Drug Arrests on Staten Island: Racial Bias or Targeting the Drug Epidemic?

Erik Wang, Frank Wunschel, Madison Volpe

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Appendix

Introduction

In recent years, New York City's drug arrests have been examined in major news outlets, such as *The New York Times* and by non-profit organizations, such as the *Innocence Project.* Both of these publications from 2018 assert that racial bias in drug arrests does exist as black and Latino people are arrested for marijuana possession more than white people. Marijuana possession/sale is not the only type of drug arrest made in New York City, but arrests can also be made for possession and/or sale of controlled substances. **Figure 1** shows the distribution of controlled substance related arrests and marijuana related arrests in NYC in 2018. It displays that there were more controlled substance related arrests last year.

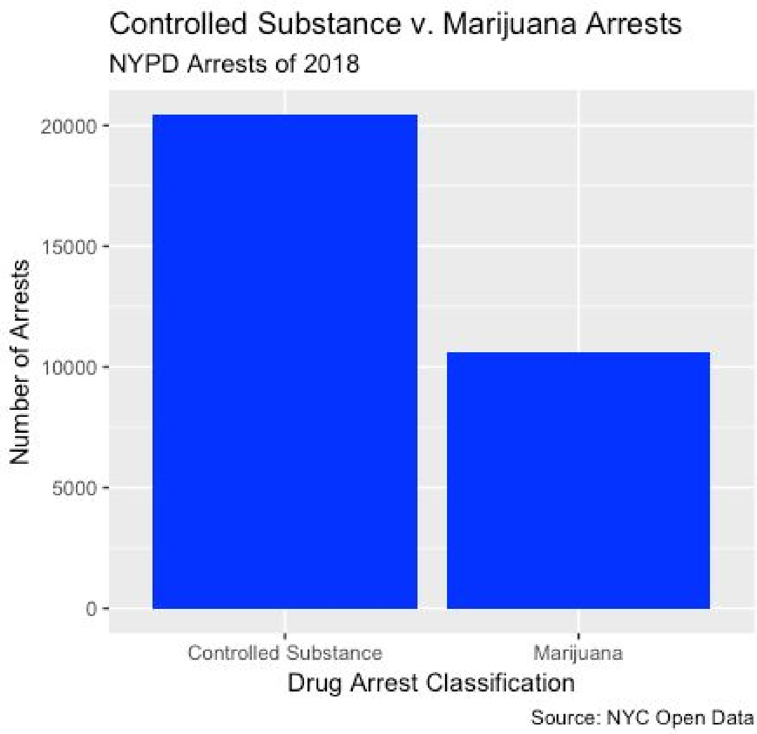


Figure 1: *Controlled Substance Related Arrests v. Marijuana Related Arrests*

Controlled substances are regulated by the US government. A typical controlled substance is any member of the opioid family of drugs. Currently, the United States is suffering from an opioid epidemic as the National Institute on Drug Abuse (2018) reports that the death rate for opioid related overdoses was 13.3 per 100,000 persons in 2016. New York City is no stranger to the drug epidemic as a Quarter One 2018 report by the NYC Department of Health and Mental Hygiene (DOHMH) states that 'every six hours someone dies of a drug overdose in NYC' and that 80% of all drug overdose deaths involve opioids.

The crisis does not discriminate against any borough in NYC, but it does affect some boroughs more than others. A NYC DOHMH September 2018 Epi Data Brief confirms that both the Bronx and Staten Island are the most affected by the opioid epidemic. In particular, in 2017 Staten Island had an overdose death rate of 27.3 per 100,000 residents.

Staten Island is known as the 'forgotten' borough of NYC. The lack of a direct subway route to Manhattan, as well as minimal public housing units has had consequences as Staten Island remains the least diverse borough. Among the minorities that live in Staten Island, most of typically reside on Staten Island's "North Shore" close to the Staten Island Ferry and New York Harbor. **Figure 2** depicts the racial makeup of Staten Island. It displays how Staten Island is racially segregated as most of the minorities typically live in the northern part of the borough, while the southern half of the borough remains overwhelmingly white.

