Grants and Contracts

Total of $2,809,111 in extramural research funding and $88,766 in internal research funding from 2016 to present.

2023-24	PI for Technical Assistance for the "Connecticut Model". Arnold Ventures via Council of State Governments. Subaward of $39,987 from $600,000.
2023-24	PI for CT Traffic Stop Evaluation. U.S. DOT. Total of $170,626.
2023-25	PI for RI Traffic Stop Evaluation. U.S. DOT. Total of $246,400.
2023-24	PI for DC Metro Traffic Stop Evaluation and Officer Analysis. U.S. DOT. Total of $40,123.
2023	Winner of Northeastern University Community-to-Community Policy Fellowship. Post-Doc equivalent to approx. $43,200.
2023	Winner of College of Social Sciences & Humanities' Multi-Generational Research Team Award: "Criminal Investigations in Communities of Color" with Ermus St. Louis (Northeastern University). SGA time equivalent to approx. $26,666.
2022-23	PI for CT Traffic Stop Evaluation and Officer Analysis. U.S. DOT. Total of $168,430.
2023	Consultant to the Commonwealth of Virginia's Attorney General's Office.
2021-23	Consultant on NOPD Consent Decree to the U.S. Department of Justice Civil Rights Division. Total of $29,640.
2021	Consultant to the New Jersey Attorney General's Office of Public Integrity & Accountability. Total of $6,968
2021-22	Winner of Blais Challenge Award: "Does More Training Mitigate Disparities in Police Use of Force? Quasi-Experimental Evidence from New Linked Data" with CarlyWill Sloan (Claremont) and David Bjerk (Claremont McKenna). Total of $18,900.
2021-22	Co-PI for Russell Sage Foundation Presidential Grant: "Does More Training Mitigate Disparities in Police Use of Force? Quasi-Experimental Evidence from New Linked Data" with CarlyWill Sloan (Claremont). Total of $29,178

2021-23	PI for CT Traffic Stop Evaluation and Officer Analysis. U.S. DOT. Total of $251,085 from 2021-23.
2020-21	Contractor for the National Science Foundation- National Center for Science and Engineering Statistics (via Coleridge Initiative): "Integrate Data Analytics Training, Data Linkage Research and Secure Data Access to Promote Evidence-based Science Policy Research". Total of $12,750.
2019-21	Co-PI for National Science Foundation (NSF) Research Award (SciSIP #1932689): "Research funding, organizational context, and transformative research: New insights from new methods and data" with Raviv Murciano-Goroff (BU), Julia Lane (NYU), and Russel Funk (UMN). Collaborative award for a total of $600,000 w/ $320,000 to NYU.
2019-21	Fellowship at Collaborative Archive Data Research Environment (CADRE) at Indiana University. Team granted clustered computing access to Web of Science (WoS) and Microsoft Academic Graph (MAG) data.
2016-19	PI for RI Traffic Stop Evaluation and Officer Analysis. U.S. DOT. Total of $222,690.
2013-19	PI for CT Traffic Stop Evaluation and Officer Analysis. U.S. DOT. Total of $571,140.
2012-16	Racial Disparities in State Contracting Phases 1-3 (sub-award) via CT Economic Resource Center and CT Academy of Science as part of a CT General Assembly award. Total of $22,400.

Smaller Awards and Honors

Fellowship w/ Cuebiq (Spectus Data for Good Initiative), Connecticut's Alvin W. Penn Award for Excellence in Civil Rights Leadership (w/ coauthors), UConn Dissertation Award (2016), IZA/CEDEFOP Travel Award (Fall 2015), Quinnipiac CAS Research Award (2015), UConn Summer Research Fellowship (Summer 2012, 2014, 2015), UConn Third Year Paper Award (2014), National Association of Business Economist's Policy Scholarship (2013), UConn Economics Fellowship (2011), UMass Alan D. Solomon Scholarship (2011), UMass Campus Catalyst Award (2011), UMass Honors (2009-11)

