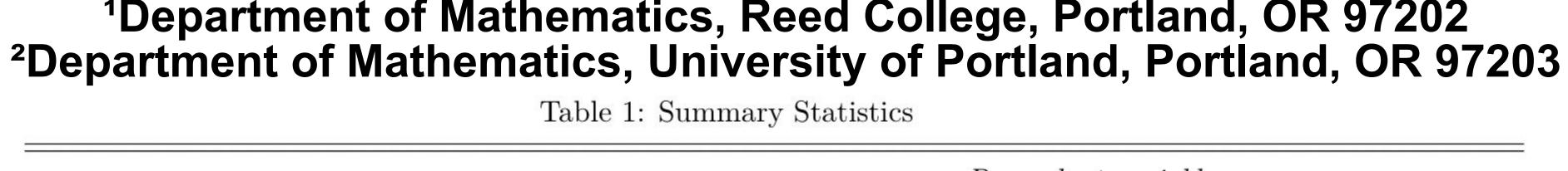
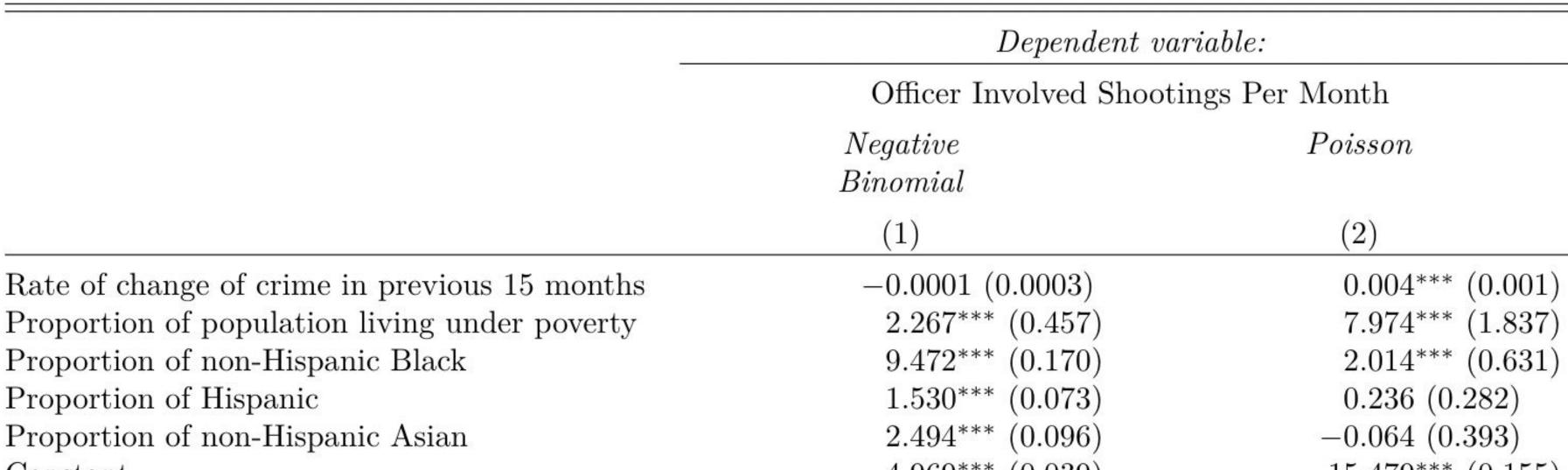


