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The Association of Gentrification and Stop-and-Frisk Policing in New York City

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B.S.
University of Georgia, 2019

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An abstract of
A thesis submitted to the Faculty of the
Rollins School of Public Health of Emory University
in partial fulfillment of the requirements for the degree of
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Abstract

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New theories propose that order maintenance policing and gentrification are positively associated, suggesting that policing is utilized as means to prepare or facilitate investment in historically divested communities. Both phenomena, associated with deleterious health effects, disproportionately affect minority and economically marginalized communities. Together, these effects may compound leading to worse health outcomes. The association between policing and gentrification is limited. This study characterizes gentrification in New York City and investigates the association between stop-and-frisk policing through mapping, descriptive statistics, and two-part general linear modelling. Our analysis indicates that gentrification was not influential on the incidence or magnitude of stop-and-frisk policing. Although no significant association was found, our results indicate that both gentrification and racially disproportionate stop-and-frisk policing continue in New York City to 2019.

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Introduction

Gentrification, the ascent of a community's socioeconomic status and the resulting changes in its cultural landscape, has become a common result of modern urban development[1]. Reduced crime, new amenities, and reinvestments in the built environment are cited as benefits of gentrification processes[2]. Despite these benefits, researchers have documented a myriad of negative consequences that can affect communities undergoing gentrification. Long-term residents, for example, experience increasing housing prices, the shifting of community norms, psychological stress and displacement [3-7]. The drivers of gentrification have been studied thoroughly, with new credence given to theories that suggest a mutualistic dynamic between owners of capital and public policies. Such theories propose that increases in order maintenance policing are utilized as means to prepare or facilitate gentrification, often at the expense of minority and low-income populations [1, 8]. Order maintenance policing, such as random police stops and questioning, has shown to have adverse health effects on those directly involved and bystanders[9-18]. Together, gentrification and policing may compound and exacerbate their health effects on individuals and the overall health of a community. However, empirical research on this gentrification-policing hypothesis is limited. This study aims to characterize the associations between gentrification and the intensity of order maintenance policing in New York City. We hypothesize that the incidence and rate of stop-and-frisk is positively associated with gentrification. To test these hypotheses, we conduct a cross-sectional study utilizing bivariate and multivariate generalized regression modeling.

Background

Gentrification

Coined in 1964 by sociologist Ruth Glass, gentrification is the process in which historically low-middle income neighborhoods transition to higher socioeconomic status (SES) neighborhoods through capital reinvestment and an influx of wealthier newcomers. Some argue that gentrification has the ability to reduce social, physical, and health inequalities among lower-income residents through the deconcentration of poverty, social mixing, and increased access to resources [2]. However, research shows the effects of gentrification are wide ranging and varying, and by some metrics increase socioeconomic segregation among residents [19]. For example, new residents of the New York City Bedford-Stuyvesant neighborhood had median household incomes nearly 180 % greater than long-term residents in 2015[20]. The introduction of wealthier, often culturally and racially divergent, newcomers can increase the demand for more expensive housing and commerce. When these demands are materialized as new housing, shops, and services, lower income residents cannot keep up with the resultant increases in the costs of living and housing. Economically vulnerable residents may face increased financial burdens or be forced to move from their long-term communities. Financial hardship that makes housing unaffordable and threatens residents with displacement has been associated with anxiety, depression, and lower self-reported health [6, 21, 22] .

An influx of privileged newcomers paired with the displacement of long-term residents can have resounding effects on the cultural and demographic composition of a neighborhood. These resulting demographic transformations have become synonymous with the gentrification. Majority black and brown communities, historically deprived of resources and investments, face significant threats of gentrification. Demographic changes also lead to shifts in cultural ownership of space and social capital. One such example is the reinvestment in the New York City neighborhood of Harlem, where historic African American churches and landmarks have been destroyed to make way for luxury housing and other amenities for younger, whiter, and wealthier populations [3].

Gentrification's Health Effects

Research into gentrification's effects on health varies. A 2020 literature review of gentrification and health identified five out of nine studies with protective effects on health[23]. However, four of these five studies operationalized health using a measure of violent crime, which is suboptimal because as it often fails in adequately representing long term health effects. Furthermore, a reduction in violent crime may indicate an increase in policing as a result of gentrification rather than improvements in access to health care, access to green spaces, or quality of life. The remaining four studies found that gentrification had either detrimental or mixed impacts on health [23]. Another literature review by Smith et al. found that most studies reported negligible or no overall association between gentrification and health. Despite an overall general lack of association, the review noted that gentrification was repeatedly associated with adverse health effects on black and economically vulnerable residents when examining subpopulations [24]. This trend is repeated within the literature. Gentrification will often have marginal protective effects on the health of new residents, while long-term minority residents experience deleterious health outcomes. In some cases the "positive" results of gentrification, such as increased access to green space, may benefit economically vulnerable groups while also harming them by socially fragmenting and isolating them within their communities [4]. This paradoxical relationship makes it difficult to assess the overall effects of gentrification on a community. Furthermore, attempts to describe displaced residents' health outcomes are often limited by the availability of adequate health data.

Gentrification's Connection to Policing

Long running debates among academics attempt to explain the driving forces of gentrification, which are generally divided into two overarching arguments [25]. The first argument explains gentrification as a result of changing social and cultural demands. For example, middle-class suburbanites drawn back to city centers in hopes to reduce commute time or participate in various cultural scenes that are unavailable in suburban areas. This demand-side theory is contrasted by a supply-side theory. Supply-side theory is positioned to explain gentrification as a result of market capitalist forces investing in land and housing development. Neil Smith's 1979 "rent gap" theory is a widely lauded example of supply-side gentrification. Smith argues that inner city neighborhoods that were previously disinvested from have a large disparity in their *current* rental prices and their *potential* rental prices [26]. Developers seeking to profit through the redevelopment of this land create a supply-side demand for gentrification. Both theories have been empirically supported but more recent critiques and studies of the phenomenon have determined that a combination of both theories most accurately depict modern gentrification trends [7, 27].

Expanding on his work, Neil Smith characterizes gentrification now as a tool of "revanchist" urbanism following the rise of neoliberalism and global capital centers. Smith asserts that the flow of global capital facilitated by public-private partnerships and a desire to "reclaim" and "sanitize" urban spaces for development is best realized through gentrification [8]. This theory and its implementation was examined by a number of case studies [28, 29]. Gibson's 2004 case study of Seattle describes the city's efforts to establish itself as a world-class financial and cultural center in the eyes of a rapidly globalizing economy. In order to garner continued investments and the cultural capital needed to rebrand Seattle, a "project of assurance" was implemented by the urban elite. Various actions that restricted access to public spaces, services to the homeless, or the presence of "anything which might evoke in the middle-class imagination images of danger, disorder, or urban decay" were implemented [28].

While there are a number of levers to achieve the "project of assurance," Elaine Sharp contests that policing is necessary for its ultimate success [1]. Sharp's postindustrial policing hypothesis puts forth an explicit causal relationship between policing and urban centers' emerging postindustrial economies. Sharpe hypothesizes that modern policing patterns are in part influenced by the desire to attract and cater to "creative classes" and business investments [1]. She states that the style of policing in cities pursuing postindustrial, creative class related development greatly differs from other cities in that it emphasizes the police role in enforcing social control. Cities moving away from industry and into tourism, art, and cultural-based economies are more likely to devote policing resources in order to maintain a level of order to assure the development of these new economies. Traditional policing as we know it emphasizes the police response to enforcing criminal law. Order maintenance policing (OMP) is concerned with the concept of order and its absence.

