# Privilege in Proximity: Neighborhood Change and Social Control in New York City

by

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Paul DiMaggio

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## DEDICATION

To my parents, Jane and Brad. And above all, to Taylor.

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## ABSTRACT

In this dissertation, I investigate the relationship between racial and socioeconomic neighborhood change and patterns of social control in New York City. Previous research on urban neighborhood change has considered change only in one dimension – socioeconomic change – and focused on its effect on crime rates, displacement of residents, and rising housing prices, yet we know very little about how neighborhood change shapes the social control experienced by local residents in their daily lives. I expand on previous definitions of gentrification to include an additional parameter of change – increases in white population – and to consider the multilayered nature of neighborhood change. In three empirical studies, I analyze data compiled from 10 administrative data sets to test my hypothesis that increases in white population in gentrifiable and gentrifying neighborhoods will be associated with higher rates of social control. I begin with an investigation of the relationship between neighborhood change and social control enacted through police stops. My findings demonstrate that increases in white population within gentrifiable and gentrifying neighborhoods are associated with subsequently higher rates of police stops of Black residents but not of Hispanic or white residents and that these disproportionate patterns are unevenly distributed across changing neighborhoods in the city. Next I explore the relationship between racial and socioeconomic neighborhood change and social control invited by neighbors in the form of complaints through the 311 system to summon forces

of social control. Complaints can be made against a long list of grievances and can be about other individuals, businesses, landlords, or city agencies and officials. The content of the complaint determines whether and how the city responds. For example, if someone makes a noise complaint against their neighbor, the 311 system will forward that complaint to the NYPD and eventually an officer will respond to the reported address. In this way, residents can effectively enact social control over their neighbors' behavior by asking a third party (i.e. a 311 operator) to send the police. In the second study, I look at complaints that are sent to the NYPD, and those that result in NYPD taking action to resolve the complaint when they respond. I find that gentrification combined with whitening predicts the highest rate of complaints sent to the NYPD. Whitening in both poor and gentrifying tracts predicts higher rates of informal action taken by the NYPD in response to a 311 complaint compared to their non-whitening poor and gentrifying counterparts. Conversely, whitening in gentrifying neighborhoods predicts lower rates of formal action taken by the police in response to complaints. Finally, in the third study I investigate how rates of noise complaints made against neighbors are associated with changes in neighborhood racial and socioeconomic composition. I find that gentrification combined with whitening predicts higher rates of complaints about residential noise, and this is particularly true of complaints about loud music and parties. Across all three studies, whitening, considered as distinct from and in interaction with socioeconomic gentrification, is associated with higher rates of social control.

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# Chapter 1

# Introduction

Inevitably, neighborhoods change. People move in and out. Businesses come and go. Communities evolve. Sometimes, change is welcomed or goes unnoticed. Sometimes, change engenders conflict and increases inequality.

Recently reported examples of racial tensions in changing neighborhoods have brought conflicts around one particular kind of neighborhood change into public awareness. White residents, like "BBQ Becky" and "Permit Patty,"[1] who call the police on their Black neighbors for innocuous behaviors, demonstrate how recent increases in economic and racial integration can affect disadvantaged residents negatively by inviting more interactions with local representatives of the state, especially (but not only) the police, through neighbor intervention. An increased presence of more

[1] For BBQ Becky, a white woman who called 911 to complain about Black people barbecuing in a public park, see https://www.newsweek.com/bbq-becky-white-woman-who-called-cops-black-bbq-911-audio-released-im-really-1103057. For Permit Patty, a white woman who called the police on a Black girl who was selling bottled water without a permit, see https://www.cbsnews.com/news/permit-patty-alison-ettel-calls-police-on-little-girl-selling-water-twitter-video/

socially privileged residents may also invite increased social control of disadvantaged residents of color through other, indirect mechanisms.

This dissertation explores the relationship between neighborhood change and social control of local residents. I consider two types of social control: control enacted directly by the police on residents in the form of street stops, and control enacted by residents via complaints to the city in which they request action by city representatives against their neighbors. We know that police react to neighborhood type (Stein and Griffith, 2017; Kearns, 2017) and that the burden of social control tends to fall more heavily on people of color (Rose, 2002; Hawkins and Thomas, 2013). But we know less about the interaction between different types of neighborhood change and patterns of social control. For example, do socioeconomic forms of neighborhood change, like gentrification, lead to more or less social control? Are the effects different for direct social control by police compared to more indirect forms of social control such as resident complaints to the city? We also know too little about the effects of demographic neighborhood change distinct from socioeconomic change because the literature on neighborhood change often conflates socioeconomic change with demographic change. Does demographic neighborhood change, like recent increases in White residents, predict the same patterns of social control as gentrification? My dissertation seeks to answer these questions by leveraging a data set I construct through harmonizing and merging data from 10 publicly available administrative data sets.