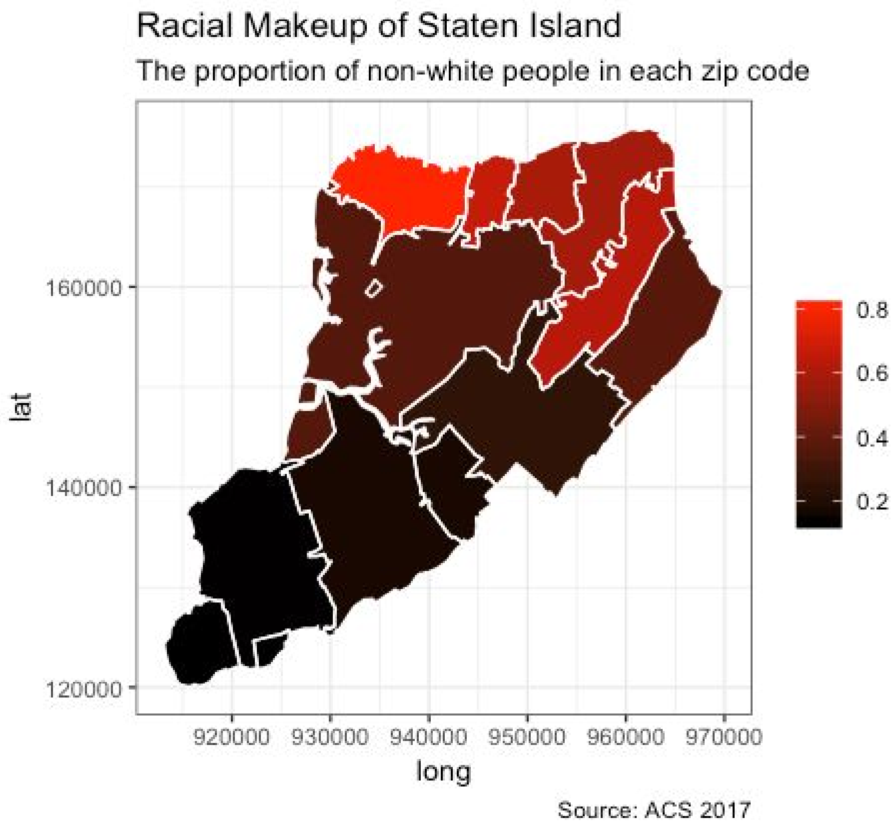


Figure 2: *Racial Makeup of Staten Island*. The darker colors represent zip codes that are more white, while red represents zip codes that have a greater proportion of non-white people.

The prominence of the opioid epidemic, as well as the racial makeup of Staten Island make it an interesting place to study drug arrests. Results from the 2014 National Survey on Drug Use and Health show that blacks and whites tend to use drugs at similar rates, while Latinos tend to use drugs less than both of these racial groups (Substance Abuse and Mental Health Services Administration, 2014, Table 1.19B). Because Staten Island is racially segregated (**Figure 2**), racial bias in drug arrests can easily be observed if we notice that most of the drug arrests are occuring in the majority non-white sections of Staten Island on the North Shore.

Ultimately, this study examines the nature of drug arrests on Staten Island. It seeks to answer the following question: On Staten Island, do neighborhoods with higher levels of drug activity experience higher occurrences of drug arrests or is there evidence of racial bias? In short, the study determines whether drug arrests occur in areas with high levels of drug activity or if they are concentrated in majority non-white sections of the borough. The study uses a combination of exploratory data analysis, spatial statistics methods, as well as Poisson regression to answer this question. Ultimately, we find that there is evidence of racial bias in drug arrests on Staten Island.

Related Law

NY has drug-related penal laws that are often considered as the toughest in the whole nation. There are mainly five sections of NY Penal Laws that are related to drug trafficking, possession, and distribution. They are:

- New York Penal Law Section 220 (controlled substances and definitions)
- New York Penal Law Sections 220.03 - 220.25 (criminal possession of a controlled substance)
- New York Penal Law Sections 220.31 - 220-44 (criminal sale of a controlled substance)
- New York Penal Law Section 220.60 (criminal possession of precursors of controlled substances)
- New York Penal Law Section 220.77 (operating as a major trafficker)
- New York Penal Law Sections 221.00 - 221.55 (marijuana offenses)

(Findlaw's team 2019)

Offenders of the above laws can either be charged with felonies or misdemeanors depending on the seriousness of the crime. Sentences vary based on the types and quantities of the illegal substances possessed, sold, and/or distributed. As an example, a minor amount of heroin possession could result in 15 years in prison, while having less than 28 grams of marijuana is decriminalized (Plessman, 2018).

While all boroughs of NYC enforce NY state penal laws, district attorneys can influence how these laws are enforced in their respective boroughs. Staten Island's district attorney, Michael McMahon, is perceived as a drug warrior. McMahon treats drug overdose related deaths as homicides. Likewise, drug arrests, prison populations, and jail sentences have all increased due to his policies.

Due to the prominence of drugs on Staten Island, Staten Island has the Staten Island Treatment Court (SITC). SITC is special court part in the Staten Island Criminal Court that helps those who have been arrested for misdemeanor and/or felony drug charges. Instead of serving time in jail, while under the supervision of SITC, offenders are brought into drug treatment programs. Under DA McMahon, there has been a 69% decrease in the number of people who entered the SITC program compared to the numbers under his predecessor (Fleming, 2019).

Overall, penal laws in NY create a harsh environment for drug offenders. This harsh environment is greatly felt in Staten Island especially as DA McMahon has tried to cut down on drug use. Ultimately, this climate leads to more policing and greater arrests for drug related offenses.

Literature Review

The War on Drugs in the 1980s has affected the criminal justice system in a profound way. Since its inception mass incarceration in particular for drug offenses has grown tremendously. For example, as the Drug Policy Alliance (2018) reports that from 1993 to 2009 there were over 3 million prison admissions due to drug related crimes (p. 1). Also within this period more people were admitted into prison for drug offenses than violent crimes (Drug Policy Alliance, 2018, p.1). Due to the effects of the War on Drugs, researchers have been studying drug arrests in the United States. Of particular interest is racial differences in regards to drug arrests. As work from the Hamilton Project at the Brookings Institution exclaims that black people are 2.7 times likely to be arrested for drug crimes compared to white offenders (Hamilton Project, 2016).

To study the impact of racial disparities in arrests, researchers have used a variety of methods common to criminology, such as Poisson regression, negative binomial regression, and logistic regression. Likewise, studies vary in the unit of analysis used; for example, some studies use neighborhood as the unit of analysis, while other studies rely on individual level data. Nevertheless, many of these studies confirm that there is some evidence of racial bias in drug arrests.

Using individual level responses from the National Longitudinal Survey of Youth, researchers Mitchell and Caudy (2015) find evidence that supports that differences in drug arrests amongst different races are largely not the result of differences in the extent of drug offending and/or the nature of drug offending (p. 293). Rather, their research shows that most black and white individuals have similar levels of engagement with drugs. Therefore, they find that African Americans' higher probability of drug arrest is largely due to racial bias in law enforcement (Mitchell & Caudy, 2015, p. 309).