Policy Reports

2023	Massachusetts Traffic Stops Analysis, 2009-22 - Partners: USA Today and Cape Cod Times MA_Traffic-Stop-Analysis-2014-22-1.pdf
2023	State of Connecticut, Traffic Stop Data Analysis & Findings, 2022 - Partners: Connecticut Racial Profiling Prohibition Project CT3RP_Traffic_Stop-2022.pdf
2023	Connecticut State Police Traffic Stop Audit - Partners: Connecticut Racial Profiling Prohibition Project CTSP_Fake-Ticket-Audit.pdf
2023	State of Connecticut, Traffic Stop Data Analysis & Findings, 2021 - Partners: Connecticut Racial Profiling Prohibition Project CT3RP_Traffic_Stop-2021.pdf
2022	New Orleans Police Department Bias-Free Analysis. - Partners: US Department of Justice NOPD_Bias-Free.pdf
2022	Internal Analysis of New Jersey State Police Traffic Stops. - Partners: New Jersey Attorney General NJSP_Traffic-Stop.pdf
2022	State of Connecticut, Analysis of Racial Profiling in Police Traffic Stops, 2020 - Partners: Connecticut Racial Profiling Prohibition Project CT3RP_Traffic_Stop-2020.pdf
2021	State of Connecticut, Traffic Stop Data Analysis & Findings, 2019 - Partners: Connecticut Racial Profiling Prohibition Project

	CT3RP_Traffic_Stop-2019.pdf
2021	State of Rhode Island, Traffic Stop Data Analysis & Findings, 2019 - Partners: Rhode Island Department of Transportation and Connecticut Racial Profiling Prohibition Project RIDOT_Traffic_Stop-2019.pdf
2021	Weathersfield Border Discontinuity Analysis - Partners: Connecticut Racial Profiling Prohibition Project CT3RP_Wethersfield.pdf
2020	State of Rhode Island, Traffic Stop Data Analysis & Findings, 2018 - Partners: Rhode Island Department of Transportation and Connecticut Racial Profiling Prohibition Project RIDOT_Traffic_Stop-2018.pdf
2020	State of Connecticut, Traffic Stop Data Analysis & Findings, 2018 - Partners: Connecticut Racial Profiling Prohibition Project CT3RP_Traffic_Stop-2018.pdf
2019	State of Rhode Island, Traffic Stop Data Analysis & Findings, 2017 - Partners: Rhode Island Department of Transportation and Connecticut Racial Profiling Prohibition Project RIDOT_Traffic_Stop-2017.pdf
2019	State of Connecticut, Traffic Stop Data Analysis & Findings, 2017 - Partners: Connecticut Racial Profiling Prohibition Project CT3RP_Traffic_Stop-2017.pdf
2018	State of Rhode Island, Traffic Stop Data Analysis & Findings, 2016 - Partners: Rhode Island Department of Transportation and Connecticut Racial Profiling Prohibition Project RIDOT_Traffic_Stop-2016.pdf
2017	State of Connecticut, Traffic Stop Data Analysis & Findings, 2015-16 - Partners: Connecticut Racial Profiling Prohibition Project CT3RP_Traffic_Stop-2015-16.pdf
2016	State of Connecticut, Traffic Stop Data Analysis & Findings, 2014-15 - Partners: Connecticut Racial Profiling Prohibition Project CT3RP_Traffic_Stop-2014-15.pdf
2016	Racial Disparities in CT's State Contracting Process, Disparity Study Phase 3 - Partners: CT General Assembly and CT Academy of Science and Engineering CASE_Disparity-Phase3.pdf
2015	State of Connecticut, Traffic Stop Data Analysis & Findings, 2013-14 - Partners: Connecticut Racial Profiling Prohibition Project CT3RP_Traffic_Stop-2013-14.pdf
2015	Shared Clean Energy Facilities - Partners: CT General Assembly and CT Academy of Science and Engineering CASE_Energy.pdf
2014	Racial Disparities in CT's State Contracting Process, Disparity Study Phase 2 - Partners: CT General Assembly and CT Academy of Science and Engineering CASE_Disparity-Phase2.pdf
2013	Connecticut's Economic Development Strategy - Partners: CT Department of Economic and Community Development
2013	Racial Disparities in CT's State Contracting Process, Disparity Study Phase 1 - Partners: CT General Assembly and CT Academy of Science and Engineering CASE_Disparity-Phase1.pdf
2012	[…] Connecticut's Skilled Workforce […] - Partners: CT General Assembly and CT Academy of Science and Engineering CASE_Workforce.pdf

2011	U.S. Skills for Green Jobs - Partners: International Labour Organization and CEDEFOP

Public Testimony

6/5/2024	United States Courthouse Courtroom of Judge Susie Morgan, New Orleans Police Department Consent Decree Hearing
4/11/2024	Massachusetts Legislature, Public Hearing on Executive Office of Public Safety and Security
8/19/2021	Connecticut Legislature, Public Hearing on Connecticut Racial Profiling Prohibition Advisory Board
10/8/2020	Connecticut Legislature, Public Hearing on Connecticut Racial Profiling Prohibition Advisory Board
6/9/2020	California Legislature, Public Hearing on California Identity & Racial Profiling Advisory Board
9/12/2019	Connecticut Legislature, Public Hearing on Connecticut Racial Profiling Prohibition Advisory Board
6/18/2015	Connecticut Legislature, Public Hearing on Connecticut Racial Profiling Prohibition Advisory Board
3/31/2015	Connecticut Legislature, Public Hearing on Connecticut Racial Profiling Prohibition Advisory Board
10/9/2014	Connecticut Legislature, Public Hearing on Connecticut Racial Profiling Prohibition Advisory Board
8/14/2014	Connecticut Legislature, Public Hearing on Connecticut Racial Profiling Prohibition Advisory Board