Additionally, I introduce a new measure of neighborhood change, which separates socioeconomic change from demographic change. Most studies of neighborhood change consider gentrification and define it around changes in the socioeconomic status of an area as measured by changes in income, property values, and education of the residents. Where demographic changes are considered, they are often assumed to be correlated with socioeconomic change and are not considered as a separate feature of change that may or may not correspond to socioeconomics. I present a new typology of neighborhoods, drawing on previous research in gentrification, that accounts for both socioeconomic and demographic change while considering that they may not always go hand in hand. In this way, I can investigate the effect of gentrification separately from the effect of neighborhood whitening and vice versa.[2]

Disaggregating socioeconomic and demographic change is important if we want to gain a clearer understanding of the ways in which different forms of change can affect residents differently. Gentrification does not require demographic change, and demographic change does not guarantee socioeconomic change. While race and socioeconomic status tend to be highly correlated, they do not have a deterministic relationship. As inequalities shift and patterns of mobility and wealth continue to change, local population dynamics will also change. Continuing to focus solely on the socioeconomic dynamics of neighborhood change will miss important parts of the picture.

Understanding how different types of neighborhood change are associated with patterns of social control enacted against local residents can inform our understanding

[2]Gentrification and increases in white population are not the only types of neighborhood change that likely affect social dynamics in residential spaces. While these are the only categories of change I consider in this dissertation, increases in same-race but higher-socioeconomic status residents in previously lower income spaces, both urban and suburban, and recent changes to rural areas should be taken up by sociologists.

of how change may impact residents' daily lives. While increased integration of residential spaces has many potential benefits, it is important to acknowledge and understand the potential problems so that public policy, community organizations, and local actors can best work to mitigate any negative consequences.

## 1.1 Background and Motivation

### 1.1.1 Social Norms and Social Control

How we interact with our neighbors and our neighborhoods is determined, in part, by social norms of acceptable behavior. Social norms are the often unspoken rules that members of groups know just by virtue of growing up in them. They are "how we do things around here." Norms are constructed through the interaction of individuals and their environments and negotiated within the context of social and historical conditions. As such, they are subject to externalities that vary by group, leading to different norms and enforcement depending on the group or situation (Hechter and Opp, 2001). According to Elster (1989), social norms and tradition are the 'vehicles' of culture.

For many, they function below the level of consciousness as part of an acquired understanding of how things work. Like our first language, we acquire our cultures and their accompanying social norms without even meaning to do so. Just like language, social norms are not biologically determined – they are socially determined. The social norms that we acquire depend on the communities within which we are raised. Bourdieu described the embodiment of social norms as *habitus*, which is acquired by individuals in reaction to their objective conditions. *Habitus* develops below the level of consciousness as an embodiment of social capital, skills, dispositions, and habits gained through lived environment and circumstance. It is an embodied understanding of the scope of the playing field and the rules of the game, such than an individual instinctively knows how to act and react in certain social situations (Bourdieu, 1977). When an individual moves to a class or realm or set of circumstances for which they are not equipped, there is a struggle against the *habitus* as they attempt to navigate the field of an unfamiliar game. In this way, *habitus* reinforces structural inequalities by demarcating ways of behaving. When individuals with more social power move into neighborhoods that have previously been associated with groups with less social power, they bring their power and their particular *habitus* with them, potentially transforming the shape of the playing field and the rules of the game under the feet of their less socially powerful neighbors.

If the more socially powerful group defines what are considered socially acceptable behaviors through its understanding of the social world, then the objective conditions of those in the socially subordinate group may not lead to the development of embodied dispositions that equip them for dealing with the dominant conception of normativity. Bourdieu referred to this as hysteresis, where embodied dispositions and acquired practices are out of sync with the social context. The mismatch sets up an inevitable tension between groups. What one group sees as the normal, acceptable social order, the other may view as completely deviant. Additionally, social power dynamics can result in the emergence of norms that target one group while benefiting another (Hechter and Opp, 2001). If the socially powerful group views the behaviors of members of the subordinate group as deviant, it may act to enforce its norms for its benefit through mechanisms of social control targeted at the subordinate group, which can lead to the reproduction of inequality and the enactment of discrimination.

To understand social control is to understand the ability of social groups to regulate themselves and to regulate individual behaviors in terms of collective morality and societal goals (Janowitz, 1975). While the details of how to define social control have differed over time and from sociologist to sociologist, there is consensus that social control refers, at least broadly, to the ways in which social groups use a variety of means to regulate individual behaviors in favor of maintaining some social order.

The exercise of power, and what is considered orderly behavior, looks different from place to place (Meier, 1982). According to Park and Burgess (1921), social control is rooted in conflict and involves the subordination of individuals to the greater community. Meier (1982, 43) described social control as a "collection of mechanisms to induce compliance to norms" where the mechanisms are wielded by those with social and political power to gain the compliance of others. Social diversity, by its nature, ensures variations in what is considered normative (Black, 1984). This suggests that where groups with different norms and different levels of social power often interact, the means of social control will be wielded to induce the less powerful group to conform to the norms of the more powerful group.