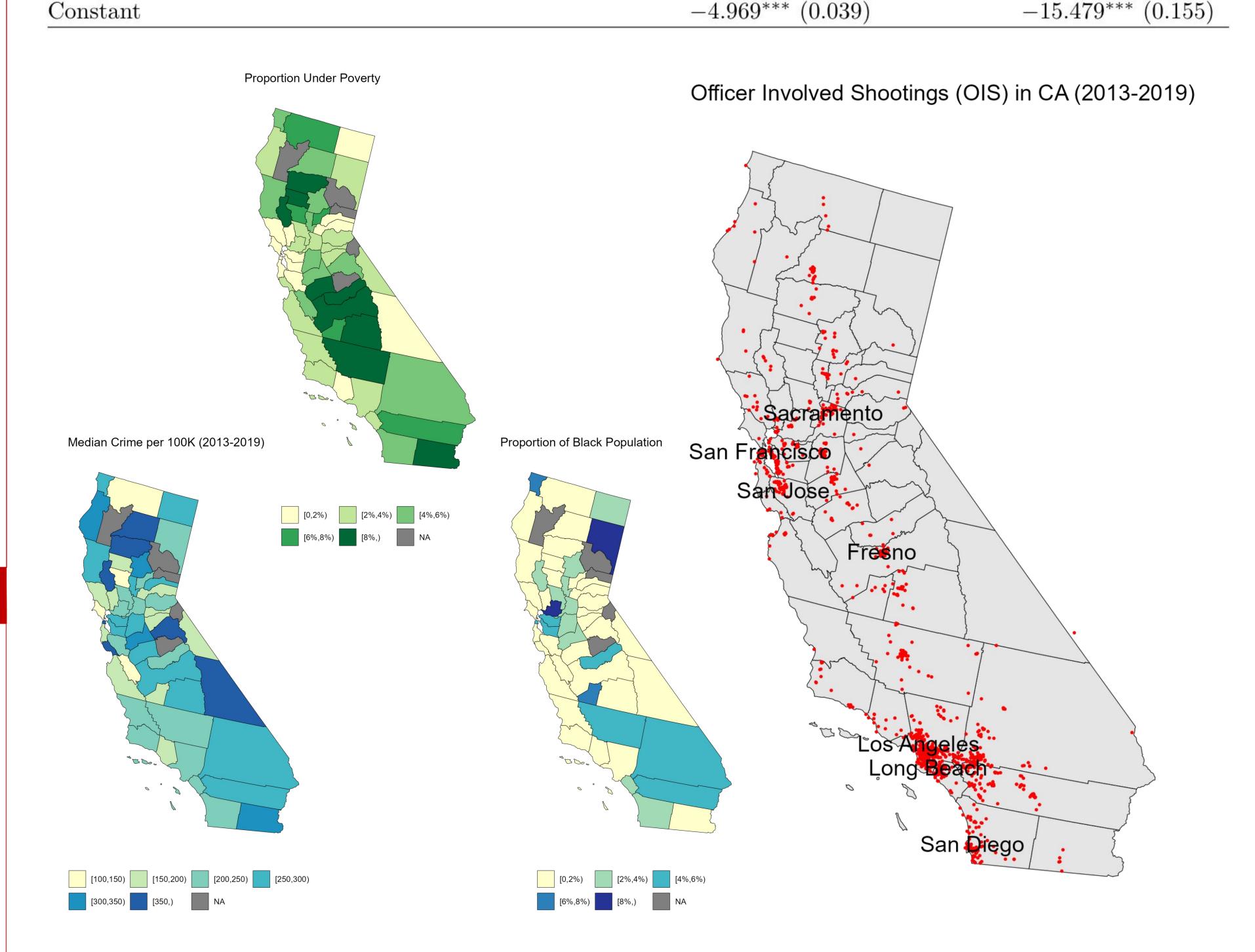
Do Police Kill More People In Poorer and Highly Segregated Regions in California?

Sajid Bin Mahamud¹ and Alex John Quijano²

¹Department of Mathematics, Reed College, Portland, OR 97202







long beach

Monthly change in crime rates

bakersfield

san diego

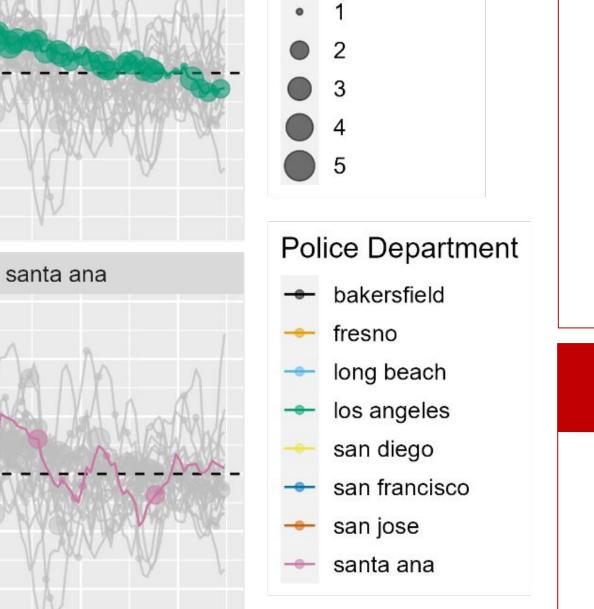
Each line represents a police department with at least 1 OIS

san francisco

2013 2015 2017 2019 2013 2015 2017

los angeles Number of OIS

one OIS



Results

 $P(Y|X) = Poisson(\lambda)$ $Y = [y_1, y_2, y_3, y_4, \dots y_n], i = 1, 2, 3, \dots n$ $X = [x_{i1}^T, x_{i2}^T, x_{i3}^T, x_{i4}^T, x_{i5}^T], i = 1, 2, 3, \dots n$ $Var(Y) = E(Y) = \lambda$

We primarily use Poisson Modeling for count data to predict OIS per month. The model produces significant results for Rate of change of crime in previous 15 months, Proportion of population living under poverty, Proportion of non-Hispanic Black. The model doesn't show any significant relationship between OIS per month and Proportion of Hispanic and non-Hispanic Asian population.