Conferences and Seminars

2023-24	Boston Federal Reserve, Global Action for Policy Conference, Western Economic Association, Chicago/LSE Crime Conference (Discussant), NBER Summer Institute- Crime / Law & Economics 2024
2022-23	Association for Public Policy Analysis & Management and Urban Economics Association
2021-22	NBER Summer Institute- Crime / Law & Economics 2022, USPTO PatentsView Symposium, Claremont McKenna, Ohio State University- UMETRICS Action Series (Coauthor), Association of Policy Analysis and Management, Scripps College, University of Hawaii at Manoa, Northeastern University, RAND Corporation, California State University at Fullerton, University of New Hampshire, Texas A&M VICE Seminar
Pre-2021	Society of Labor Economists, Urban Economics Association, University at Albany, Ohio State University, APPAM Research Conference, Society of Labor Economists, NBER Summer Institute- Law & Economics 2018, APPAM Research Conference, North American Regional Science Conference, Society of Labor Economists, Western Economic Association, Syracuse University, Urban Economics Association, Southern Economic Association, Ohio State University, Miami University Ohio, Western Economic Association, Boston Federal Reserve Bank, Atlanta Federal Reserve Bank. IZA/CEDEFOP Workshop on Skills and Skill Mismatch, Southern Economic Association, University of Massachusetts Lowell, CT Data Collaborative Conference, CT Racial Profile Advisory Board, CT General Assembly: Methods for an Analysis of Policing Data, Census Bureau: LEHD: Benchmarking Competitiveness in STEM, Boston Foundation, National Neighborhood Indicators Partnership, Urban Institute, NE Sociological Association, CT General Assembly: Econometric Methods for Examining Racial Disparities in CT's State Contracting Process, CT General Assembly: The Connecticut STEM Workforce Pipeline, Boston University School of Law, American Economic Association (2019 & 2020), Georgia Institute of Technology (Policy), NBER Productivity Seminar, University of Michigan (IRIS), University of Connecticut, NYU Crime & Policing Workshop, Society of Labor Economists, APPAM Research Conference, Conference on Empirical Legal Studies

(Claremont McKenna)*, Connecticut Racial Profiling Prohibition Advisory Board, Ohio State University (x2), San Diego State University, Simon Fraser University (Policy), Naval Postgraduate School, Claremont Graduate University

External Professional Service

Peer Reviews in Economics: Quarterly Journal of Economics; Journal of Policy Analysis & Management; European Economic Review; Labour Economics; Journal of Human Resources; Journal of Public Economics; Journal of Urban Economics; Journal of Empirical Legal Studies; Research Policy; IZA World of Labour; International Journal of Manpower; PLoS On; Regional Science and Urban Economics.

Peer Reviews in Criminology: Criminology & Public Policy; Crime & Delinquency; Journal of Race, Ethnicity, & Politics; American Journal of Criminal Justice.

Grant & Other Reviews: Public Policy Institute of California; Russell Sage Foundation; Sloan Foundation; Criminal Justice Expert Panel.

Program Committee: APPAM Fall Research Conference Program Committee, 2024 (Chair: Crime, Justice, Drugs), 2022 and 2023 (Chair, Science and Technology), 2021, and 2017, NYU Policing and Crime Workshop 2018 (Organized w/ Ingrid Gould Ellen and Morgan Williams); Eastern Economic Association 2016; University of Massachusetts Lowell Master of Science in Economics Advisory Board.

Memberships: American Economic Association; Association for Public Policy Analysis and Management; Urban Economics Association; Society of Labor Economists; American Association for the Advancement of Science.

Internal Professional Service

Northeastern University: Master of Public Administration Admission Committee (Public Policy, 23-24) Graduate Program Committee (Economics, 23-24); Undergraduate Program Committee (Economics, 22-23); AEFIS Graduate Program Evaluation (Economics); Digital Economies Search Committee (Public Policy); Interdisciplinary Crime Lunch (Public Policy).

Claremont Graduate University: Admissions Committee; PhD/MA Curriculum Program Committee