Order Maintenance Policing

Order maintenance policing, also known as "quality of life policing," is the proactive practice of policing non-criminal activity and minor offenses and is motivated by the belief that lack of enforcement against minor offenses will lead to an increase of more serious crime [1]. This belief is rooted in Wilson and Kelling's influential 1982 "broken windows theory." The theory posits that "one broken window becomes many," meaning that "broken windows" in the form of panhandlers, litter, graffiti, and rowdy teens lower the overall community standards and social order of a neighborhood [30]. The broken windows theory has greatly influenced modern policing practices where the function of police has shifted from crime response to proactive crime control [31]. Proactive policing, specifically order maintenance policing, is implemented in a variety of tactics and scales. One such strategy is Stop, Question, and Frisk (SQF).

Stop, Question, and Frisk, often shortened to "stop-and-frisk," has become an increasingly controversial policing strategy despite its legal affirmation from the Supreme Court ruling *Terry v. Ohio* (1968) and other related decisions [32]. Police are granted the authority to stop a person if they have reasonable suspicion that said person is about to commit, currently committing, or has committed a crime. The police may conduct a frisk of if they have additional reasonable suspicion that the stopped person is armed and dangerous [14]. In the past, police have reactively used stop-and-frisk in response to crimes that have occurred and have been reported or are occurring and have been witnessed. Today, police executives view SQF programs as critical functions in crime prevention in the application of order maintenance policing and proactive policing in large [14].

Stop-and-frisk emerged as a nationwide controversy largely in part to the New York City Police Department's (NYPD) aggressive and wide sweeping implementation of the tactic. Initiated under Rudy Giuliani and expanded by Michael Bloomberg, stop-and-frisk peaked in 2011 at a staggering 685,724 annual stops. Ascribing to the broken windows theory, the NYPD has policed low level offenses such as public drinking, public urination, graffiti, and fair evasion in order to maintain social order and quality of life for New York City residents [14]. Previous analyses of stop-and-frisk has shown that NYPD has disproportionately stopped young people of color. Between 2014 and 2017, Black and Latino males aged 14 to 24 accounted for 38% of reported stops while only making up 5%

of NYC's total population. In 2010, more than 600,000 stops were recorded. Of those who were stopped, 54% were black, 33% were Latinx, 9% were white, and 86% were innocent [33]. The court case *Floyd v. City of New York* (2013) ruled that stop-and-frisk had been unconstitutionally implemented and that the NYPD was "deliberately indifferent to the need to train, monitor, supervise, and discipline its officers adequately in order to prevent a widespread pattern of suspicionless and race-based stops" [34]

Since then, the number of reported stops has significantly decreased almost each year. However, the NYPD reported in 2019 that it made 13,459 stops, an 22% increase from 2018 and the highest number of stops since 2015 [35]. Despite a trending reduction in the total number of stops, the court ordered independent monitor of NYPD's stop-and-frisk practices reported that statistically significant racial disparities still exist in practice [36]. Among those stopped in 2019, 60.3% were black, 29.2% were Hispanic, and 8.1% were white [35].

Stop-and-Frisk Health Effects

Research shows that involuntary police contact can threaten health in a variety of ways. The frequency and intensity of such stops have been associated with adverse social and psychological outcomes, which may affect future physical health outcomes [10]. As stated previously, minority populations are disproportionately stopped and engaged by police in NYC. Because black and brown communities already experience a number of health, social, and economic inequities [37], additional exposure to policing likely has a compounding effect on health. Current research supports this particularly in black men, who are disproportionately stopped by the NYPD.

Physical contact during a stop-and-frisk is a regular occurrence. From 2014 to 2017, the NYPD reported that at least one act of force was used in 28 % of all stops [33]. These "acts of force" can be aggressive and physically invasive, increasing the risk of injury to citizens. Qualitative research reveals that young men are [10, 38, 39] often slammed against walls or thrown to the ground during interactions with police. Police stops are also associated with adverse mental health consequences among a variety of populations. Geller and Fagan found that young men in NYC were more likely to report more symptoms of trauma and anxiety as the number, level of intrusiveness, and level of perceived unfairness of police encounters increased [10]. Police harassment towards Black men who have sex with men (BMSM) are positively associated with psychosocial vulnerability and psychological distress [15]. Racist and homophobic comments towards citizens during encounters have been documented and are also associated with added distress [15].

Policing has been shown to even affect individuals who are not personally stopped. 2020 research by Turney revealed positive associations of depressive symptoms among adolescents who witness police contact [18]. Mothers of urban youth stopped by police are more than twice as likely to report sleep difficulties related to anxiety and depression compared to their counterparts [11]. Simply living in highly policed communities may have deleterious health consequences. Research suggests that heightened policing can become an environmental stressor, as it can elicit hypervigilance and a "climate of fear" among individuals and communities [16, 40]. Chronic stress and repeated states of hypervigilance can lead to the body's production of harmful physiological responses such as elevated blood pressure, heart rate, and stress biomarkers [16, 41]. Sewell and Lee found that residents in neighborhoods with higher chances of pedestrian police stops and physical use of force experience higher levels of anxiety, feelings of worthlessness, and poor self-reported health [17].

The effects of order maintenance policing go beyond health. Research has shown that interactions with police strongly influence youths' perceptions of the legal system and those who enforce it. Adults and youth from heavily policed neighborhoods are more likely to be cynical and have diminished perceptions of police legitimacy [9, 12]. This may lead to future adversarial interactions with police or other elements of the legal system. Additionally, exposure to increased policing has been associated with reductions in education achievement and significant reductions in test scores for black male adolescents [13, 42].

Literature Review of Gentrification and Policing's Relationship

A variety of qualitative case studies have demonstrated the relationship between policing and gentrification. However, quantitative empirical research into the associations between gentrification and policing remains scarce. In 2013 Sharp empirically tested her postindustrial policing hypothesis among 180 U.S. cities with populations over 100,000. A cross-sectional research design was used and controlled for "variables representing the racial threat thesis, governing institutions, community policing, and policing demands and constraints" [1]. The analysis found a strong, positive association between postindustrial development and increased order-maintenance policing.

Laniyonu has provided likely the most robust spatial analysis of the relationship utilizing spatial Durbin models of gentrification from 2000-2014 and NYPD stop-and-frisk data from 2010-2014. Gentrification was operationalized by first categorically distinguishing tracts that were ineligible to gentrify, tracts with the potential to gentrify but did not, and tracts that did gentrify. Gentrification-eligible tracts were determined if they had populations over 500 and ranked in the bottom half of all NYC tracts in both median household income and median rent price. Among these eligible tracts, tracts were classified as having gentrified if they experienced an increases in both median rent prices and in the population with bachelor's degrees while ranking in the top tercile of (1) increases in the population with bachelor's degrees as well as (2) median rent price. Laniyonu's spatial Durbin model suggested an overall strong and positive effect between gentrification and police stopping rates[43].