Due to the over-dispersion of the data, the coefficients of the poisson model show, with 95% confidence, that rate of change of crime is not a significant predictor of OIS per month in California. However, holding the rest constant, for 10 percent increase in the share of people living under poverty, mean OIS per month is expected to increase 2.21 times. Similarly, A 20% increase in Black population is expected to increase the mean OIS per month by 49%.

Table 2: Anti-log of Poisson Coef	${ m ficients}$
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(Intercept)	0.000
Rate of change of crime in previous 15 months	1.004
Proportion of population living under poverty	2,903.527
Proportion of non-Hispanic Black	7.493
Proportion of Hispanic	1.266
Proportion of non-Hispanic Asian	0.938

Conclusion

While the results of both the negative binomial model and the poisson regression model provide significant evidence for our hypothesis, it is well evident that the coefficients vary by significant amount. There are several possible explanations for it. The most important one is accounting for over-dispersion of the data. Our future goal is to perform more accurate models with precise parameters. However, it is worth noting that both our models estimate that proportion of people living under poverty and black population affect death in the hands of Police.

Limitations and Future Direction

- Our analysis does not account for the variation of county-level gun related deaths which has historically been proven to be associated with Officer Involved Shootings.
- We do not account for county Sheriff's office's due to their intertwined jurisdictions with local police departments.
- Because no reliable data exist on assault and killing of police officers, we could not account for its effect on the outcome.
- Since Poisson distribution is a special case for Negative Binomial Distribution, some of its assumption weren't met precisely, which opens room for further analysis.

Acknowledgments

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Introduction

Research Question: Does the Racial and Social demography of the local population influence the use of lethal force by police departments in California?

Due to the lack of a comprehensive database documenting all instances of use of force by law enforcement in the U.S., it's not possible to draw a conclusion on the absence or presence of racial bias in police use of force. Moreover, present research on the relationship between police violence and crime rates measures the effect of crime by aggregating data across the state or county. This approach, albeit producing significant results, masks the heterogeneity of the data.

Our study addresses the shortcomings in two layers:

- (1) We analyze crime and shooting data on a monthly-unit basis for each individual agency, instead of aggregating the data across the year and states or counties;
- (2) Instead of analyzing the race of the deceased or the LEO involved, we focus on the spatial and temporal circumstances of the incident;

Objectives:

Estimate the Spatio-temporal effect of the following on OIS in California:

- (1) The racial composition of the population,
- (2) The proportion of the population living **below poverty.**

Since the difference in the state's interpretation of the current federal civil statute established in Tennessee v. Garner gives the police different latitude in using deadly force, we limit ourselves to only one state. We choose California because of its mixture of urban and rural geographical settings.

Data and Methods

Data Sources:

- 1. Mapping Police Violence, 2013-2020. Campaign Zero.
- 2. Law Enforcement Agency Identifiers Crosswalk (LEAIC), United States, 2012.
- 3. Offenses Known and Clearances by Arrest (OKLE), 2011-2019.
- 4. Law Enforcement Officers Killed and Assaulted 2011-2019.
- 5. U.S. Census Bureau (2014-2018). American Community Survey 5-year Estimates.

Explanatory Variables:

- 1. Rate of change of violent and property crimes
- 2. Proportion of population under poverty
- 3. Proportion of Black, Hispanic, Asian population

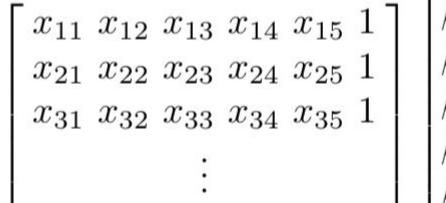
Response Variable: Officer Involved Shootings Per Month

Exposure Variable: Population

Total Number of Observations, n: 26,628

Since our study spatiotemporally analyses civilian deaths in police custody, we only select local police departments which have (1) mutually exclusive jurisdiction, (2) corresponding census-designated place, (3) reported all 108 months (2011-2019) to the UCR, and (4) reported employee data for all 9 years. This filtration process discards all sheriffs offices, state law enforcement agency, federal agencies, constable/marshal's office, and special jurisdictions.





 $x_{n1} x_{n2} x_{n3} x_{n4} x_{n5}$

- μ_1 μ_2
- $(\frac{\lambda}{P}) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots$ $\lambda = \text{Officer-Involved-Shootings Per Month}$
- P = Population
- $\beta_i = i$ -th coefficient
- = i-th predictor variable