Deadly Police Force: Implications for Policing, Planning, and Neighborhood Policy

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Presentation Outline

1. Research Questions

2. Comparison of Deadly Force Datasets

3. Exploratory Mapping of “Fatal Police Encounters”
    a. Determining the Proper Geographic Unit of Analysis

4. Neighborhood Analysis and Statistical Testing
    a. Spearman’s Correlation Results
    b. Poisson Regression Results
    c. Next Steps
        i. Poisson Regressions at CBSA Level with Residuals
        ii. Spatial Autocorrelation with Residuals

Research Questions

How can we better understand the contemporary geography of fatal police encounters?

1. How can we currently collect and document police use of deadly force across the U.S.?

2. Which social and demographic factors best predict the urban neighborhood context of fatal police encounters?

Public Scholarship Agenda: Can urban studies and planning scholars play a larger role in the analysis <u>and prevention</u> of fatal police encounters?

Background Literature

- Planning scholarship and practice has not had a clear and direct role in creating safer spaces and policing although there is compelling evidence that violence has a direct relationship to neighborhood revitalization and overall quality of life (Steil & Mehta, 2017).

- Police surveillance, harassment, and mass incarceration "mark" particular neighborhoods as dangerous in the minds of police, vicious cycles are created which makes police bias and use of force self-fulfilling prophecies (Clear, 2007; Pager, 2007).

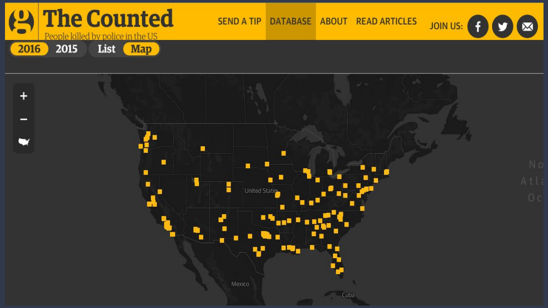
- Currently, official government datasets are limited to the Federal Bureau of Investigations' (FBI) voluntary registry of police killings. (Lartey, 2015).

- Based on all reputable data sources, including the FBI database, there are more police-related deaths over the course of a few days than many countries have over a decade. Some of this may be due to higher crime rates overall, particularly gun-related crime which requires police to use force.