Newberry also utilized the same datasets to study the influence crime and gentrification on Black and non-white Hispanic stops in NYC. The analysis employed a stepwise regression to select among seventeen demographic and economic variables from 2010 and 2016 American Community Surveys to determine the most influential environmental factors on minority police stops in 2012 and 2017. The models indicated that gentrification did not significantly influence the stop rate for black people in either 2012 or 2017, but crime rates did. Conversely, gentrification was a significant predictor for stops of Hispanic people across both time periods while crime rates had an inverse relationship with stop rates[44].

Beck conducted a 2009-2015 analysis of gentrification and low-level policing, notably utilizing property values as an indicator of gentrification. Three low-level policing variables – street stops, order maintenance arrests, and proactive arrests – were modelled with measures of gentrification via a log-log regression. Beck found that police responded differently to demographic changes compared to real estate market changes. Racial changes of gentrification were not indicative of increased policing. Conversely, tracts experienced 0.2 % more order-maintenance and 0.3 % more discretionary arrests every 5% increase in their property values. These findings may support Smith's notion of development-directed policing [45].

While previous research indicates a positive relationship between gentrification and policing, it is unclear if this phenomenon persists to 2019. The NYPD's use in stop-and-frisk has decreased from its peak in 2011, yet development continues. While the magnitude of order maintenance policing has decreased in recent years, evidence suggests that policing patterns are still influenced by racial and environmental factors. Marginalized minority populations remain especially at risk to adverse health effects associated with gentrification and policing. In order to better assess the health effects of gentrification and policing, the nature of their relationship must be characterized. To this end, we have developed two hypotheses, informed by Sharp's postindustrial policing hypothesis. They are as follows:

> **H_1: The odds of a police stop occurring in a given census tract is positively associated with gentrification**
>
> **H_2: The rate of police stops is positively associated with gentrification**

Methods

The study is a cross-sectional analysis of the association between policing and gentrification in New York City, New York, United States. Census tracts were the units of analysis. Existing administrative data from 2010 and 2019 were utilized to generate all variables. All variable creation and analyses were conducted in R [46]. Documentation for variables and their creation can be found in Table 1. Descriptive statistics and generalized linear models were created to test hypotheses.

Study Sample

To be eligible for inclusion, census tracts had to be located in one of NYC's five boroughs. We then excluded tracts with less than 500 residents in either 2010 or 2019 because gentrification was not relevant in these tracts. Additionally, tracts with incomplete data regarding total population, median household income, median rent price, and educational attainment status for residents 25 and older were excluded in the analysis. The final study sample consisted of 2,071 census tracts. Census tract and New York City boundary shapefiles were obtained from the New York City Department of City Planning Website. All shapefiles were projected for the NAD 1983 State Plane New York Long Island FIPS 3104 Projection in feet.

Descriptive Statistics

Descriptive statistics and visualizations were created to provide temporal and spatial context to our study. Descriptive statistics for each tract type in 2010, 2019, and their degrees of change were produced. The distribution of stops per capita stratified by tract type for 2010 and 2019 was visualized in boxplots using R [46]. Tract type and stoppage rate were also visualized with ArcMap 10.7. Census tract and New York City boundary shapefiles were obtained from the New York City Department of City Planning Website. All shapefiles were projected for the NAD 1983 State Plane New York Long Island FIPS 3104 Projection in feet.

Independent Variable – Gentrification Status

An overarching theme of gentrification studies is the challenge of operationalizing and measuring gentrification. To measure gentrification, I employed a two-step operationalization scheme utilized by a number of other gentrification studies [43, 47-49]. The scheme first categorizes census tracts by their eligibility to gentrify at given time. Depending on their first categorization, eligible tracts are then further categorized as having gentrified or not by a later given year. This type of initial eligibility categorization was necessary in our research because it ensured our study sample did not include tracts that were unable or had already gentrified prior to 2010. A number of economic and demographic measures can be used to form the criteria for gentrification eligibility and status. We obtained data from the American Community Survey (ACS) 5 Year Estimates 2006-2010 and 2015-2019 to represent measures from 2010 and 2019 respectively. Socioeconomic measures from 2010 were inflation-adjusted to 2019-dollar values. Following prior methods by Freeman and Laniyonu [43, 48], the criteria and categorization process of our independent variables is as follows.

First, a tract's eligibility to gentrify was determined by the following criteria:

1. The tract is among the bottom 50th percentile of median household income when compared to all New York City tracts in 2010
2. The tract is among the bottom 50th percentile of median rent price when compared to all New York City tracts in 2010

Tracts that met both conditions in 2010 were categorized as eligible for gentrification (N=809). Tracts that failed to meet both conditions were categorized as ineligible for gentrification (N=1,262). It is worth noting that, as a result of our categorization criteria, tracts eligible to gentrify are of lower socioeconomic status compared to tracts that are ineligible for gentrification. Ineligible tracts are less likely to experience large and sudden reinvestments, which would constitute gentrification in most cases.

To determine whether gentrification occurred in a tract from 2010 to 2019, tracts eligible for gentrification were then categorized by the following criteria:

1. From 2010 to 2019, the tract increases in median rent price and in the population of residents older than 25 that hold a bachelor's or more advanced degree (includes master's, professional, and doctorate degrees)
2. The tract is in the top tercile of growth from 2010 to 2019 in residents over 25 that hold a bachelor's or more advanced degree
3. The tract is in the top tercile of growth from 2010 to 2019 in median rental price [43]

Following this process, a three-level categorical variable of gentrification status was created. Tracts that failed to meet both criteria in the first classification step were defined as "ineligible to gentrify" (N=1,262). Tracts that met both criteria in the first step and all three criteria in the second step were defined as "eligible to gentrify and did gentrify" or simply "gentrified tracts" (N=87). Tracts met both criteria in the first step and did *not* meet all three criteria in the second were defined as "tracts eligible to gentrify but did not" or simply as "tracts that did not gentrify" (N=722). Further documentation of this variable creation can be found in Table 1.

Dependent Variables – Police Stop Occurrence & Intensity

In order to test our first hypothesis, a binary dependent variable was created. This variable, called "stop occurrence," categorized census tracts based on if at least one police stop occurred in that given tract in 2019. To represent the magnitude of order maintenance policing in New York City, we opted to use a stops per capita measure as my outcome variable. This measure is consistent with other related studies [16, 43-45]. Stops per capita was calculated by dividing the total number of stops within a tract by the total population of the tract for a given year. Data used for the stop per capita variable were taken from the New York City Police Departments' Stop-Question-Frisk open database and the American Community Survey (ACS) 5 Year Estimates 2006-2010 and 2015-2019. This data was geolocated and projected in NAD 1983 State Plane New York Long Island FIPS 3104 in feet. Due to skewness in the variables' distribution, the logs of the measures were taken. Further documentation of this variable creation can be found in Table 1.

Two-Part Model

For the statistical analysis we used a two-part model process. A two-part model is used to model strictly positive (>0) outcome variables that have are accompanied with a large number of zero values. This is appropriate for the analysis due to the stops per capita outcome variable, where 311 out of 2071 (15.0%) tracts had no police stops in 2019. Previous attempts to normalize the variable's distribution were unsuccessful due to the large spike of zero values. To account for this, data was sequentially applied to a (1) logistic model and a (2) zero-truncated normal model. The process is similar to a zero-inflated model but differs in that the distributions are separately modelled rather than simultaneously.