The results of Mitchell & Caudy's research are further supported by sociological fieldwork conducted by Beckett, Nyrop, and Pfingst. In their fieldwork and data analysis that studied drug delivery in Seattle, they find that even though white people are the majority deliverers for a wide variety of drugs except crack, 64% of arrested drug deliverers are black (Beckett, Nyrop, & Pfingst, 2006, p. 121). Through their ethnographic analysis, they come to the conclusion that differences in arrests between white and black offenders result from implicit racial bias(Beckett et al., 2006, 130).

Studies, such as those by Mitchell & Caudy and Beckett et al., focused on different units of analysis, individuals and sites across Seattle,respectively. However, neither study examined the influence of a neighborhood on drug arrests. Researcher Shytierra Gaston used neighborhood counts of drug arrests in 78 neighborhoods located in St. Louis to analyze what influences white drug arrests versus black drug arrests. Gaston (2019) finds that the racial composition measure is the strongest of all models, which provides evidence for racial bias in drug law enforcement (p. 515).

Most of the research reviewed supports the notion that differences in drug arrests between races is largely owed to racial bias. The following methods employed in this analysis will attempt to show similar results for Staten Island. Namely, we want to show that racial bias accounts for differences in drug arrests. To accomplish this, a variety of datasets and methods were used, which are explained in further detail in the following sections.

Data

The datasets used in this study include NYPD Arrest Data (YTD + Historic) from NYC Open Data, EMS Incident Dispatch data from NYC Open Data, statistics related to drug activity from the Staten Island Drug Prevention Portal, demographic data from the American Community Survey, and a shapefile of NYC zip codes.

NYPD Arrest Data

The original NYPD Arrest datasets were combined and in total contained 18 columns and 247k observations. Variables included arrest date, law code, and the types of crime committed, as well as, the precincts and boroughs where the arrest occurred. At the date the data was downloaded, arrests ranged from 2013-2018 with complete arrest data from 2014-2017. Along with descriptive variables, the dataset also contains coordinates of the arrest, which we used to assign arrests to geographic units of interest, in our case zip codes. Ultimately, the data was filtered to only include arrests in Staten Island and only drug related offenses were retained. We used this dataset to obtain the counts of drug arrests in each zip code, the outcome variable of interest.

EMS Incident Dispatch

The original EMS data from the FDNY is also from NYC Open Data, it originally contained 8.56 million rows and 31 columns. The columns of importance are the initial and final call types because they contain all call codes that indicate why the EMS service was dispatched. Ultimately, we filtered for drug related call types and kept only observations in which the final call type was for a drug related incident. We filtered specifically on the final call type because upon receiving the 911 call, forwarded from the dispatcher, the EMS service will assess the situation to decide the initial call type, and when the ambulance arrives, a final call type will be decided based on their assessment of the situation. Therefore, the final call type is a more accurate measure of whether the EMS was dispatched for situations involving drugs. Similar to the NYPD data, the EMS Incident data was filtered for drug dispatches that occured on Staten Island. The data range from 2013-2018 with complete data for the years 2014-2017. Ultimately, we used this dataset to obtain counts of EMS dispatches in each zip code. This variable serves as a proxy for measuring drug activity.

Staten Island Drug Prevention Portal

The Staten Island Drug Prevention Portal contains datasets that measure drug activity on Staten Island. Datasets include naloxone saves by zip code, overdose deaths by zip code, opioid emergency department visits by race + age, and hospital admission for opioid overdose by race + age. For our purposes, we used the naloxone saves by zip code and overdose deaths by zip code datasets to serve as proxies for drug activity.

American Community Survey

We used the American Community Survey to obtain demographic data for each zip code. Since our data spanned from 2013 to 2018, we obtained data from the 2014-2017 ACS 5-year estimates. The variables we obtained included total population, as well as estimates for the total white, black, and Hispanic populations in each zip code.

Methods

To see whether there is racial bias in drug arrests on Staten Island, we used three different methods of analysis: exploratory data analysis (EDA), spatial analysis, and Poisson regression. Due to limited availability of drug activity data, we had to constrain our analyses to drug arrest counts in the twelve zip codes of Staten Island. In certain analyses, the observations are aggregated counts across 2013-2018. In the aggregated case, the demographic data was obtained from the 2017 ACS. In other analyses, in order to obtain more observations, the observations are counts of a zip code in a given year. In this case, demographic data was obtained from the ACS that corresponds to the given year.

In Criminology, exploratory data analysis has often been overlooked for typical inferential statistics techniques, however it is important to use it to discover patterns in datasets, as well as to make sure data fit the assumptions of models (Maltz, 2010, p.49). Chapter three in the *Handbook of Quantitative Criminology* (2010) describes the importance of EDA and various methods one can use to visualize criminal justice data. Likewise, visualization methods, such as scatterplots with fitted regression lines as seen in Chohlas-Wood, Goel, Shoemaker, and Shroff (2018, p. 5) are also examples of effective EDA.

When working with data that has a geographic component, it is needed to understand if this geographic component has an effect on the variable of interest as well as if spatial proximity to other occurrences holds an effect. To do so many tests and methods are carried out in attempts to detect structure. If this step is neglected, and structure exists the estimates taken from a model, in this case a Poisson dependent generalized linear model, would be inaccurate as a significant portion of the variance would not be correctly explained. Thus, it is imperative to run spatial analysis and check for structure, because in the case that it exists, the final model would be rendered useless.