Comparing Deadly Force Datasets

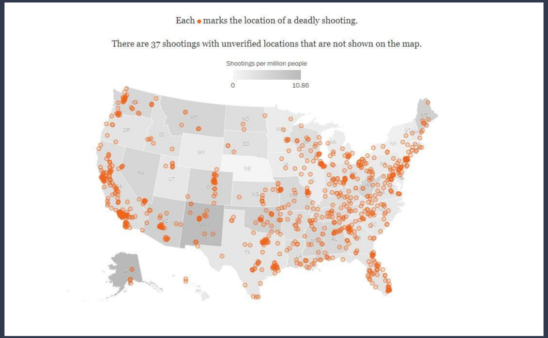
January 1, 2015 - December 31, 2015

The Counted by The Guardian



Total Deaths Recorded: 1,140

Fatal Force by The Washington Post



Total Deaths Recorded: 991

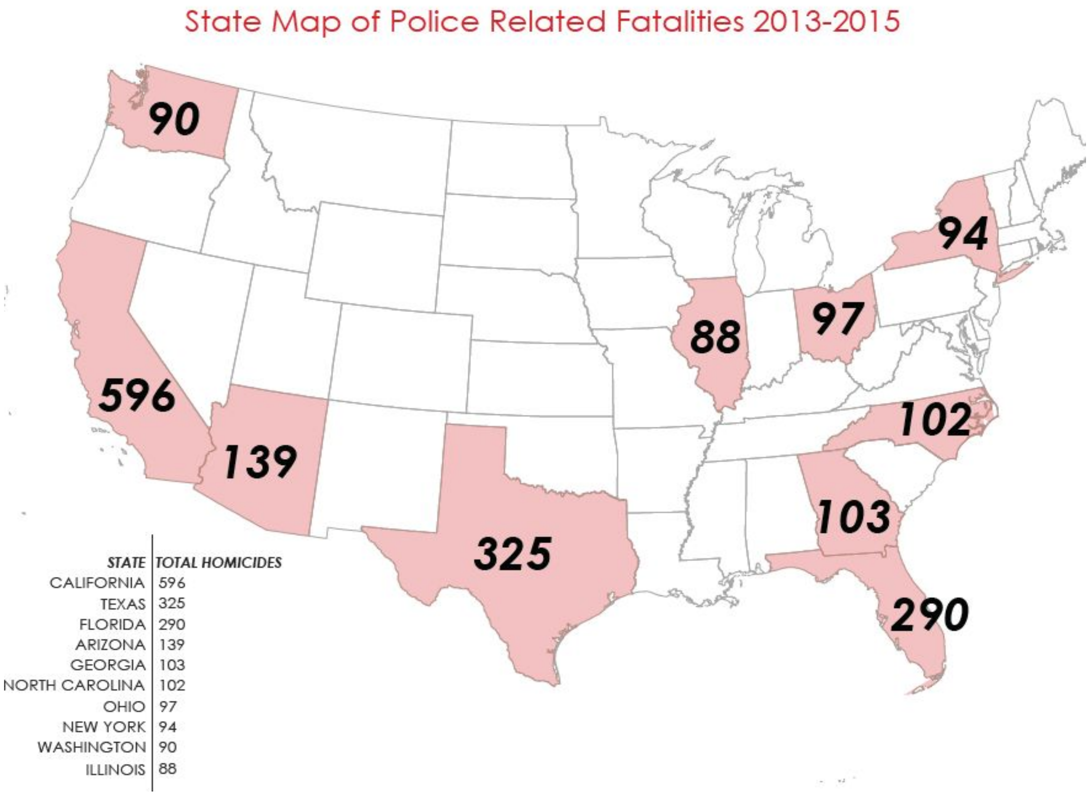
Mapping Police Violence by Independent Researchers

Total Deaths Recorded: 1,196

Selecting the Data: Mapping Police Violence Database

We chose the Mapping Police Violence Database[1] for the following reasons:

- Accurate Geocoded Addresses
- Verified and Properly Formatted XY Coordinates
- Data was sourced from multiple outlets and primary sources
- Least restrictive methodology for data collection
- Most exhaustive list of all three databases



[1] www.mappingpoliceviolence.com

Selecting the Data: Mapping Police Violence Database

Fatal Encounters with Law Enforcement 2013 - 2015

3485
TOTAL
people killed by police 2013-2015

Race	Total Fatalities
White	1522
Black	949
Latino	571
Unknown	335
Asian	68
Native American	27
Pacific Islander	13

Law Enforcement Agency	Total Fatalities
Los Angeles Police Department	65
New York Police Department	49
Chicago Police Department	45
Phoenix Police Department	42
Houston Police Department	36

Variables

- Core-Based Statistical Area
- Median Household Income
- Households in Poverty
- Vacant Housing Units
- Multi-Family Housing Units
- Renter Occupied Housing Units
- Median Year House Built
- No Vehicle in Household
- Pct. White Population
- Pct. Black Population
- Pct. Latinx Population
- Pct. American Indian Population
- Pct. Asian Population
- Pct. Pacific Islander Population
- Pct. Other Race
- Pct. Two or More Races

Exploratory Analysis
Mapping of “Fatal Police Encounters”

For this study, we examined the context of police violence by first gathering data from the Mapping Police Violence database and identifying the core-based statistical areas (CBSAs) with the highest counts of police-related fatal counters between 2013-2015.

- Mapped FPEs by county but found that many city boundaries crossed county boundaries (e.g. NYC’s five counties) which eliminated them.

- Mapping FPEs on a per capita basis rose many cities (e.g. Bakersfield, CA) to the top of the list thus making comparative analysis more difficult.

- Mapping at a CBSA level, allowed for the best inter-county, metropolitan level analysis

1. Overlaid incidents on maps for different variables using American Community Survey 2011-2015 five-year estimates.

2. Preliminary analysis showed that the most compelling patterns were incidents overlaid on census tracts by percent of non-white population.

3. Using ArcGIS, we used a directional distribution technique to understand how clustered FPEs were in each of the five selected regions by race.

4. The results of the directional distribution were added to our data sets as a variable (i.e. within the ellipse = 1; outside of the ellipse = 0).

5. After completing the Poisson regression analysis, we mapped FPEs over our most significant variable income to find a new spatial pattern.