First, a logistic model determined the odds of a tract having at least one police stop in a given year based on its gentrification status. Crude and adjusted odds ratios were calculated from respective models. Following the logistic models, tracts with zero stops per capita were truncated and excluded from study sample. The remaining positive, non-zero stops per capita rates were logged to account for skewness. Generalized linear models were created to determine the association between gentrification status and stops per capita. Both non-adjusted and adjusted predictors were calculated with the inclusion of selected covariates. Statistical significance was determined at a 0.05 alpha.

Covariates

Prior studies of stop-and-frisk practices have reported positive associations between the amount of stops and crime rate. However, the accuracy and distribution of police reported data may not be reflective of actual crime, especially for low-level criminal offenses. In order to depict a more accurate measure of crime distribution in New York City, I subset felonies from the NYPD's Historical Complaint Database for the years 2010 and 2019. Felonious crimes are a more robust measure as their occurrence subsequent reporting is not at an officer's discretion, contrary to minor low-level criminal offenses. A felony per capita measure was calculated by dividing the number of reported felonies by a tract's total population. Population counts were taken from ACS 5-Year Estimate for 2019. Various demographic measures from the ACS 5-Year Estimate for 2019 were also utilized in the modelling.

Ethics Statement

Both the American Community Survey and the NYPD's Stop-Question-Frisk data are publicly available and de-identified. Per the DHHS Common Rule this research does not utilize human subjects, nor does it meet federal guidelines as a clinical investigation. As a result, it does not require prior IRB approval.

Results

Descriptive Statistics

Table 2 compares economic and demographic measures by tract gentrification status. Percent change from 2010 to 2019 was calculated for each measure. All NYC tracts experienced some level of economic or demographic change from 2010 to 2019. Trends emerged among the three different tract types, likely in part to our classification scheme, which categorized tracts by educational and economic metrics and their levels of change. The percent changes in median household income were similar among ineligible tracts and eligible tracts that did not gentrify (+9.01 and +8.81 percent change respectively). Gentrified tracts experienced large increases in median household income and median gross rental prices (+42.87 and +36.63). The proportion of residents with bachelor's degrees or other secondary degrees almost doubled in gentrified tracts (+98.99 percent change).

There are notable differences between tract classifications when observing racial composition changes in Table 2. We compared non-Hispanic white, non-Hispanic black, and Hispanic population shares, referring to them respectively as white, black, and Hispanic groups. In 2019, the proportion of white residents was highest in ineligible tracts (52.22%) despite decreasing from 2010 to 2019 (-7.74% change). Tracts eligible to gentrify increased in the proportion of white residents regardless of if they gentrified or not. Among eligible tracts that did not gentrify, the proportion of white residents increased 14.46% (19.57% to 22.40%). Gentrified tracts experienced a larger 22.16% increase in the proportion of white residents, going from 23.06% in 2010 to 28.17% in 2019.

The demographic changes of select minorities appear to be inversed to white population changes. While the proportion of white residents decreased in ineligible tracts and increased in eligible and gentrified tracts, the opposite occurred for black and Hispanic populations. In 2019, tracts ineligible to gentrify had the smallest percentage of black (4.78%) and Hispanic (5.26%) residents compared to the other tract types. From 2010 to 2019, both groups slightly increased in the proportion of residents in ineligible tracts. Tracts that were eligible to but did not gentrify had the largest proportion of Hispanic residents (14.74%) following a 5.06% increase from 2010 to 2019. The proportion of black residents decreased slightly (-3.23%) from 31.70% to 30.68% in eligible non-gentrifying tracts.

The proportion of black residents was largest in gentrified tracts in both 2010 and 2019 (42.77% and 39.94% respectively). There was a 6.62% reduction in the proportion of black residents in tracts that gentrified from 2010 to 2019. Gentrified tracts also experienced a large reduction (-18.35%) in the proportion of Hispanic residents, going from 14.22% to 11.61%.

Table 2 also presents median values of crime and stoppage rates stratified by tract gentrification status. From 2010 to 2019, both the number of reported felonies per capita and the number of stops per capita decreased for all three tract types. Tracts ineligible to gentrify had the lowest number of reported felonies per capita in both 2010 and 2019 (0.0124 and 0.0107 respectively) when compared to other tract types. Ineligible tracts also had the lowest number of stops per capita in 2010 and 2019 (0.0094 and 0.0008 respectively) when compared to the other tract types. Tracts that did not gentrify experienced a 10.34% reduction in the number of felonies per capita (0.0185 to 0.0166) from 2010 to 2019. Additionally, the number of stops per capita was reduced by 91.62% in tracts that did not gentrify. This decrease in stops per capita is similar to the decrease seen in ineligible tracts (-91.15%). Gentrified tracts had the highest median values in both felonies per capita and stops per capita for both years compared to other tract types. In 2019, the median number of felonies per capita in gentrified tracts was 0.0201 felonies per capita. This is 21% greater than tracts that did not gentrify and nearly 88% greater compared to ineligible tracts. Interestingly, gentrified tracts also had the greatest percent change in the number of felonies per capita, a 20.17% reduction from 2010 to 2019. As previously stated, tracts that gentrified experienced the highest median number of stops per capita in both 2010 and 2019 (0.0277 and 0.0018 respectively). Gentrified tracts also had the greatest percent change in stops per capita, with a 93.65% reduction from 2010 to 2019.