Since the outcome variable in this study is counts of drug arrests that occur in Staten Island zip codes, Poisson regression and its variants are an appropriate statistical technique. Poisson regression typically beats out other common methods, such as OLS regression due to the skewed nature of count data (MacDonald & Lattimore, 2010, p. 684). Chapter ten in the *Handbook of Quantitative Criminology* (2010) further details why Poisson regression is useful for studying rates of outcome variables. Likewise, Poisson methods used in Chohlas-Wood et al. (2018) are useful when trying to estimate whether rates of arrests are associated with the racial composition of a geographic unit of interest.

Exploratory Data Analysis

The EDA employed in this study includes mapping of drug arrests over zip code choropleth maps that indicate the racial composition of the zip code. Likewise, scatter plots that compare the amount of drug arrests to measures of drug activity in a zip code are also utilized. In this case, zip codes are labeled as majority white or majority non-white based on their racial composition.

Spatial Analysis

The process that was used in attempts to detect possible spatial autocorrelation within the data contained four steps. The first was general visualization aggregating by race and the composition of each region, if certain points appeared clumped or structured there was reason to do a more thorough investigation. The next step was to run k-value monte carlo simulations on the sample and compare it to a completely randomized sample in the same area, though this check tells you minimal information finding that the data is completely random can save a lot of tests and work in the long run. Once it is understood that the sample is not completely random, the Moran I and Geary C tests are implemented which calculate regional neighbors and compare the number of occurrences in different strata compared to neighboring regions in attempts to detect structure. If possible structure is detected overall, a more granular approach is used in the form of a local indicator of spatial correlation (LISA) such as a local Moran I followed by a more intensive Kulldorff test which attempts to identify *outlier* or hotspots of sorts, in order to explain where the spatial correlation is highest and/or where it originates.

Poisson Regression

In addition to the EDA and spatial analysis, the final technique we employed was Poisson regression. Poisson regression is useful for count data because count data tends to be right skewed. Poisson regression fixes this problem as it belongs to the class of log-linear models. Therefore, Poisson regression uses the log-link to associate linear predictor variables and the mean of the expected distribution of the outcome variable. Poisson regression is also useful because it can predict expected rates with the addition of an exposure variable typically called the offset.

We utilized three models to see if there was an association between the racial composition and the rate of drug arrests in zip codes on Staten Island. Drug arrests are simply the counts of drug arrests in each zip code. Racial composition refers to the proportion of non-white people in each zip code. Also included in the models were measures of drug activity. Controlling for drug activity is important because it allows us to better measure the differences in arrest due to the racial composition of zip codes. Ultimately, in any of the models, significant and positive coefficients on the racial composition variable would indicate that primarily non-white zip codes are being targeted at higher rates for drug arrests than primarily white zip-codes with similar levels of drug activity. We will now discuss our models in more detail.

Model One - Aggregated Counts Across Zip Codes

$$s_g = Poisson(p_g * e^{\mu + \alpha c_g + \beta r_g})$$

Model 1

In **Model 1**, G refers to the unit of analysis, the zip code. S_g refers to the count of drug arrests in each zip code that occurred between 2013-2018. P_g refers to the total population over age 18. This variable is the offset or exposure variable. C_g is the count of EMS dispatches for drug related reasons that occured between 2013-2018. R_g is the proportion of non-white people in each zip code. In this model, the demographic variables are estimated from the 2017 ACS.

Model Two - Counts by Year Across Zip Codes

$$s_{g,t} = Poisson(p_{g,t} * e^{\mu + \alpha c_{g,t} + \beta r_{g,t}})$$

Model 2

Again, in **Model 2**, G refers to the unit of analysis, zip code. This model measures zip codes at specific years, therefore T represents a given year from 2014- 2017. $S_{g,t}$ refers to the count of drug arrests in each zip code in a given year between 2014-2017. $P_{g,t}$ refers to the total population over age 18 in a given year between 2014-2017. This variable is the offset or exposure variable. $C_{g,t}$ is the count of EMS dispatches for drug related reasons that occured in a given year between 2014-2017. $R_{g.t}$ is the proportion of non-white people in each zip code in a given year between 2014-2017. In this model, the demographic variables are estimated from the ACS of a given year between 2014-2017.

Model Three - Aggregated Counts Across Zip Codes with Extra Drug Activity Variables

$$s_g = Poisson(p_g * e^{\mu + \alpha c_g + \beta r_g + \beta d_g + \beta z_g})$$

Model 3

Model 3l returns to the aggregated form of **Model 1.** The variables are the same as in **Model 1** except with new additions D_g , the total number of drug overdose deaths from 2016-2018, and Z_g, the total number of naloxone saves from 2016-2018.

All models were tested for overdispersion and significant overdispersion was found in all three. Therefore, quasiPoisson models were fit to the data to adjust for the variance being greater than the expected mean.

Results

Exploratory Data Analysis

As previously stated, our exploratory data analysis focused on maps and scatter plots. **Figure 3** shows the distribution of drug arrests on Staten Island. A large amount of drug arrests are concentrated on the island's North Shore. Likewise, most drug offenders on the North Shore are black and Hispanic. There are drug arrests on the island's South Shore. The map reveals that offenders on the South Shore are typically white.