Descriptive Statistics

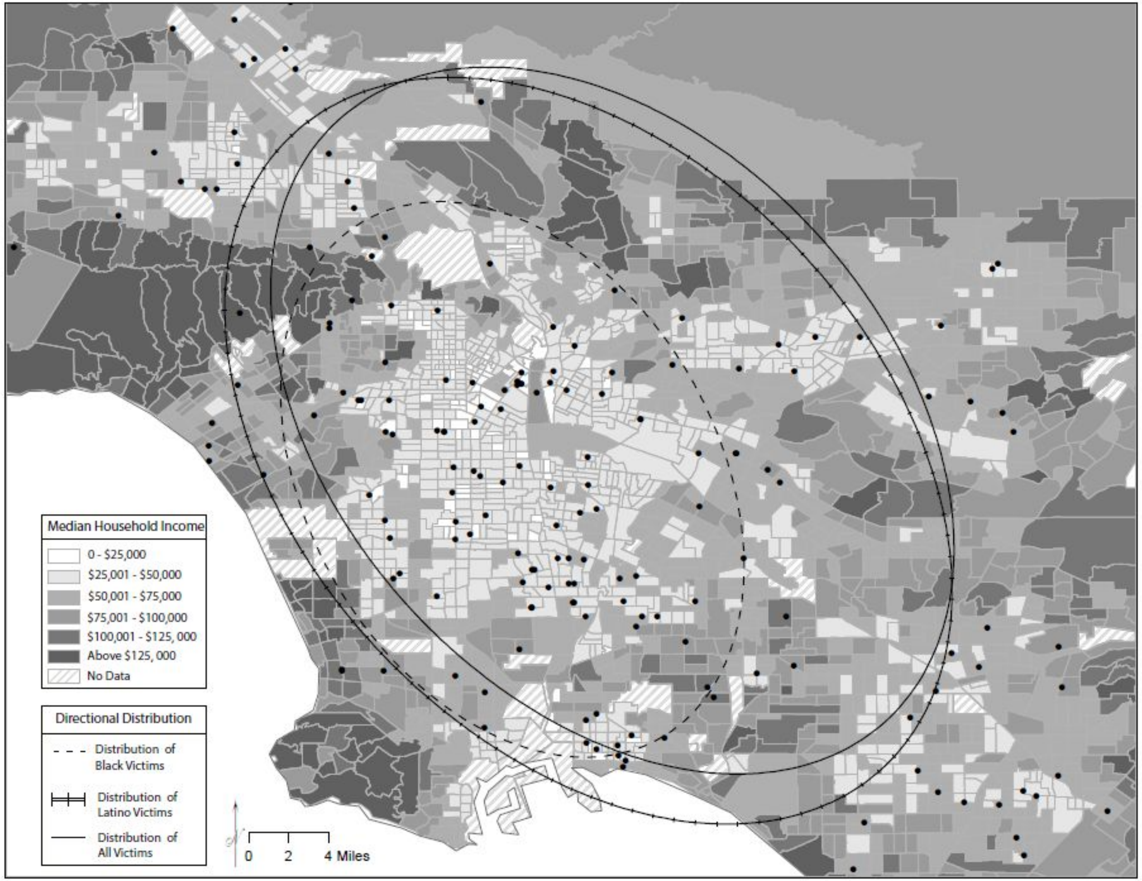
Variable	CBSA	Tracts with No Fatal Encounters *(Mean)*	Tracts with Fatal Encounters *(Mean)*
Median Household Income	Phoenix-Mesa-Scottsdale, AZ	60,167.63**	47,205.87**
	Los Angeles-Long Beach-Anaheim, CA	65,947.79**	53,912.03**
	Miami-Fort Lauderdale-West Palm Beach, FL	55,078.68**	46,895.38**
	New York-Newark-Jersey City, NY NJ CT PA	73,624.39**	56,655.92**
	Dallas-Fort Worth-Arlington, TX	66,056.88**	51,186.31**
Pct. Of Households in Poverty	Phoenix-Mesa-Scottsdale, AZ	13.9%**	21.1%**
	Los Angeles-Long Beach-Anaheim, CA	14.23**	18.83%**
	Miami-Fort Lauderdale-West Palm Beach, FL	14.18**	18.48%**
	New York-Newark-Jersey City, NY NJ CT PA	12.38**	18.31%**
	Dallas-Fort Worth-Arlington, TX	13.07**	19.21%**
Percent of Renter-Occupied Housing Units	Phoenix-Mesa-Scottsdale, AZ	37.93%**	47.11%**
	Los Angeles-Long Beach-Anaheim, CA	50.56%**	56.93%**
	Miami-Fort Lauderdale-West Palm Beach, FL	38.5%**	46.9%**
	New York-Newark-Jersey City, NY NJ CT PA	47.21**	59.42%**
	Dallas-Fort Worth-Arlington, TX	39.51**	50.15%**
Percent of Households with No Vehicle	Phoenix-Mesa-Scottsdale, AZ	7.06%*	9.28%*
	Los Angeles-Long Beach-Anaheim, CA	9.02%**	11.55%**
	Miami-Fort Lauderdale-West Palm Beach, FL	9.29%**	12.84%**
	New York-Newark-Jersey City, NY NJ CT PA	28.98%**	36.94%**
	Dallas-Fort Worth-Arlington, TX	5.69%**	9.07%**