Social control can be divided into indirect and direct control, and direct control can be further subdivided into informal and formal social control. Farley and Flota (2018) lay out a very clear summary of the different types of social control, which I summarize here. Indirect social control refers to ideologies and cultural practices that regulate behavior. Here we might apply the concept of *habitus* – individuals acquire ideologies and cultural practices that regulate their behavior through their implicit understanding of the rules of the game. Direct social control, on the other, refers to explicit sanctions used to enforce social conformity. Direct social control can be informal or formal in nature. Informal social control consists of sanctions imposed by members of society against each other through social interaction. Informal social control can be positive in nature – gestures, praise, attention, like positive reinforcement through social interaction – or negative – gossip, avoidance, shunning, interpersonal violence, etc. Formal social control refers to sanctions imposed through institutional means and applied by actors with the appropriate institutional credentials. Positive formal social control might take the form of awards or diplomas, while negative formal social control might be expulsion from an organization or school, civil punishment in the form of fines, or criminal punishment. Formal sanctions, particularly legal sanctions, are used relatively rarely, except as a means for those with power to control the behavior of those without power (Black, 1984).[3]

Social control can be bilateral where one individual sanctions another, or it can be trilateral where an intermediary is involved in mediating the sanctioning process (Farley and Flota, 2018). Variation in the methods of social control depends on social diversity, in variation in norms among the people who are in conflict, and the normative positioning of the third party intermediary relative to the individuals

[3]While this might seem to be a nonsensical sentiment given that the United States has the largest prison population as a percentage of its citizenry, there are huge racial disparities in contact with our systems of formal social control. Additionally, the rarity of the use of formal legal sanctions should be viewed in the context of the number of daily interactions we each have with others in society in which we are expected to follow social norms of some sort. Given that denominator, the use of formal legal sanctions is quite rare.

or groups in conflict (Black, 1984). We can look at police stops as an example of bilateral social control where an officer sanctions an individual for a perceived norm violation.[4] Complaints to 311, on the other hand, better fit the pattern of trilateral social control where the representative of whatever agency 311 sends to deal with the complaint becomes the intermediary responsible for judging the conflict and assigning the sanction.

The history of the United States is full of examples of formal social control explicitly directed against people of color, specifically Black Americans, for example, slave patrols (Blauner and Blauner, 1972; Bass, 2001a), vagrancy laws (Blackmon, 2009), Sundown towns Loewen (2005), and Jim Crow laws. There is also a long history of formal social control not explicitly directed at people of color, but used in a fashion that has a disparate effect on people of color compared to white Americans, such as disproportionate drug enforcement not explained by differences in offending (Mitchell and Caudy, 2017), disproportionate police contact (Crutchfield et al., 2012a; Engel and Calnon, 2004a; Lundman and Kaufman, 2003; Fagan and Davies, 2000; Fagan et al., 2016, 2012a), and disparities in mass incarceration (Forman Jr, 2012). Taken in the context of both legal and continuing residential segregation (Rothstein, 2017; Trifun, 2009), and given the long history of formal social control used disproportionately against people of color, it stands to reason that changing neighborhoods, where individuals from different social groups with differential social power begin to live in closer proximity, will become fertile ground for conflicts over social norms and concomitant attempts at both informal and formal social control to resolve those

[4]In the case of police stops, the norm violation may be a violation of law, which is just an officially codified norm.

conflicts.

### 1.1.2 Social Control in Changing Neighborhoods

Much of the literature on neighborhood change focuses on the process of gentrification. Gentrification has several meanings depending on the context. Ordinarily, in the academic literature, gentrification refers to "the process by which central urban neighborhoods that have undergone disinvestment and economic decline experience a reversal, reinvestment, and in-migration of a relatively well-off, middle- and upper-middle-class population" (Smith, 1998, 198). The term has also been used to refer to the replacement of lower-income residents by higher-income residents; the change in an urban area due to the demolition of old buildings and construction of upscale housing; and neighborhood change as driven by commercialization to attract increasingly affluent residents (Kirkland, 2008).

Recent research suggests that predominantly Black and Latino neighborhoods are less likely to experience gentrification than other lower-income neighborhoods (Ellen and O'Regan, 2011; Hwang and Sampson, 2014; Timberlake and Johns-Wolfe, 2017). However, when a change towards higher socioeconomic status does occur in lower income, predominantly Black and Latino neighborhoods, it is more likely to involve an inflow of higher-SES white residents than in other gentrifying areas (Owens and Candipan, 2018).

Racial changes appear to be particularly salient to residents of the affected neighborhoods: "in urban lore, the pre-gentrified neighborhood is inhabited mostly by African Americans or other people of color when the rumblings of change begin, and the rumblers are typically white – white, upper-middle-class, professional homebuyers, displacing the original residents" (Kirkland, 2008, 18). Even when white people are not the majority of gentrifiers in a particular neighborhood, residents perceive the changes as being related to increased white population (Freeman, 2006). White people walking around in changing neighborhoods are perceived as signs of significant change because "black neighborhoods perhaps differ from other types of minority areas in that not only do they have a black majority but they have historically been relatively homogeneous with few whites" (Freeman, 2006, 80). Elijah Anderson points out that Black Americans have to navigate white spaces on a daily basis, while white Americans can largely avoid Black spaces (Anderson, 2015). When white spaces, and their accompanying white clientele, move into Black neighborhoods, they represent a "cultural and economic manifestation" of the neighborhood changes taking place (Anderson, 2015, 19).