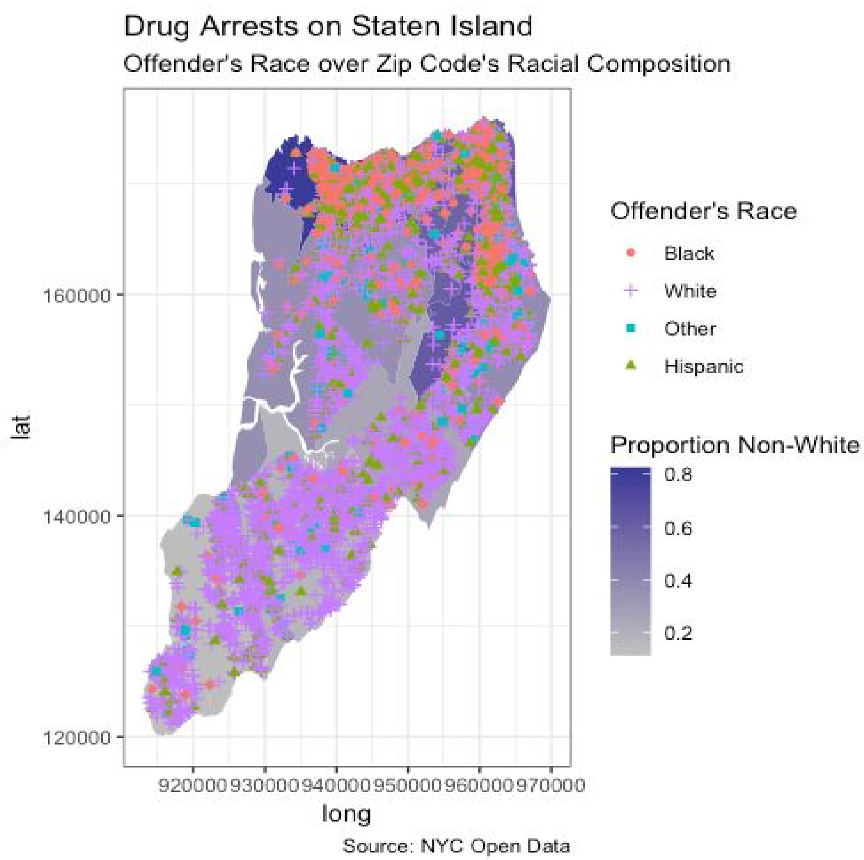


Figure 3: *Drug Arrests on Staten Island*. The map shows that most minority drug arrests are focused in zip codes with high minority populations and most white drug arrests are focused in zip codes that are highly white.[1] The drug arrest data ranges from 2013-2018.

[1] In this figure "Other" includes Asian, American Indian, and Unknown races.

Like **Figure 3**, **Table 1** also supports the notion that within non-white majority zip codes mostly blacks and sometimes Hispanics are arrested for drugs more than whites. However, in mostly white zip codes, whites are arrested more than blacks or Hispanics. Moreover, **Table 1** clearly shows that arrest rates for drugs are higher in minority zip codes.

Table 1: Drug Arrests by Zip Code

Zip	White	Black	Hispanic	Other	Total	NonWhite Majority	Arrest Rate
10302	473	553	318	43	1387	Yes	9.664832
10301	928	1065	563	44	2600	Yes	8.520679
10303	362	597	242	28	1229	Yes	6.640731
10304	516	1111	423	42	2092	Yes	6.453006
10310	222	424	215	19	880	Yes	5.001421
10309	790	16	90	19	915	No	3.514770
10305	741	138	171	49	1099	No	3.302184
10307	280	9	29	5	323	No	2.829610
10306	834	78	118	23	1053	No	2.435132
10314	1144	198	232	77	1651	No	2.314075
10312	958	25	85	29	1097	No	2.294979
10308	287	14	29	7	337	No	1.397007

Table 1: A table version of the map produced in **Figure 3**. Drug arrest rates were calculated by dividing the total population over age 18 (2017 ACS) by the total drug arrests in each zip code. [2]

Along with the results in **Table 1**, we ran a two sample t-test to see if the mean differences in the drug arrest rates for minority and white zip codes were not equal to zero and we obtained a significant result.

When comparing the drug arrest rates across zip codes, it is necessary to see if other factors are potentially influencing the drug arrest rates. Such variables that could influence drug arrest rates are measures of drug activity. It would make sense that police are patrolling areas with high levels of drug activity. **Figure 4** shown below compares the drug arrest rate to three different variables that serve as measures of drug activity. The first panel shows that EMS dispatches tend to occur at a higher rate in zip codes that are primarily non-white. The arrest rates in these zip codes also tend to be higher compared to their primarily white counterparts. In contrast to EMS dispatches, other measures of drug activity are not as conclusive. For example, in the second and third panels, there are white zip codes that have higher naloxone save rates and higher drug overdose death rates compared to non-white zip codes, but the non-white zip codes have higher drug arrest rates.

[2] In this figure "Other" includes Asian, American Indian, and Unknown races.