*Statistically significant difference at the 95% confidence interval.
**Statistically significant difference at the 99% confidence interval.

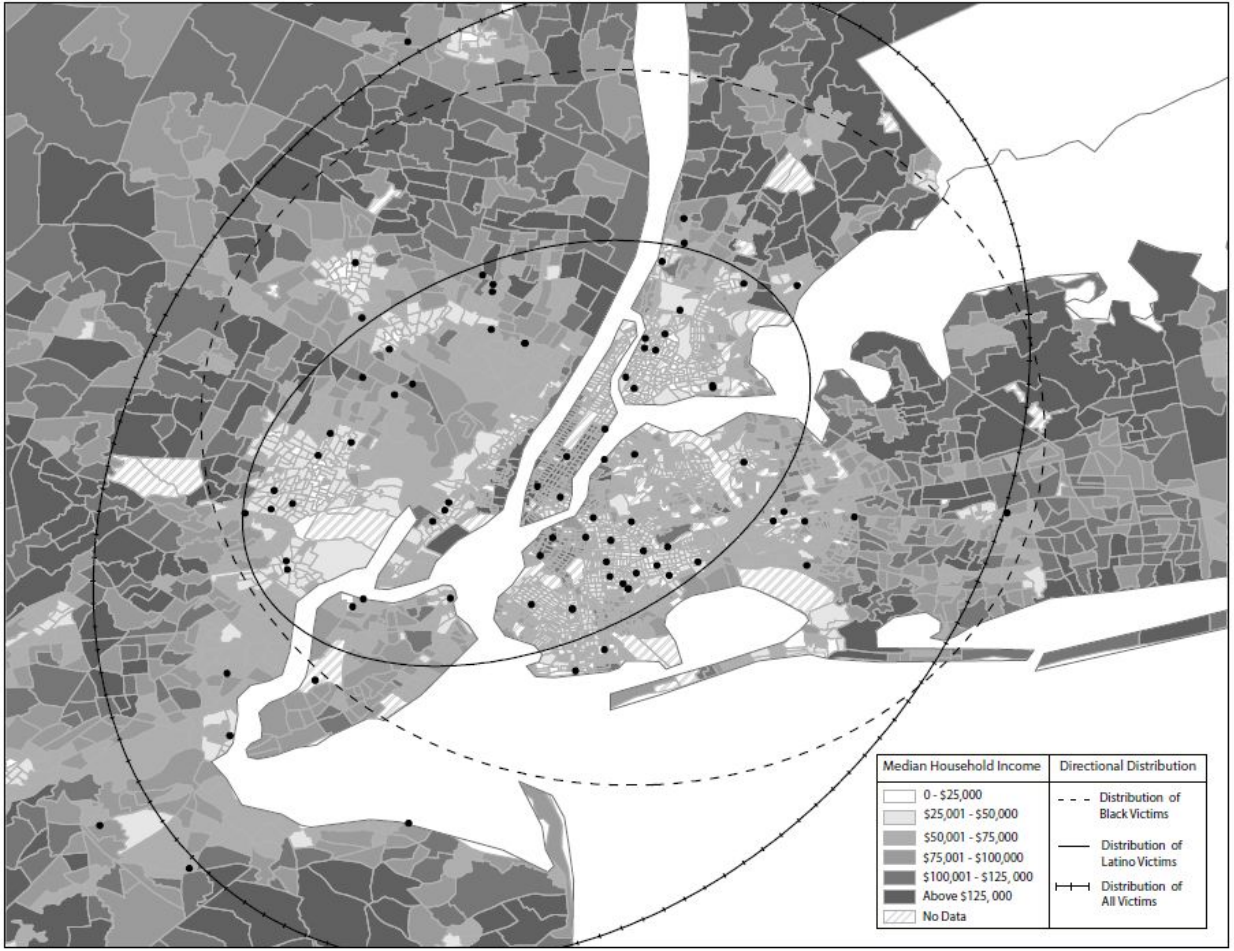
County Based Statistical Areas – Top 5 Areas of Analysis