Neighborhood change brings potential benefits of increased investment, improved public services, increased integration, and long term decreases in crime rates (Kirk and Laub, 2010; Papachristos et al., 2011; Zheng and Kahn, 2013). Despite this, in everyday usage, gentrification is often presumed to bring negative consequences for original residents of the changing neighborhood. One such presumed consequence is a displacement of lower income, minority residents, although the evidence on this is mixed. (For evidence that gentrification leads to displacement see (Atkinson, 2000); for evidence that gentrification does not lead to displacement see (Freeman and Braconi, 2004; Dragan et al., 2019). It seems likely that the link between neighborhood change and displacement is highly dependent on context. For example, displacement should be more likely in neighborhoods where new middle-class housing takes the place of low-income housing compared to areas where new housing is built on previously vacant lots without reducing low-income housing stock. Additionally, local regulations for renters, such as rent control and stabilization in NYC, may mitigate displacement.

Beyond the fear of displacement, there are other negative implications of neighborhood racial change, "including marginalization, isolation, alienation – wherein original residents remain in gentrified neighborhoods, but through the transformation of their neighborhood, their quality of life is diminished" (Kirkland, 2008, 20). Neighborhood change can place new racially and socioeconomically privileged residents in spatial proximity to those who are less privileged but have longer standing ties to and greater stakes in their neighborhood. As Freeman puts it, "when whites move into predominantly black neighborhoods, they upset the prevailing notion of who belongs in particular areas" (Freeman, 2006, 82). Additionally, there is the potential threat to the culture of a neighborhood when more privileged residents move in and exercise their power to redefine the space and its associated cultural and social meanings and uses (DeSena, 2012; Freeman, 2006; Kasinitz, 1988). Sharing space does not guarantee that communities will bridge cultural differences and create larger more inclusive communities (Chaskin and Joseph, 2011; Kleit, 2005). The evidence suggests that residents with more power exercise it to enforce their norms over those of their less powerful neighbors, and that there are particular white cultural habits of anxiety and ambivalence – anxiety from perceived danger in multiracial/ethnic spaces and ambivalence between fear and appreciation for "diversity," which manifests as a reaffirmation of social boundaries – that work to reproduce racial inequalities through social control and the maintenance of social distance in mixed-race neighborhoods (Walton, 2018).

What the literature does not yet adequately address is how different combinations of neighborhood change are related to patterns of social control. There is anecdotal evidence that increases in white population are perceived to be accompanied by increases in social control on the part of the police (Freeman, 2006). Additionally, there is a common narrative in popular and social media that new white residents move into Black and Hispanic neighborhoods and impose their social norms (Walton, 2019; Moore, 2019; Wong, 2014). Despite this, there has not been a systematic, explicit study of the relationship between neighborhood change and social control. Furthermore, studies of neighborhood change tend to look at change in one dimension rather than considering the layers of change that occur over time in the same place. In this dissertation, I take a layered view of neighborhood change, parsing out increases in white population from socioeconomic gentrification, and consider how layered change is associated with patterns of social control enacted directly by the NYPD and indirectly by individual citizens calling the NYPD to action. I argue that increases in residents with greater socioeconomic and racial privilege compared to their neighbors, particularly the combination of the two, are paired with increases in social control, and that this relationship can be explained by power structures around individual and institutional social norm negotiation and enforcement.