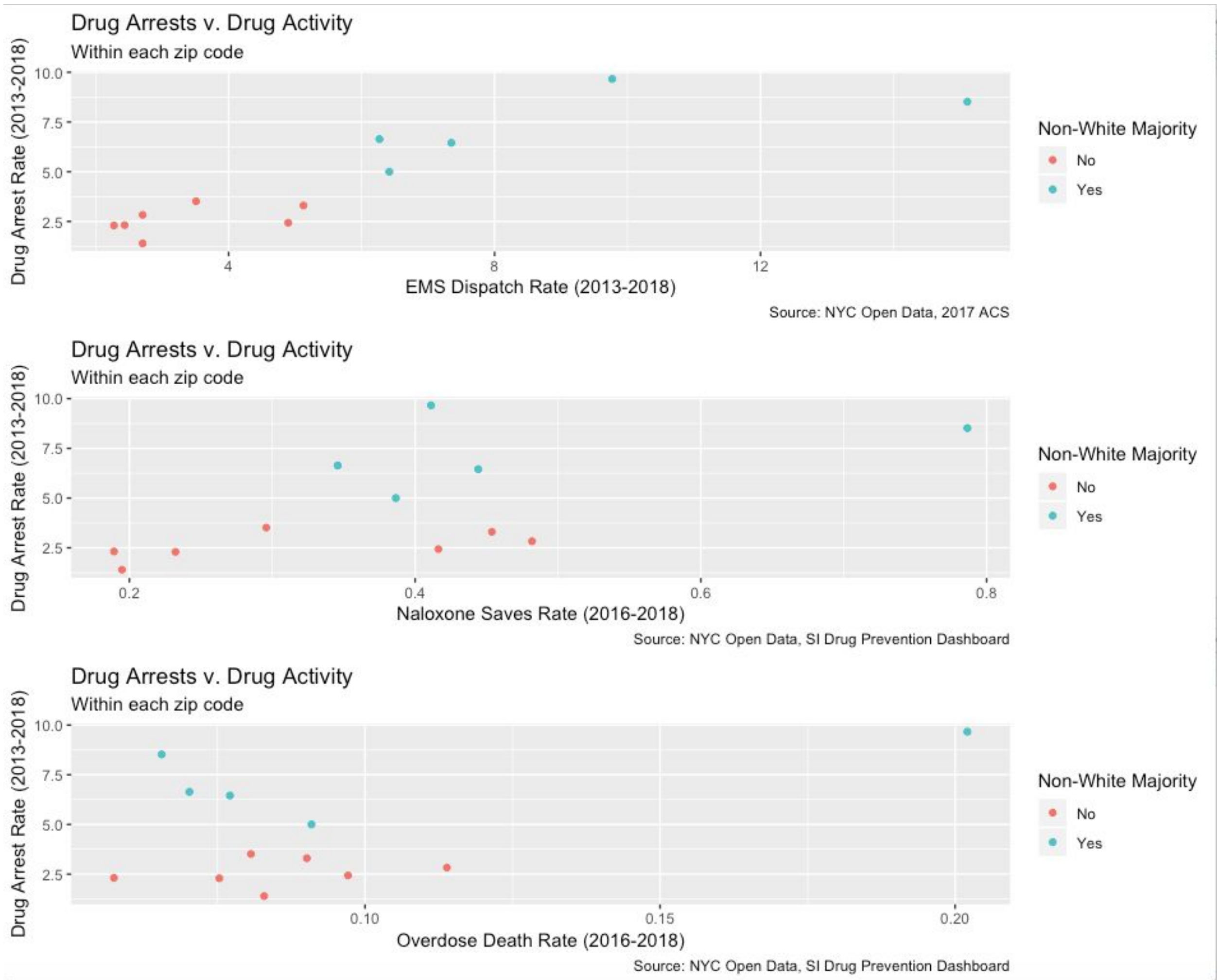


Figure 4: *Drug Arrest Rates v. Measures of Drug Activity.* The first panel compares the drug arrest rate to the EMS dispatch rate. The second panel compares the drug arrest rate to the naloxone saves rate. Finally, the third panel compares the drug arrest rate to the overdose death rate. All points represent a zip code. Points are shaded blue if the zip code is primarily non-white and shaded red if the zip code is primarily white. [3]

As seen in **Figure 5,** when the data is not aggregated, the differences in drug arrest rates compared to drug overdose death rates are even more apparent. In a given year, drug overdose deaths are more prominent in the white majority zip codes, but drug arrests tend to be higher in majority non-white zip codes.

[3] All rates are found by dividing the total population over age 18 (ACS 2017 estimate) by the drug activity variable of interest.

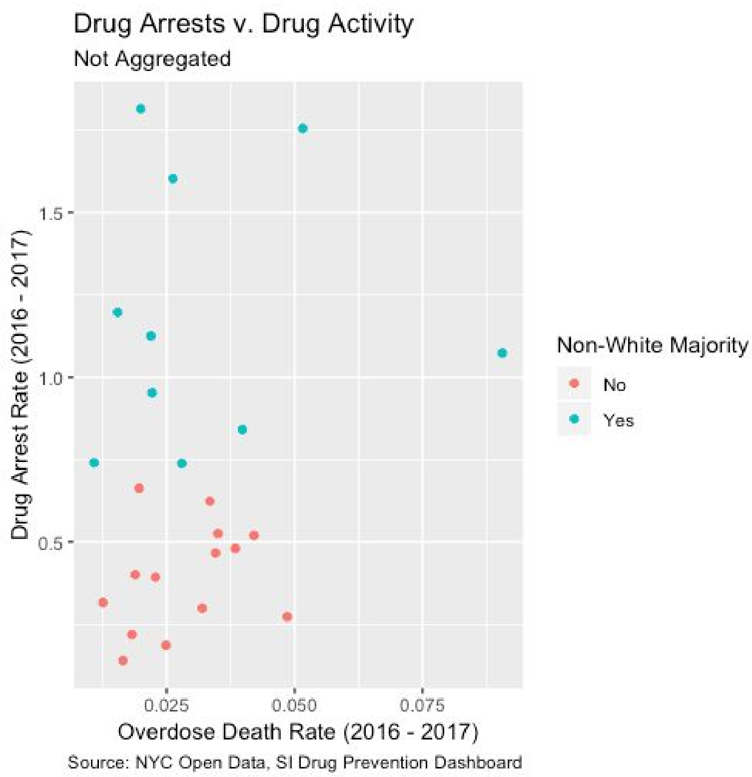


Figure 5: *Drug Arrest Rates v. Overdose Death Rate*. Points represent the twelve zip codes in Staten Island in 2016 and 2017. Points are shaded blue if the zip code is primarily non-white and shaded red if the zip code is primarily white.