Figure 1. New York City gentrification status by census tract, 2019

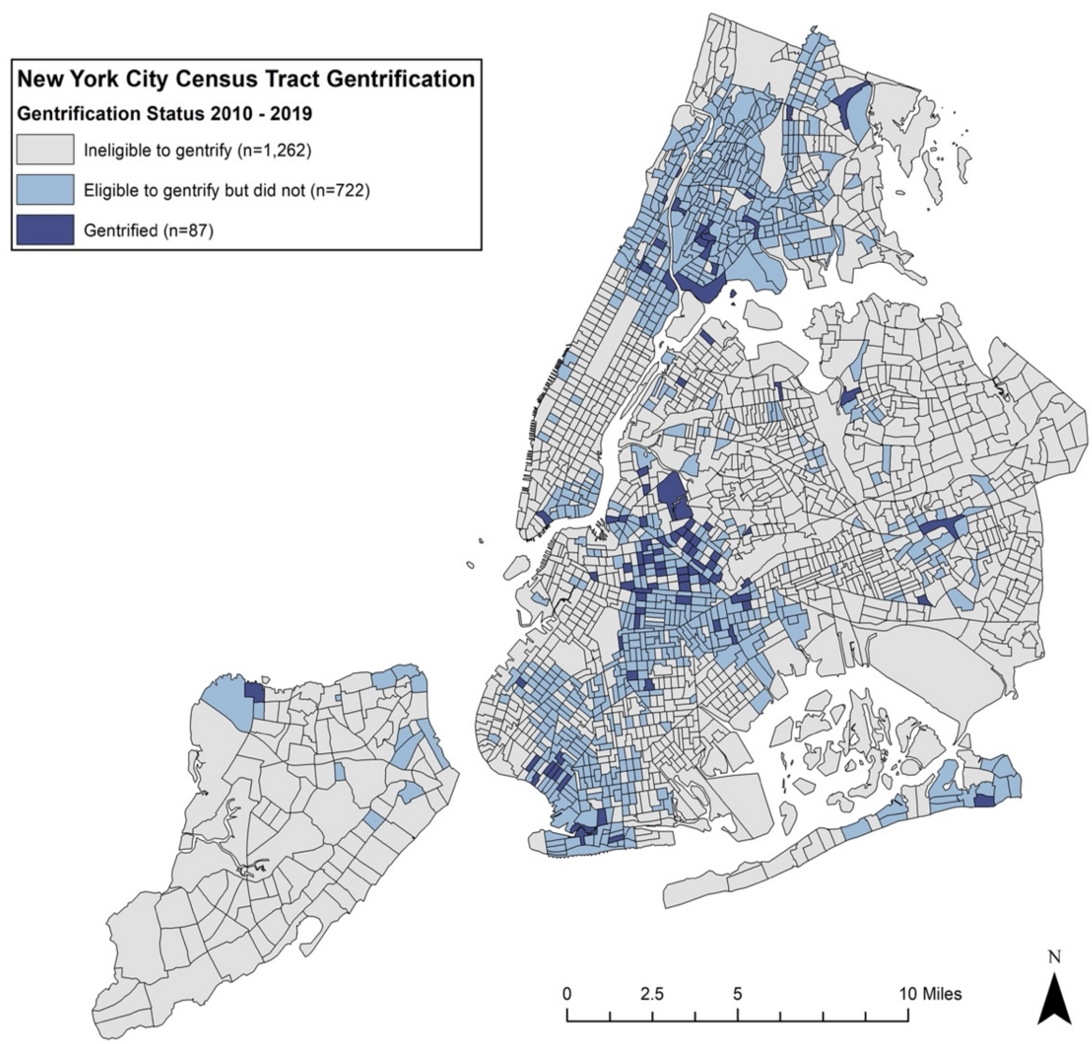

Figure 1 shows the spatial distribution of gentrification for New York City census tracts from 2010 to 2019. Cursory visual inspection supports previous assumptions with gentrification primarily occurring in South Bronx, the Brooklyn neighborhoods of Williamsburg, Bushwick, and Bedford-Stuyvesant, as well as neighborhoods in southern Brooklyn near Coney Island. Each borough had at least one tract gentrify by 2019. The number of gentrified tracts (n=87) is lower than Laniyonu's and Maciag's studies, which predicted 233 gentrified tracts from 2000 to 2014 and 128 gentrified tracts from 2000 to 2015 respectively [43, 49].

Figure 2. New York City police stops per capita by census tract, 2019

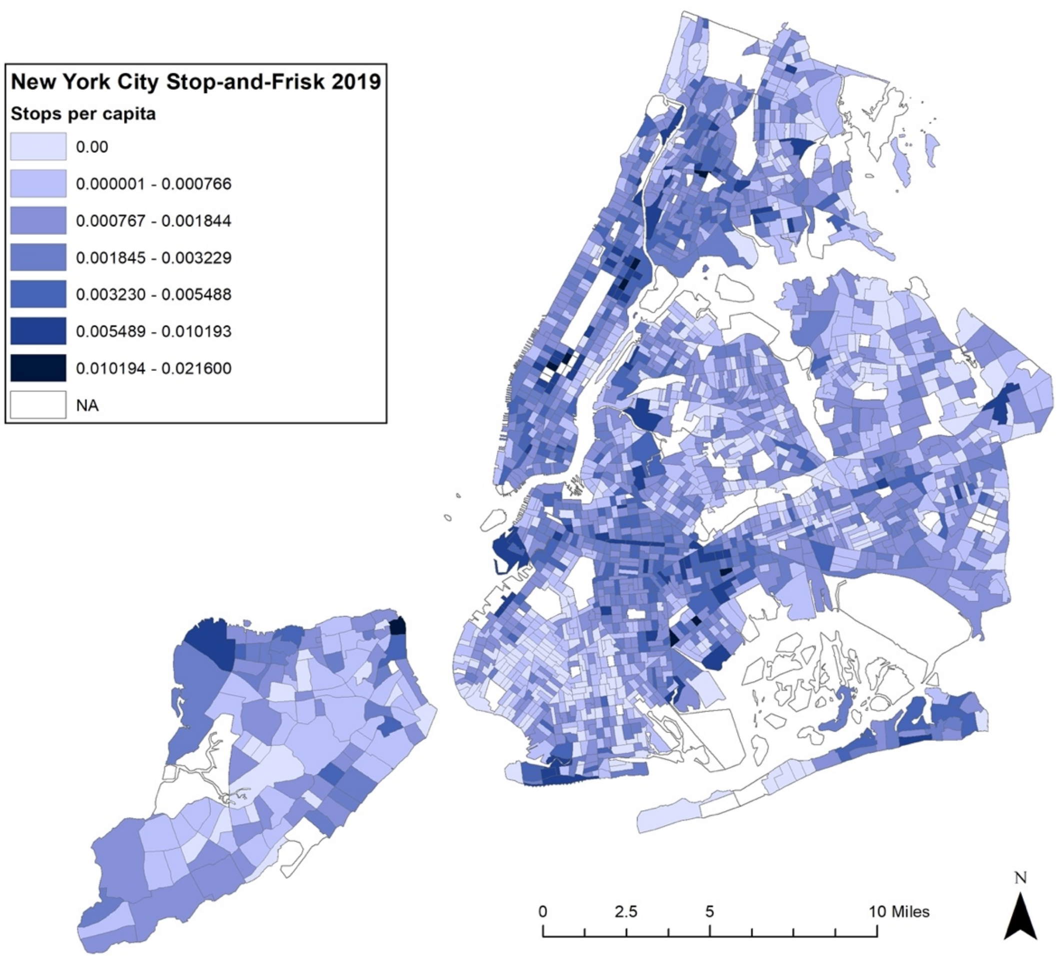

Figure 2 maps the distribution of stop-and-frisk intensity among all tracts in 2019. Tracts with the most stops per capita were located in the Bronx, upper Manhattan, Brooklyn, Coney Island, and Rockaway, Queens. The distribution of stop-and-frisk intensity is heterogeneous when compared to the distribution of gentrification in Figure 2, likely in part to the large amount of foot traffic around transit and tourist centers in the city. When comparing Figure 1 and Figure 2, some tracts with high stop-and-frisk intensity overlap or are in close proximity to eligible and gentrified tracts.