Core-Based Statistical Area (CBSA)	Count of Fatal Police Encounters	CBSA Population	Fatal Police Encounters Per 100,000
Los Angeles-Long Beach-Anaheim, CA	191	13,187,465	1.448
New York-Newark-Jersey City, NY-NJ-PA	107	20,020,397	0.954
Phoenix-Mesa-Scottsdale, AZ	92	4,486,153	4.258
Miami-Fort Lauderdale-West Palm Beach, FL	90	5,896,851	3.239
Dallas-Fort Worth-Arlington, TX	86	6,957,123	2.745
Riverside-San Bernardino-Ontario, CA	86	4,430,646	4.311
Houston-The Woodlands-Sugar Land, TX	79	6,482,592	2.945
Chicago-Naperville-Elgin, IL-IN-WI	77	9,466,000	2.018
San Francisco-Oakland-Hayward, CA	60	4,577,530	4.173
Atlanta-Sandy Springs-Roswell, GA	58	5,612,777	3.403
Baltimore-Columbia-Towson, MD	47	2,778,647	6.874
Washington-Arlington-Alexandria, DC-VA-MD-WV	45	6,008,369	3.179
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	43	6,047,721	3.158
St. Louis, MO-IL	42	2,803,449	6.813
Las Vegas-Henderson-Paradise, NV	42	2,070,153	9.226
Seattle-Tacoma-Bellevue, WA	40	3,664,963	5.212
Oklahoma City, OK	39	1,337,075	14.285
San Diego-Carlsbad, CA	35	3,250,867	5.875
Denver-Aurora-Lakewood, CO	35	2,752,056	6.940
Tampa-St. Petersburg-Clearwater, FL	34	2,921,311	6.538
Orlando-Kissimmee-Sanford, FL	32	2,328,508	8.202
Bakersfield, CA	31	871,337	21.920
Indianapolis-Carmel-Anderson, IN	31	1,968,768	9.701
San Antonio-New Braunfels, TX	30	2,332,345	8.189
Kansas City, MO-KS	30	2,070,147	9.226