## 1.2 The Case of New York City

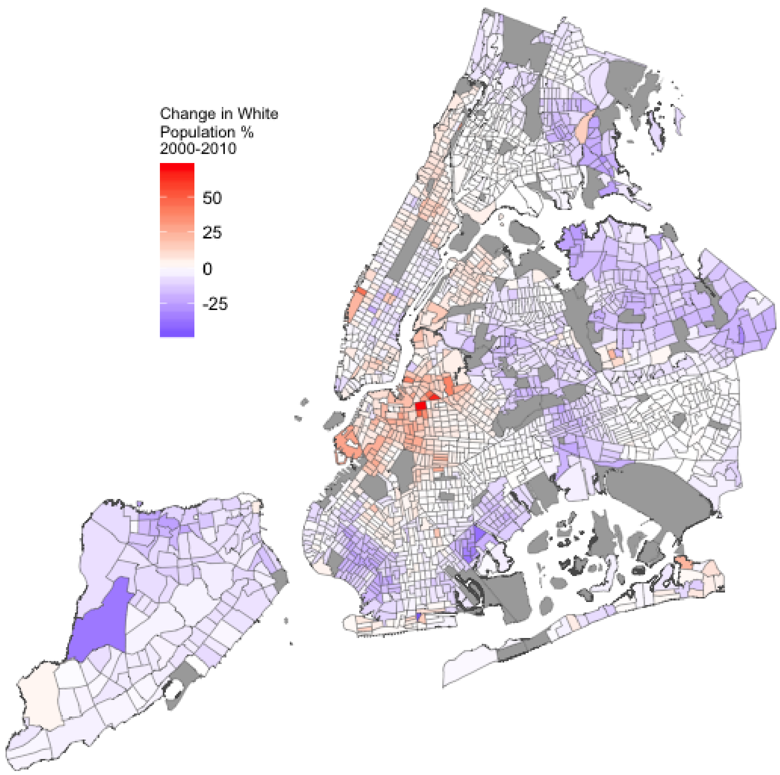
I take New York City (NYC) as a case study to investigate the relationship between neighborhood change and social control. While in many ways NYC is an outlier among United States cities, it presents several benefits for the purposes of this research. NYC has experienced a large amount of population change over the last several decades (Angel and Lamson-Hall, 2014). In 2000, the population of NYC was 8.015 million people. By 2010, the population of the city was up to 8.19 million. Over that decade, the white population went from 36% of the city population to 33%, while the Hispanic population increased from 24 to 26% and the Black population decreased from 28 to 26% of the city population. This change did not, however, happen uniformly across the city. There is a great deal of variation across boroughs and between neighborhoods. While some neighborhoods lost white population, others gained. Figure 1.1 shows a map of change in white population percent across the city between 2000 and 2010. Figure 1.2 shows those tracts where there was any increase in white population versus those where these was no increase in white population.[5]

There remains a high degree of both residential and school segregation. Figure 1.3 is a map of residential segregation in 2010. This map shows the dissimilarity index between Black and Hispanic residents and non Black and Hispanic residents disaggregated to the tract level, following an approach detailed by Barbieri (2017). The dissimilarity index measures the evenness of the spread of two groups across some larger geographic unit, like a city (Massey and Denton, 1988). The index is generally

[5] I operationalize increase in white population as any increase in white population percent conditional on an increase in white population numerically. This eliminates those tracts where white population increased due solely to a decrease in other residents.

Figure 1.1: Change in White Population 2000 to 2010

*Note: Greyed out tracts are those covering parks, cemeteries, and Riker's Island, which do not have regular residential population.*

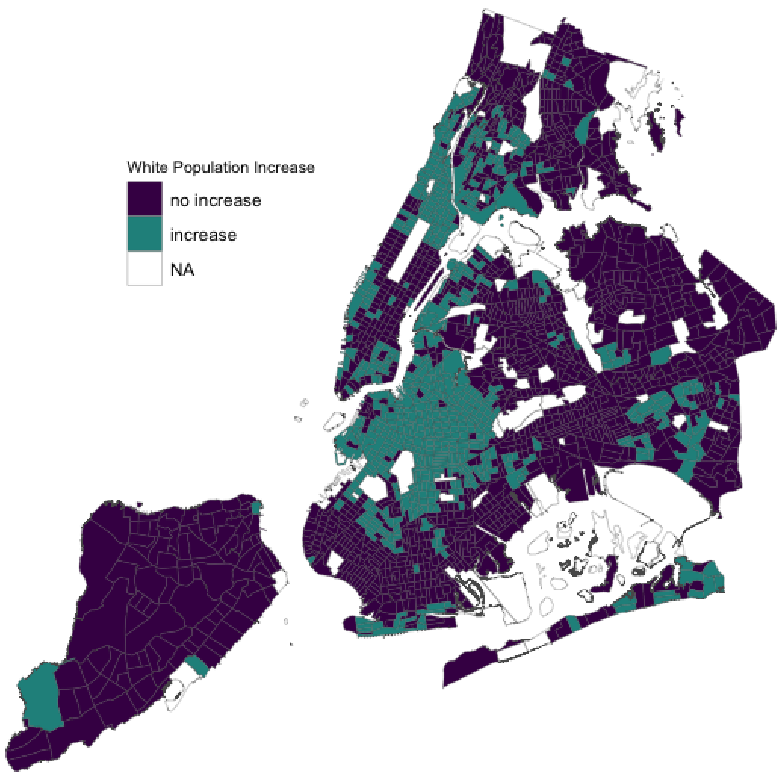



calculated to provide one number for a city, which is the sum of the absolute value of differences in proportions from smaller units that make up the city.[6] This map shows the dissagregated values for each tract that would normally be summed to

[6]The Dissimilarity Index is calculated by summing the absolutely value of the differences in representational proportion between two groups for each smaller geographic unit within the city (where $a_i$ is the population of group $a$ in an individual tract, $A$ is the total population of group $A$ in the city, $b_i$ is the population of group $b$ in an individual tract and $B$ is the total population of group $B$ in the city: $D = \frac{1}{2}\Sigma\left|\frac{a_i}{A} - \frac{b_i}{B}\right|$.