Figure 3 displays boxplots of the logged stops per capita by tract gentrification status for 2010 and 2019. In both years, the red leftmost boxplots show the distribution of stops

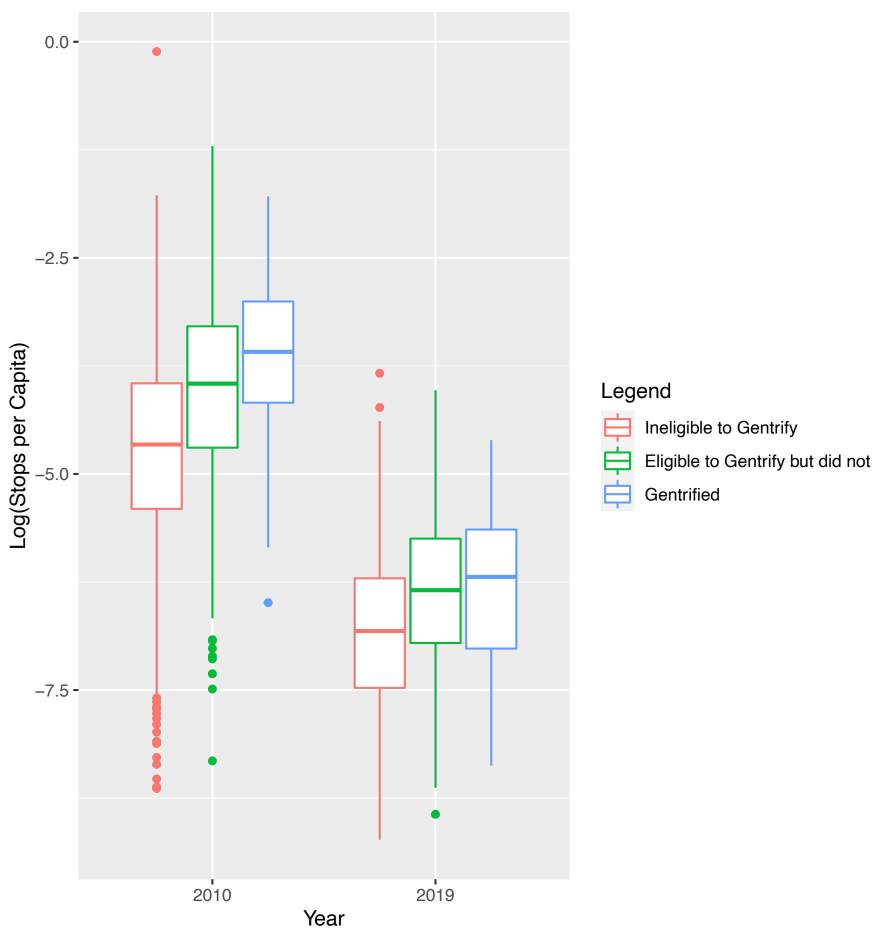

Figure 3. Log(Stops per Capita) boxplot distributions, by year and tract gentrification status

per capita in tracts deemed ineligible to gentrify. The green boxplots in the middle show the distribution of stops per capita in tracts that were eligible to gentrify but did not, while the rightmost blue boxplots depict the distribution of stops per capita in tracts that did gentrify.

Each tract type experienced an overall decrease in stops per capita from 2010 to 2019. For both years, the distribution of stops per capita follow a similar trend. Tracts ineligible to gentrify experienced the lowest median number of stops per capita while gentrified tracts had the highest median number of stops within their respective years. The lower median stops of the red boxplot are consistent with expectations that fewer stops would occur in tracts with higher median rent and household incomes.

Logistic Model Results

The first step of the two-part model analysis consists of logistic regression modelling to test our first hypothesis: the likelihood of a police stop occurring is positively associated with gentrification. The outcome variable was a binary measure of whether a police stop occurred at least once in a given tract in 2019. The predictor variable of focus was the three-levelled gentrification status variable. Both bivariate and univariate logistic regression models were produced. Table 3 presents crude odds ratios (OR), 95% confidence intervals, and p-values of a number of bivariate logistic regressions. Table 4 and Table 5 adjusted odds ratios (aOR), 95% confidence intervals and p-values from multivariate models. Table 4 presents model results from the entire study (N=2071) whereas the model depicted by Table 5 excluded tracts that were ineligible to gentrify (N=809).

Gentrification status had significant harmful associations when tracts ineligible to gentrify was the reference class. When compared to a tracts ineligible to gentrify, tracts that did not gentrify had increased risk of a stop occurring (OR: 2.66, 95% CI: 1.98-3.61). Gentrified tracts also had an increased risk of a stop occurring compared to tracts that were ineligible to gentrify (OR: 3.25, 95% CI: 1.52-8.44). When controlling for race and crime in the multivariate model, there was a significant harmful association for a stop occurring in tracts that did not gentrify (Table 4, aOR: 1.42, 95% CI: 1.09-3.81) compared to ineligible tracts. There were no significant associations between tracts that gentrified and ineligible tracts when controlled for race and crime. There were no significant associations of policing intensity for gentrified tracts compared to tracts that did not gentrify. Furthermore, no significant associations were found when controlled for race and crime.

Linear Model Results

The second step of the modelling process utilized generalized linear models to test our second hypothesis: gentrification would be associated with higher intensity of order maintenance policing. The outcome variable used was the log transformed stops per capita measure. As previously mentioned in our methodology, our analysis study sample only included census tracts had at least one police stop in 2019 (N=1,760). Both bivariate and multivariate models were created. Beta coefficients, 95% confidence intervals, and p-values were calculated and reported in Tables 6-8. Results from models that excluded ineligible tracts (N=743) were also reported in Table 6 and Table 8.

Our bivariate model reported significant associations between policing intensity and gentrification eligible tracts (tracts that did not gentrify and tracts that gentrified) when compared to ineligible tracts. Change from an ineligible tract to a gentrified tract was significantly associated with a 62.5% increase in stops per capita (Beta: 0.486, 95% CI: 0.287-0.684). An ineligible tract that became eligible but did not gentrify was significantly associated with a 53.8% increase in stops per capita (Beta: 0.431, 95% CI: 0.345-0.517). The multivariate model (Table 7) reported a significant harmful effect among ineligible tracts that became eligible but did not gentrify (Beta: 0.140, 95% CI: 0.063-0.218). No other associations between policing intensity and ineligible tracts that changed to gentrification-eligible tracts were found. Similarly, there were no significant associations between policing intensity and gentrified tracts when compared to eligible non-gentrified tracts.

Discussion

Both gentrification and the order maintenance policing within communities have been linked to poor health outcomes. Together, these environmental features may compound and exacerbate their health effects on individuals and the overall health of a community. New theories suggest a positive and mutualistic relationship between in gentrification and order maintenance policing. However, there is limited research regarding this association. The present analysis builds on existing literature by characterizing the associations between gentrification and order maintenance policing within New York City in 2019. We hypothesized that 1) the odds of a police stop occurring and 2) the rate of police stops are positively associated with gentrification.

Our study developed a measure of gentrification that used baseline measures and relative change between 2010 and 2019. First, census tracts were classified as eligible for gentrification using median rent price and median household income as a proxy for disinvestment. Eligible tracts had substantially lower rent prices and household incomes compared to tracts ineligible to gentrify, in part to our classification scheme. However, eligible tracts also had lower proportions of adults with bachelors or other advanced degrees, demonstrating our measure's ability to define marginalized tracts that are often considered at risk for gentrification.