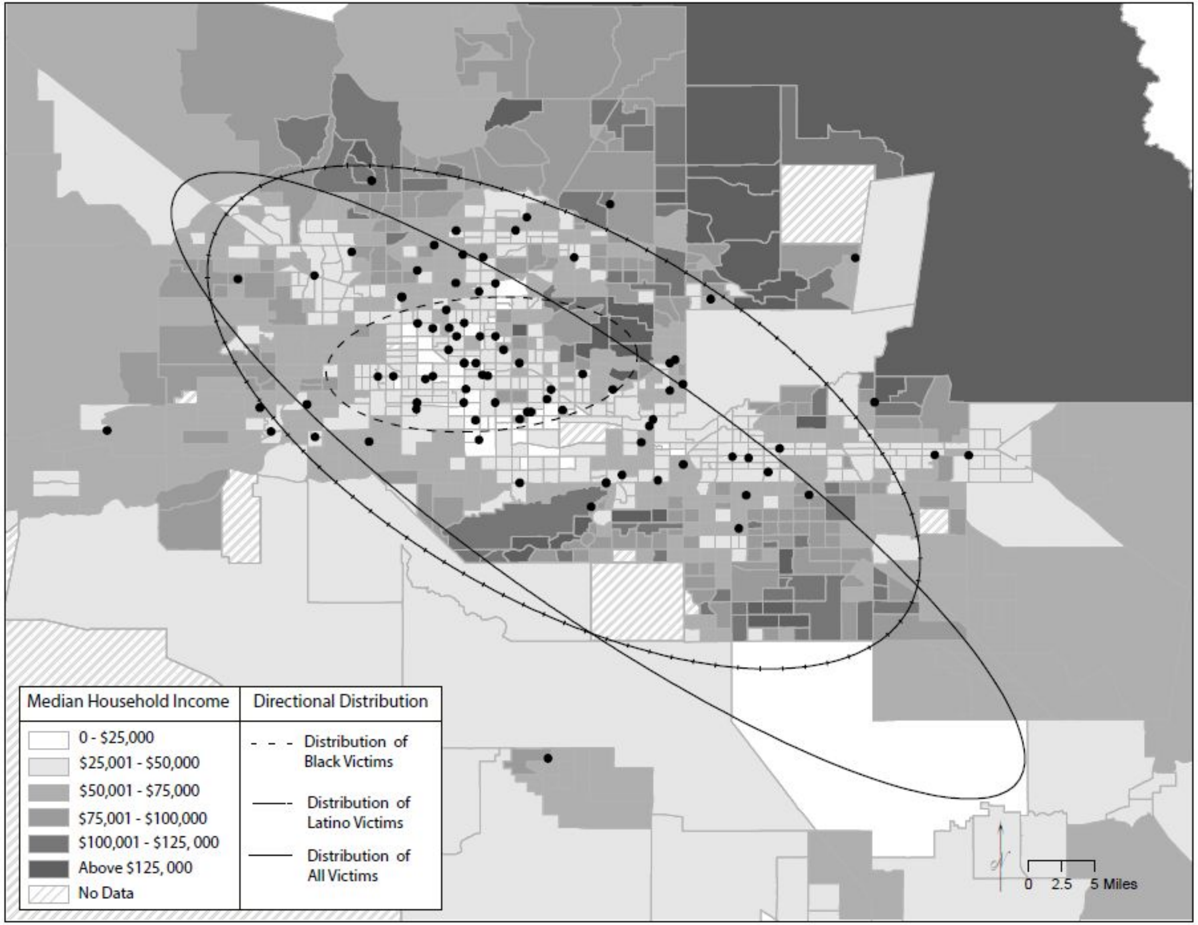
Los Angeles-Long Beach-Anaheim CBSA



New York–Newark–Jersey City CBSA



Phoenix-Mesa-Scottsdale CBSA



Miami-Dade-Fort-Lauderdale West Palm Beach CBSA

Dallas–Fort Worth–Arlington CBSA

Spearman’s rho Correlation Table

	Total Population	Median Household Income	Households in Poverty	Vacant Housing Units	Multi-Family Units	Median Year Built	Total F.P.E.s Per Tract	Black F.P.E.s	Latinx F.P.E.s	White F.P.E.s
Median Household Income	.071**									
Households in Poverty	-.023*	-.842**								
Vacant Housing Units	-.199**	-.237**	.142**							
Multi-Family Units	-.138**	-.473**	.417**	.210**						
Median Year Built	.182**	.107**	-.159**	.159**	-.166**					
Total F.P.E.s Per Tract	.038**	-.117**	.110**	.045**	0.017	0.001				
Black F.P.E.s	0.019	-.095**	.088**	.041**	.042**	-.026*	.527**			
Latinx F.P.E.s	.032**	-.082**	.085**	-0.011	0.001	-.027*	.548**	.024*		
White F.P.E.s	0.021	-0.014	0.011	.040**	-0.013	.053**	.542**	0.009	0.007	
Unknown Race F.P.E.s	-0.001	-.045**	.030**	.036**	0.006	0.011	.313**	.033**	0.017	0.018