Figure 1.2: Increase in White Population 2000 to 2010

*Note: Increase in white pop from 2000 to 2010 operationalized as any increase in white population percent conditional on numeric increase in white pop. Areas in white are parks, cemetaries, and Riker's Island, which are excluded from the analytic sample due to lack of regular residential population.*




create the overall index value. Here, I grouped Black and Hispanic residents together and compared them to the remaining population of NYC. The values for each tract are the absolute value of the difference in proportions between the representation of Black and Hispanic residents in the tract compared to their representation in the city as a whole and the representation of all other residents in the tract compared to their representation in the city as a whole. Higher values represent more segregation and lower values represent less segregation. As is evident from the map, there is a great deal of residential segregation, but there are also heterogeneous neighborhoods where residents from different races and ethnicities live close together (Foner, 2007; U.S. Census Bureau, 2010).The same is true for residents of different socioeconomic classes – not only are public housing units interspersed throughout the city, there are also regulations requiring many landlords to provide affordable housing for those making significantly below the area median income so as to provide access to higher income neighborhoods to people who otherwise would not be able to live there (Glen, 2014).

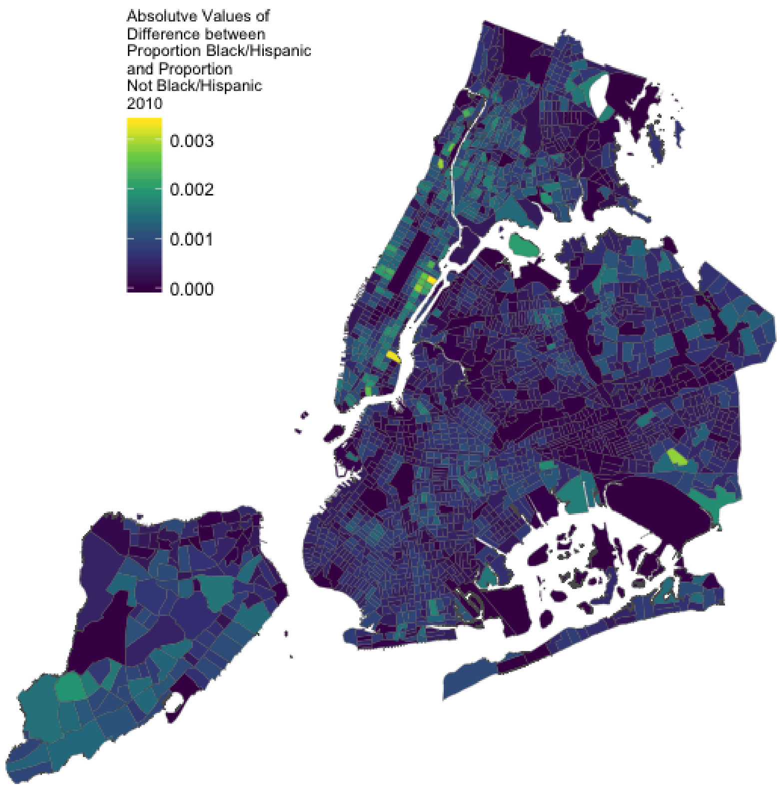
Additionally, there is a great deal of variation in social control across the city. While police stops happen throughout NYC, the numbers and rates of police stops are not evenly spread out across neighborhoods (see Figure 1.4 for a map of the distribution of stops in 2011). Complaints made through the 311 system are also spread across the city, varying in the geographic patterns based on the type of complaint. In this respect, NYC represents a good test case. As William Julius Wilson argued for Chicago in his foreword to Sampson's Great American City, NYC is "an excellent laboratory for testing theoretically driven hypotheses" (Sampson, 2012, viii)

Some may argue that since the NYPD has moved away from extensive use of SQF tactics since the ruling in *Floyd v. City of New York*[7] in 2013, SQF in NYC is no longer a fruitful topic of investigation. While the NYPD may have shifted

[7] *Floyd v. City of New York* (Scheindlin, 2013) was a class action suit that was brought against the City and the NYPD. The judge ruled that the NYPD was applying SQF (Terry Stops) in a manner inconsistent with the 4th (protection against search and seizure) and 14th (right to equal protection under the law) Amendments and inconsistent with the constraints set out in *Terry v. Ohio*. The case corresponded with a drastic reduction in the number of SQF stops made by the NYPD.

Figure 1.3: Dissagregated dissimilarity index Black & Hispanic Residents compared to remaining NYC population 2010