Ultimately, the results of the EDA provide three unique insights. First, minorities are arrested more in primarily non-white zip codes, while white people are arrested more in primarily white zip codes. Second, drug arrest rates are higher in primarily non-white zip codes. Third, in some white zip codes, overdose death rates and naloxone save rates are higher than those in non-white zip codes, however the non-white zip codes have higher drug arrest rates. These results show that drug arrests are typically focused in non-white zip codes even though drug activity appears to be prominent in white zip codes of the South Shore. Therefore, policing does not seem to target the borough's drug epidemic.

As previously stated, to further examine the evidence of racial bias in drug arrests, we also conducted spatial analysis and ran Poisson regression models. We will now discuss the results of the spatial analysis in more detail.

Spatial Analysis

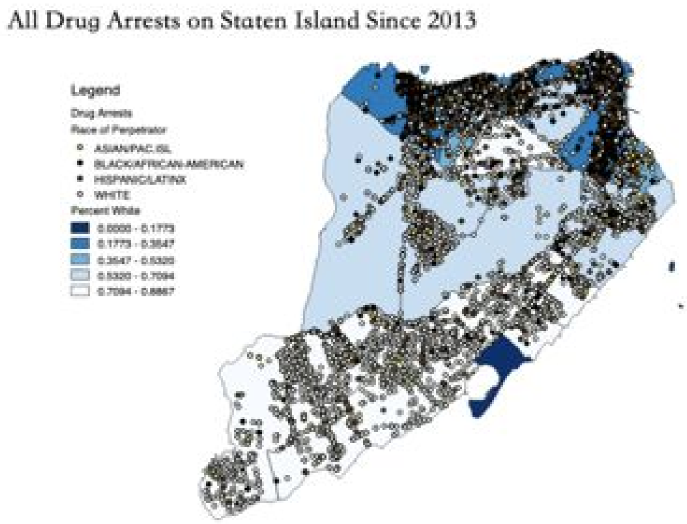
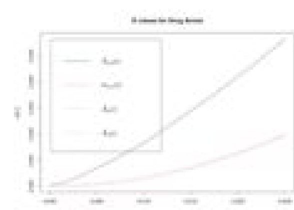


Figure 6: *Racial Makeup of Staten Island and Race of Drug Arrestees since 2013.*

After observing the distribution of drug arrests on Staten Island (**Figure 6)**, and aggregating the instances by the race of the arrestee, there was cause to believe spatial correlation could be present within the data. This spatial correlation could be detrimental in the construction of our model skewing the direct correlation between our variables of interest such as race and the arrest variable of probability of an arrest. As many datasets were explored most, if not all, had to be examined for spatial correlation in deciphering which would be used to create the models.

It began by simple Monte Carlo simulations which produced K-values for each dataset pooled and by year. These k values were plotted against the K values of a Completely Randomized Sample (CRS) in the same region (Right). Tough almost all of the datasets and time points did not follow the randomized plot this did not mean that there was direct structure between points it simply shows the possibility.



After seeing a stray from the CRS line, the next step was to explore the data for general clusters based on the overall population. More specifically if there were spatial clusters in all arrests without observing possible confounders. To do so, rates were constructed for each zip code depending on what the data provided this meant a mix of analysis at NTA and zip code level. From the implementation of Moran's I, Geary's C, and local Moran I scans a p value for each sector and its direct neighbors was computed. The Moran I was then simulated many times (n=999) to insure the results. Out of all the models, the most significant model obtained a p-value of .049 (on the direct drug arrest data). Though in many realms this would constitute significance at a .05 level, due to the lack of standard controls for

multiple comparisons of regions, think Tukey-test, it is difficult to take this at face value and mark it truly significant though it is nearing a generic threshold. Though structural correlation would make sense as an anomaly as the zip code sat in the middle of the two shores and has high diversity, lending itself to produce inconsistent arrests by population.

From this finding, it revealed to look at a more granular level taking into account the confounding variable of racial distribution per zip code. To do this the Kulldorff method was implemented, which controlled for both general population of a region and its aggregated racial breakdown. When conducting this test a similar result was produced, unfortunately the only cluster that was found was the spit like cluster colored on the Moran local at the bottom right, unfortunately this is Great-Kills Park and thus we find no true clusters to show autoregressive spatial relationships. Though no definitive clusters or hotspots were found, this is positive in the direct implications of the models to come as we can ignore the possibility of spatial effects between zip codes which could render the results of our models inaccurate.

Poisson Regression

Table 2 displays the results from the Poisson regression models. The coefficients in the table are not the exponentiated results. However, exponentiating the coefficients will give the multiplicative effects of each covariate.

Table 2: Poisson Regression Results

	Dependent variable:		
	Drug Arrests (2013-2018) Aggregated	Drug Arrests (2014-2017)	Drug Arrests (2013-2018) Aggregated
	(1)	(2)	(3)
EMS Calls 2013-2018	0.0001		0.0005
	(0.0001)		(0.0003)
EMS Calls 2014-2017		0.001^{**}	
		(0.0003)	
Proportion Non-White	2.070^{***}	2.126^{***}	1.320^{*}
	(0.467)	(0.297)	(0.563)
Naloxone Saves			−0.007
			(0.006)
Drug Overdose Deaths			−0.005
			(0.012)
Constant	-4.369^{***}	-6.073^{***}	-3.680^{***}
	(0.251)	(0.160)	(0.447)
Observations	12	48	12
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 2: *Model Results*[4]

The racial composition coefficient, Proportion Non-White, remains significant in all three models. However, it does become less significant ($p < 0.1$) in the third model as other measures of drug activity are added to the model. Ultimately, because all three models have significant and

[4] The coefficients are not exponentiated.

positive coefficients on the Proportion Non-White variable, this reveals that predominantly non-white zip codes are being targeted at higher rates for drug arrests than predominantly white zip-codes with similar levels of drug activity.