From 2010 to 2019, gentrified tracts experienced the largest increases in the proportion of college educated adults, median rent prices, and median household incomes. Conversely, tracts eligible for gentrification but did not gentrify had lower rates of change for the aforementioned measures. These differences are notable but expected as our classification scheme for gentrification utilized these measures. More notable are the changes in tracts' total population counts as well as changes in racial composition. Gentrified tracts experienced a large increase in the number of residents while ineligible and ungentrified tracts did not. This drastic population growth may be indicative of increased investment within these tracts, potentially creating more housing stock to support a larger population. Alternatively, the population increase may be due to new residents seeking low rent prices. However, this notion does not adequately explain the difference in population growth when comparing gentrified and ungentrified tracts, especially in later years where gentrified tracts' rental prices exceeded ungentrified tracts. Regardless, gentrified tracts experienced a large influx of new residents from 2010 to 2019, indicating major demographic changes. We consider this additional evidence supporting the robustness of our gentrification classification scheme.

Our descriptive statistics also revealed differences between tract types for both baseline and relative change measurements of racial composition. Tracts eligible for gentrification had large proportions of both black and Hispanic residents in 2010 compared to all NYC tracts. Tracts that would eventually gentrify had the largest proportion of black residents (42.77%) in 2010. By 2019, the proportion of both black and Hispanic residents in gentrified tracts decreased substantially and to greater extents compared to similar minority populations in tracts that did not gentrify. Conversely, the proportion of white residents in gentrified tracts increased by 22.16%, the largest percent change for any race in all tract types. The reductions in both Hispanic and black population shares within gentrified tracts contrast with the increase of white residents. This may be representative of demographic changes often associated with gentrification, namely that white residents who move into neighborhoods coincide with the displacement of legacy minority residents. This contrast in demographic change highlights gentrification's disproportionate effect on minority populations. Prior research of gentrification in the U.S. also supports this notion [3, 4, 27, 37].

The reduction of crime (felonies per capita) across all tract types was generally expected and is consistent with previous studies from Laniyonu and the NYACLU [33, 43]. Gentrified tracts had the highest rate of felonies per capita in both 2010 and 2019, despite also seeing the largest reduction of said rate. By 2019, we expected gentrified tracts to have less felonies per capita than non-gentrified tracts due to increased investment as well as our hypothesized increase in order maintenance policing. However, higher rates of stop-and-frisk may result in more officer reported felonies, explaining why gentrified tracts continue to have more felonies per capita than ungentrified tracts. Similar patterns emerged for our stops per capita measure.

Table 2 and Figure 3 show that tracts that gentrified experienced higher rates of stop-and-frisk than similarly marginalized tracts that did not gentrify. This tentatively supports our second hypothesis, that gentrification is associated with higher rates of stop-and-frisk. However, the majority of our models failed to report a significant p-values, indicating that they failed to reject our null hypotheses and support our alternative hypotheses. A significant harmful association between gentrification and a stop occurrence was reported by our bivariate logistic model when ineligible tracts were used as a reference class. Despite the significance of this relationship, it is unlikely to occur in real world gentrification processes. This is because we interpret the relationship as a 325% increase in the risk of a stop occurring when an ineligible tract switches to a gentrified tract. Based on our classification scheme, tracts ineligible for gentrification were ineligible due to their already high socioeconomic status. It is unlikely for an ineligible tract to experience rapid investment that would constitute as gentrification. We also conclude that the divestment of an ineligible tract in order to become an eligible non-gentrifying tract is equally if not more unrealistic, especially in NYC. To account for this, eligible non-gentrified tracts were used as the reference class compared to eligible gentrified tracts. No significant associations were reported for either model. We can conclude that the both the odds of a police stop occurring and the rate of police stops in a given tract are not significantly associated with gentrification among eligible tracts. Our results contrast with Laniyonu's findings, which suggested a positive effect between gentrification and police stop rates between 2010 and 2014 [43]. However, Laniyonu utilized a spatial model, taking into account the spatial autocorrelation of gentrification and police stops. Our findings, being limited to general linear models, are more aligned with Newberry's. They reported that gentrification did not significantly influence the stop rate of black people while crime rates did [44]. Our models also found significant associations between felony rates, implying that increased felonies per capita was positively associated with increased stop rates.

This study is not without its limitations. First, our measures for gentrification eligibility and gentrification status were derived from ACS 5-Year Estimates. This data source has limitations due to small sample sizes, large margins of errors, and in the geographies of the census tracts. Census tracts boundaries may not adequately capture the social, economic, and racial boundaries that can determine boundaries of gentrification. Second, we assumed a level of homogeneity among tracts that were eligible to gentrify. Variation in socioeconomic and demographic distributions may have been overlooked, preventing more nuanced comparison of tracts that did gentrify and those that did not. Third, the use of a zero-truncated linear model may have overestimated the mean stops per capita via selection bias. In reality, it is likely that tracts with zero stops per capita exist naturally. A zero-inflated model could be utilized to address this limitation.

Our study adds to the literature on gentrification by characterizing the distribution of gentrification in New York City, and exploring its association with order maintenance policing. While gentrification has been linked to increases in order maintenance policing, our study did not find evidence of this. Although no association between gentrification and policing was found, we observed large demographic and economic changes from 2010 to 2019, suggesting that gentrification remains a concern for economically and racially marginalized populations. Our study also found evidence that NYPD's stop-and-frisk program continues to disproportionately target minority populations and economically marginalized neighborhoods, despite reductions of the program's overall implementation. Although no association was found between these phenomena in 2019, prior research has in past years. Further research should be conducted to better characterize the process of gentrification and its temporal relationship to order maintenance policing. Such studies could distinguish whether gentrification precludes order maintenance policing increases or vice versa, giving context to previous and future gentrification studies. Additionally, gentrification and policing research should be expanded internationally beyond New York City, as more cities begin to invest in urban development and policing efforts. To do so is necessary in order to address the health effects policing and gentrification have on vulnerable populations and communities worldwide.

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Table 1. Variable Methodology and Definitions

Construct	Operationalization	Source
Independent Variables – Logistic and GLM		
Eligible to gentrify	< 50^{th} percentile median household income AND < 50^{th} percentile median rent price	ACS 5 Year Estimate: 2006-2010
Ineligible to gentrify	≥ 50^{th} percentile median household income OR ≥ 50^{th} percentile median rent price	ACS 5 Year Estimate: 2006-2010
Eligible to gentrify but did not	Eligible to gentrify in 2010 AND Increase in median rent price OR Increase in residents aged 25+ years with bachelor's degree or higher OR < 66^{th} percentile in increase of median rent price OR < 66^{th} percentile in increase of residents 25+ years with bachelor's degree or higher	ACS 5 Year Estimate: 2006-2010, 2015-2019
Gentrified	Eligible to gentrify in 2010 AND Increase in median rent price AND Increase in residents aged 25+ years with bachelor's degree or higher AND ≥ 66^{th} percentile in increase of median rent price AND ≥ 66^{th} percentile in increase of residents 25+ years with bachelor's degree or higher	ACS 5 Year Estimate: 2006-2010, 2015-2010
Dependent Variable – Logistic Model		
Stop occurred in tract	Stop did not occur: Stops per capita = 0 Stop did occur: Stops per capita > 0	NYPD Stop-Question-Frisk Database
Dependent Variable – Generalized Linear Model		
Stops per capita	$\frac{\text{Number of stops}}{\text{Total population}}$	Numerator: NYPD Stop-Question-Frisk Database Denominator: ACS 5 Year Estimate: 2006-2010, 2015-2019
Covariates – Logistic and GLM		
Crime per capita	$\frac{\text{Number of felonies}}{\text{Total population}}$	Numerator: NYPD Historic Complaint Database Denominator: ACS 5 Year Estimate:2006-2010, 2015-2019