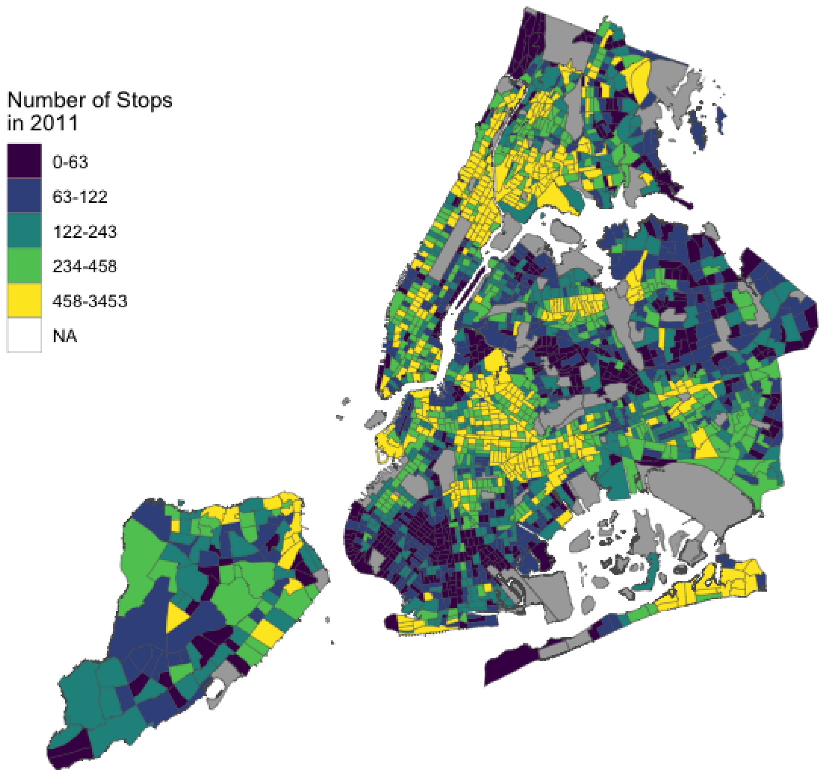
*Note: Values are from the disaggregated Dissimilarity Index. To calculate the Dissimilarity Index for the city, add up the values for each tract and divide by 2. Higher values are more segregated and lower values are less segregated. Severe outlier, Co-op city, excluded from this map.*




and curtailed its use of the tactic, NYC is one of the few major cities in the United States that provides extensive and relatively complete data on street stops. Other U.S. cities continue to use reasonable suspicion stops, and insights from the case of NYC may help researchers better understand the range of mechanisms at play in everyday low-level interactions between police and civilians. Additionally, there is

Figure 1.4: Distribution of SQF Stops in 2011

*Note: Scale is divided by quintile.*




a fruitful comparison to be made between different types of social control and their relationship to neighborhood change.

## 1.3 Data and Methods

The three studies presented in the three substantive chapters that follow present different models, but they are built on the same data set and the same underlying methodology. Below I will detail the data sources as well as the construction of the master data sets and the basic method of analysis. I will provide more specific descriptions of the outcomes, explanatory and control variables, and models for each of the three studies in their respective chapters.

### 1.3.1 Data

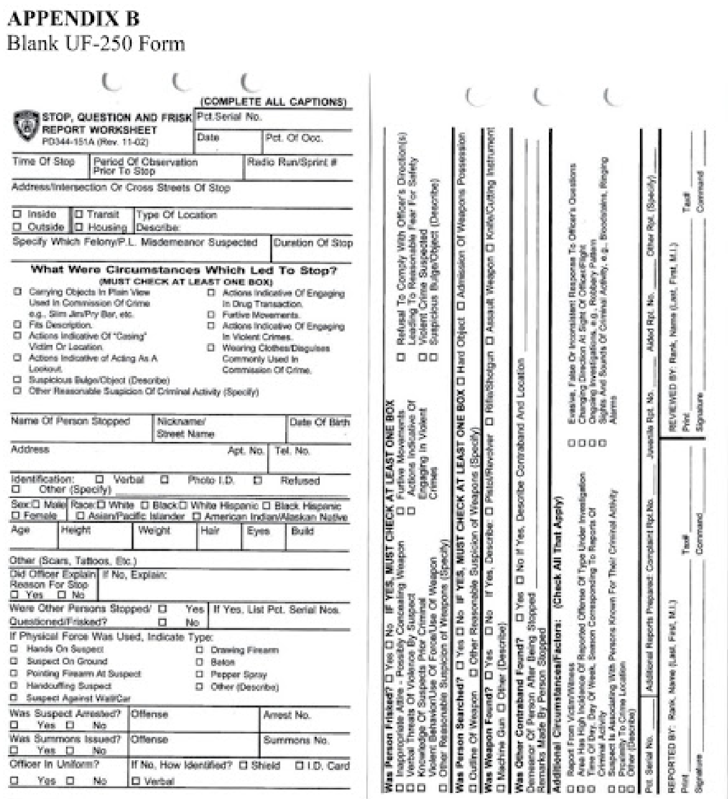
I use data from several publicly available administrative data sets to construct a master data set from which to run my analyses. New York City makes a large amount of data available to the general public. Data can be accessed both via the official websites for NYC government agencies and via NYC Open Data, a platform that provides continually updated downloadable data files from many city agencies.

#### Stops

Data on police stops come from the New York Police Department (NYPD) Stop and Frisk Database. This database provides downloadable files containing data on individual stops under the Stop Question and Frisk (SQF) program for each year beginning in 2003 through 2018. Data quality for the first 3 years is poor – there is excessive missingness for many variables. The data are considerably more complete beginning in 2006. Starting with the data set for 2017, the NYPD changed the way the data sets are coded (likely due to a new digital input system rather than the prior system of handwritten UF-250 forms that were digitized after the fact) and they are no longer directly compatible or comparable to those from 2006-2016. For the purposes of this analysis, I focus on stops in 2011, which, with 685,742 stops, was the peak of use of SQF in NYC.