More specifically, in the first model, the exponentiated coefficient is 7.92 (1.01, 3.13). Therefore, the proportion of non-white people in a zip code multiplies the expected count of drug arrests by 7.92. In the second model, the exponentiated coefficient is 8.38 (1.53, 2.72). Therefore, the proportion of non-white people in a zip code multiplies the expected count of drug arrests by 8.38. Finally, in the third model, which includes other measures of drug activity in addition to EMS calls, the exponentiated coefficient on the proportion non-white variable is 3.74. Therefore, the proportion of non-white people in a zip code multiplies the expected count of drug arrests by 3.74.

In the first model, the variable that represents drug activity is an aggregated count of EMS dispatches from 2013-2018. The variable is not significant, therefore we cannot say that neighborhoods experiencing greater drug activity (EMS dispatches) are being targeted at higher rates for drug arrests than neighborhoods experiencing less drug activity with similar racial composition. In other words, it appears that drug activity is not associated with the expected count of drug arrests.

In the second model, the variable that represents drug activity is a count of EMS dispatches that occured in each year from 2014-2017. In this case, EMS calls appear to be associated with the expected count of drug arrests. However, the exponentiated coefficient on this variable produces a multiplicative effect of 1; therefore, the total EMS dispatches in a zip code multiplies the expected count of drug arrests by 1. This is not such an informative result.

Finally, in the third model, we included three measures of drug activity, EMS dispatches from 2013-2018, naloxone saves from 2016-2018, and overdose deaths from 2016-2018. None of the three measures of drug activity are significant. Therefore, we come to the same conclusion found in **Model 1** that we cannot say that neighborhoods experiencing more drug activity are being targeted at higher rates for drug arrests than neighborhoods experiencing less drug activity with similar racial composition.

In conclusion, the models reveal two insights regarding drug arrests on Staten Island. The first insight is that the racial composition of a zip code is associated with the expected count of drug arrests. A zip code with a higher proportion of non-white people will have a greater amount of drug arrests than a zip code with a lower proportion of non-white people when controlling for the level of drug activity. The second insight is that measures of drug activity do not appear to be associated with the rate of drug arrests in zip codes on Staten Island. As a result, it appears that police are targeting non-white neighborhoods rather than neighborhoods with substantial drug activity.

Discussion

The results from the EDA, spatial analysis, and Poisson models all suggest evidence of racial bias in drug arrests on Staten Island. **Figure 5** clearly shows that predominantly white zip-codes with higher rates of drug overdose deaths tended to have lower drug arrest rates than predominantly non-white zip codes with lower rates of drug overdose deaths. Even though the opioid epidemic greatly affects Staten Island, drug arrests do not appear to be targeting this issue. The spatial analysis found minimal structure in how arrests occurred which made it possible for a more straightforward and interpretable model to be fit. Though significance was found during one level of analysis, the p-value and results were close to a significant threshold and as these methods do not control for multiple comparisons, it is hard to take this case seriously. In the instance where significance was discovered, it occured in a region that lay between the two shores and the uncommon racial diversity of the area makes sense for it to stray from the norm, on such a divided island. Finally, the model results support the EDA and spatial analysis in that racial composition of a zip code remains a significant and positive indicator of drug arrest rates, while measures of drug activity are not significant predictors of drug arrest rates.

While the results provide evidence of racial bias in drug arrest rates on Staten Island, there are limitations to this study because of data availability. The study was constrained to zip codes, and with only 12 zip codes on Staten Island, the power of the models are greatly reduced. Another limitation is defining what constitutes a measure of drug activity. The use of EMS data as a measurement of drug activity, might be questionable because the recorded call types in the EMS data may not necessarily reflect the situation. Finally, there is another issue in that opioid consumption and subsequent overdose deaths typically occur in the home. For example, statistics from Staten Island law enforcement show that 80 of the 90 heroin-overdose victims in 2016 died inside their own homes and apartments (Annese & Mcshane, 2017). This could be a reason why naloxone saves and overdose deaths are not associated with drug arrests in **Model 3**.

Ethical Implications

Taking the model results into account, there is an association between the racial composition of a neighborhood and the rate of drug arrests controlling for the level of drug activity, this conclusion is compatible with previous results found in the literature. Although there is not sufficient evidence to make causal claims, one may speculate that the efficiency of policing is largely reduced because the police force might not be deployed to areas where drugs proliferate, but instead are deployed to areas where racial minorities reside. Such a strategy, regardless what the motivation is, will produce civil rights issues and can damage the image of the NYPD as the guardians of citizens.

Because the results of the study suggest racial bias, researchers should further confirm these results. Likewise, the results of this study could be further advanced with greater data availability. Therefore, we call on researchers to consider alternative model options to further expand on and improve our research.

Conclusion

The borough of Staten Island is faced with many issues, such as a racially divided population and an opioid epidemic. The data has shown that drug use tends to be similar across races. Yet, the trends in policing are anecdotally known to arrest those non-white offenders at a higher rate. After the creation of the models, while controlling for the possibility for spatial autocorrelation, this understanding of race based policing has shifted from anecdote to a statistically significant and supported claim. Staten Island has a narcotics problem, the results from this analysis also provide evidence that it has a racially biased policing problem. The two are one in the same, and for the borough to restabilize and change for the better, policies, police trainings and checks and balances need to be utilized to make Staten Island a safer and more equitable place for all of its residents.

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