Table 2. Summary Statistics by Tract Gentrification Status

	Ineligible (N=1,262)			**Eligible but did not gentrify** (N=722)			**Gentrified** (N=87)		
	2010	2019	% Change	2010	2019	% Change	2010	2019	% Change
Total Population	4,593,110	4,700,404	3.55	3,181,950	3,309,439	4.01	306,498	360,340	17.57
Household Income($)	74,365	81,064	9.01	39,865	43,376	8.81	36,241	51,776	42.87
Gross Rent($)	1,472	1,642	11.59	1,114	1,289	15.72	1,073	1,466	36.63
% BA or greater	31.79	36.29	14.13	17.25	21.85	26.63	15.40	30.65	98.99
% NH White	58.77	54.22	-7.74	19.57	22.40	14.46	23.06	28.17	22.16
% NH Black	4.16	4.78	15.04	31.70	30.68	-3.23	42.77	39.94	-6.62
% Hispanic	5.11	5.26	2.94	14.03	14.74	5.06	14.22	11.61	-18.35
Crime per capita	0.0124	0.0107	-14.08	0.0185	0.0166	-10.34	0.0251	0.0201	-20.17
Stops per capita	0.0094	0.0008	-91.15	0.0191	0.0016	-91.62	0.0277	0.0018	-93.65

Table 3. Bivariate Logistic Regression

Variable	N	OR	95% CI	p-value
Gentrification Status (ineligible tracts excluded)	809			
Eligible to gentrify but did not		Ref	Ref	
Gentrified		1.224	0.552582, 3.24729	0.65
Gentrification Status (ineligible tracts included)	2071			
Ineligible to gentrify		Ref	Ref	
Eligible to gentrify but did not		2.65798	1.98468, 3.61122	<0.001
Gentrified		3.25221	1.52386, 8.43876	0.006
Total Population	2071	1.00035	1.00027, 1.00044	<0.001
Population Density	2071	1.00002	1.00001, 1.00002	<0.001
Median Gross Rent($)	2071	0.99965	0.99941, 0.99989	0.004
Median Household Income($)	2071	0.99999	0.99999, 1.00000	<0.001
% White	2071	0.98252	0.97828, 0.98671	<0.001
% Black	2071	1.02149	1.01586, 1.02759	<0.001
% American Indian	2071	1.00341	0.894117, 1.14550	0.957
% Asian	2071	0.98628	0.98014, 0.99261	<0.001
% Pacific Islander	2071	0.927892	0.689416, 1.35034	0.651
% Hispanic	2071	1.0289	1.01854, 1.04013	<0.001
% 2 or More Races	2071	1.05464	1.00843, 1.10583	0.024
log(Crime per Capita)	2071	5.255568	4.194443, 6.645458	<0.001
% BA or greater	2071	0.583142	0.332343, 1.03537	0.063

OR = Odds Ratio, CI = Confidence Interval

Table 4. Multivariate Logistic Regression (ineligible tracts included)

Variable	aOR	95% CI	p-value
Gentrification Status			
Ineligible to gentrify	Ref	Ref	
Eligible to gentrify but did not	1.51674	1.09267, 2.12798	0.014
Gentrified	1.41752	0.628766, 3.81279	0.44
% White	1.09098	0.96648, 1.22019	0.139
% Black	1.09689	0.97142, 1.22733	0.117
% Asian	1.08852	0.96404, 1.21775	0.15
% Hispanic	1.09781	0.97045, 1.23054	0.119
% 2 or More Races	1.12483	0.98851, 1.27057	0.064
log(Crime per Capita)	4.28705	3.33996, 5.56122	<0.001

aOR = Adjusted Odds Ratio, CI = Confidence Interval

Table 5. Multivariate Logistic Regression (ineligible tracts excluded)

Variable	aOR	95% CI	p-value
Gentrification Status			
Eligible to gentrify but did not	Ref	Ref	
Gentrified	0.93036	0.376598, 2.67068	0.883
% White	0.95544	0.683585, 1.19146	0.737
% Black	0.97199	0.695026, 1.21199	0.834
% Asian	0.95272	0.681242, 1.18741	0.721
% Hispanic	0.96043	0.685345, 1.19987	0.768
% 2 or More Races	0.95933	0.676317, 1.22173	0.773
log(Crime per Capita)	5.92589	3.29768, 11.1645	<0.001

aOR = Adjusted Odds Ratio, CI = Confidence Interval

Table 6. Bivariate Linear Model

Variable	N	Beta	95% CI	p-value
Gentrification Status (ineligible tracts excluded)	743			
Eligible to gentrify but did not		Ref	Ref	
Gentrified		0.054897	-0.146188, 0.255982	0.593
Gentrification Status (ineligible tracts included)	1760			
Ineligible to gentrify		Ref	Ref	
Eligible to gentrify but did not		0.430771	0.344797, 0.516745	<0.001
Gentrified		0.485668	0.286907, 0.684428	<0.001
Total Population	1760	-0.000046	-0.000065, -0.000027	<0.001
Population Density	1760	0	-0.000001, 0.000001	0.877
Median Gross Rent($)	1760	-0.000255	-0.000339, -0.000171	<0.001
Median Household Income($)	1760	-0.000004	-0.000005, -0.000003	<0.001
% White	1760	-0.006866	-0.008319, -0.005413	<0.001
% Black	1760	0.007362	0.005985, 0.008739	<0.001
% American Indian	1760	0.028761	-0.015015, 0.072537	0.198
% Asian	1760	-0.010673	-0.013148, -0.008198	<0.001
% Pacific Islander	1760	0.060224	-0.067193, 0.187641	0.354
% Hispanic	1760	0.00823	0.005516, 0.010945	<0.001
% 2 or More Races	1760	0.001857	-0.012692, 0.016406	0.802
log(Crime per Capita)	1760	0.8410219	0.7917282, 0.8903155	<0.001
% BA or greater	1760	5.255568	4.194443, 6.645458	<0.001

CI = Confidence Interval

Table 7. Multivariate Linear Model (ineligible tracts included)

Variable	Beta	95% CI	p-value
Gentrification Status			
Ineligible to gentrify	Ref	Ref	
Eligible to gentrify but did not	0.140426	0.062639, 0.218213	<0.001
Gentrified	0.024195	-0.138980, 0.187370	0.771
Total Population	-0.000016	-0.000031, 0.000000	0.044
% White	-0.000453	-0.001741, 0.000835	0.491
% Asian	-0.003541	-0.005596, -0.001486	<0.001
log(Crime per Capita)	0.786127	0.732057, 0.840197	<0.001

CI = Confidence Interval

Table 8. Multivariate Linear Model (ineligible tracts excluded)

Variable	Beta	95% CI	p-value
Gentrification Status			
Eligible to gentrify but did not	Ref	Ref	
Gentrified	-0.130734	-0.282764, 0.021295	0.092
Total Population	0.000016	-0.000005, 0.000038	0.143
% White	-0.000606	-0.003009, 0.001797	0.621
% Asian	-0.001592	-0.004858, 0.001674	0.34
log(Crime per Capita)	0.95601	0.864787, 1.04724	<0.001

CI = Confidence Interval