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).
c. Listwise N = 8639

Poisson Regression Parameter Estimates

	Los Angeles-Long Beach-Anaheim		New York-Newark-Jersey City		Phoenix-Mesa-Scottsdale		Miami-Fort Lauderdale-West Palm Beach		Dallas-Fort Worth-Arlington	
	Beta	*Std. Error*	*Beta*	*Std. Error*	*Beta*	*Std. Error*	*Beta*	*Std. Error*	*Beta*	*Std. Error*
(Intercept)	-2.248	8.0235	10.452	7.8658	8.451	7.8835	2.303	7.7591	2.073	7.7444
Median Household Income	-1.755E-05**	3.6332E-06	-1.118E-05**	3.5080E-06	-1.496E-05**	3.6453E-06	-1.659E-05**	3.6578E-06	-1.668E-05**	3.6393E-06
Households in Poverty	0.943	0.5672	0.733	0.5657	0.789	0.5688	0.935	0.5687	0.949	0.5684
Vacant Housing Units	0.834	0.6439	0.351	0.6738	0.287	0.6777	0.674	0.6556	0.633	0.6498
Multi-Family Housing Units	-0.816*	0.3181	-0.553	0.3223	-0.646*	0.3272	-0.893**	0.3242	-0.908**	0.3171
Renter Occupied Housing Units	0.940*	0.4514	0.710	0.4401	1.079*	0.4425	1.194**	0.4488	1.212**	0.4353
Median Year House Built	0.001	0.0037	-0.007	0.0037	-0.005	0.0037	-0.001	0.0036	-0.001	0.0036
No Vehicle in Household	-1.412**	0.4549	-0.143	0.5075	-1.796	0.4445	-1.659**	0.4431	-1.676**	0.4449
Pct. White Population	-1.394	2.9649	0.083	3.0406	-1.522	2.9813	-2.120	2.9401	-2.151	2.9335
Pct. Black Population	-0.648	2.9488	0.827	3.0203	-0.469	2.9683	-1.359	2.9274	-1.396	2.9165
Pct. Latinx Population	-1.350	2.8948	0.023	2.9687	-1.204	2.9201	-1.936	2.8800	-1.984	2.8710
Pct. American Indian Population	-0.991	3.3411	0.568	3.4342	-2.247	3.6063	-1.758	3.3326	-1.828	3.3353
Pct. Asian Population	-2.124	2.9991	-0.612	3.0799	-1.678	3.0301	-2.540	2.9870	-2.585	2.9815
Pct. Pacific Islander Population	6.354	6.1047	8.024	6.2384	6.690	6.1180	6.507	6.0205	6.451	6.0316
Pct. Other Race	-6.407	6.7188	-1.670	6.7361	-7.118	6.6474	-7.696	6.6641	-7.817	6.6797
Pct. Two or More Races	0[a]		0[a]		0[a]		0[a]		0[a]	
[x = CBSA=1]	0.280*	0.1314	-1.018**	0.1798	0.600**	0.1545	-0.020	0.1441	-0.050	0.1345
[x = CBSA=0]	0[a]		0[a]		0[a]		0[a]		0[a]	
(Scale)	1[b]		1[b]		1[b]		1[b]		1[b]	

Conclusions

- Median household income was negatively and significantly correlated with all variables except for White fatal encounters (Spearman's rho)

- On average, for every $10,000 increase in median household income, the odds of a fatal police encounter dropped 14.2 percent. In three CBSAs, Miami-Fort Lauderdale-West Palm Beach, Dallas-Fort Worth-Arlington, and Phoenix-Mesa-Scottsdale, the odds were greater, 15.3, 15.4, and 16.1 respectively.

- On average, a ten percent increase in the amount of vacant housing in an area increased the likelihood of fatal police encounters by 5.7 percent.

- Unlike other recent studies of fatal police violence, race <u>did not prove</u> to be statistically significant in any of our model.

- In three of our five CBSAs, the variable "Percent of Households without a Vehicle" was statistically significant. Theoretically, this may be about cars being the pretext for police stops and subsequent police violence.

Next Steps

Based on feedback from reviewers and collaborators:

A. Use a two-step Hurdle approach to test for spatial autocorrelation for fatal police encounters to better understand clustering of incidents.
   a. Re-run Poisson regression to derive residuals
   b. Map residuals across all five CBSAs
   c. Run an spatial autocorrelation in each CBSA to derive Moran’s i statistics

B. Explore CBSAs by per capita FPEs (e.g. Oklahoma City, St. Louis, Tampa, Bakersfield) to understand geography of FPEs in smaller regions with proportionally higher incidences of FPEs (Paper #2)

C. Add 911 call data and longitudinal data as variables to understand the relationship between FPEs, racial succession, gentrification, and change (Paper #3)