Figure 1.5: UF250 form used by the NYPD to document street stops.

*Note: This image of a blank paper UF-250 form comes from the Community Service Society. https://www.cssny.org/news/entry/stop-and-frisk*



**APPENDIX B**
Blank UF-250 Form

(COMPLETE ALL CAPTIONS)

STOP, QUESTION AND FRISK REPORT WORKSHEET
PD344-151A (Rev. 11-02)

Pct.Serial No.
Date | Pct. Of Occ.
Time Of Stop | Period Of Observation Prior To Stop | Radio Run/Sprint #
Address/Intersection Or Cross Streets Of Stop
☐ Inside ☐ Outside | ☐ Transit ☐ Housing | Type Of Location Describe:
Specify Which Felony/P.L. Misdemeanor Suspected | Duration Of Stop

**What Were Circumstances Which Led To Stop?**
(MUST CHECK AT LEAST ONE BOX)
☐ Carrying Objects In Plain View Used In Commission Of Crime e.g., Slim Jim/Pry Bar, etc.
☐ Fits Description.
☐ Actions Indicative Of "Casing" Victim Or Location.
☐ Actions Indicative of Acting As A Lookout.
☐ Suspicious Bulge/Object (Describe)
☐ Other Reasonable Suspicion Of Criminal Activity (Specify)
☐ Actions Indicative Of Engaging In Drug Transaction.
☐ Furtive Movements.
☐ Actions Indicative Of Engaging In Violent Crimes.
☐ Wearing Clothes/Disguises Commonly Used In Commission Of Crime.

Name Of Person Stopped | Nickname/ Street Name | Date Of Birth
Address | Apt. No. | Tel. No.
Identification: ☐ Verbal ☐ Photo I.D. ☐ Refused ☐ Other (Specify)
Sex: ☐ Male ☐ Female | Race: ☐ White ☐ Black ☐ White Hispanic ☐ Black Hispanic ☐ Asian/Pacific Islander ☐ American Indian/Alaskan Native
Age | Height | Weight | Hair | Eyes | Build
Other (Scars, Tattoos, Etc.)
Did Officer Explain Reason For Stop ☐ Yes ☐ No | If No, Explain:
Were Other Persons Stopped/ Questioned/Frisked? ☐ Yes ☐ No | If Yes, List Pct. Serial Nos.
If Physical Force Was Used, Indicate Type:
☐ Hands On Suspect
☐ Suspect On Ground
☐ Pointing Firearm At Suspect
☐ Handcuffing Suspect
☐ Suspect Against Wall/Car
☐ Drawing Firearm
☐ Baton
☐ Pepper Spray
☐ Other (Describe)
Was Suspect Arrested? ☐ Yes ☐ No | Offense | Arrest No.
Was Summons Issued? ☐ Yes ☐ No | Offense | Summons No.
Officer In Uniform? ☐ Yes ☐ No | If No, How Identified? ☐ Shield ☐ I.D. Card ☐ Verbal

**Was Person Frisked?** ☐ Yes ☐ No **IF YES, MUST CHECK AT LEAST ONE BOX**
☐ Inappropriate Attire - Possibly Concealing Weapon
☐ Verbal Threats Of Violence By Suspect
☐ Knowledge Of Suspects Prior Criminal Violent Behavior/Use Of Force/Use Of Weapon
☐ Other Reasonable Suspicion of Weapons (Specify)
☐ Furtive Movements
☐ Actions Indicative Of Engaging In Violent Crimes
☐ Refusal To Comply With Officer's Direction(s) Leading To Reasonable Fear For Safety
☐ Violent Crime Suspected
☐ Suspicious Bulge/Object (Describe)

**Was Person Searched?** ☐ Yes ☐ No **IF YES, MUST CHECK AT LEAST ONE BOX** ☐ Hard Object ☐ Admission Of Weapons Possession ☐ Outline Of Weapon ☐ Other Reasonable Suspicion of Weapons (Specify)

**Was Weapon Found?** ☐ Yes ☐ No If Yes, Describe: ☐ Pistol/Revolver ☐ Rifle/Shotgun ☐ Assault Weapon ☐ Knife/Cutting Instrument ☐ Machine Gun ☐ Other (Describe)

**Was Other Contraband Found?** ☐ Yes ☐ No If Yes, Describe Contraband And Location
Demeanor Of Person After Being Stopped
Remarks Made By Person Stopped

**Additional Circumstances/Factors: (Check All That Apply)**
☐ Report From Victim/Witness
☐ Area Has High Incidence Of Reported Offense Of Type Under Investigation
☐ Time Of Day, Day Of Week, Season Corresponding To Reports Of Criminal Activity
☐ Suspect Is Associating With Persons Known For Their Criminal Activity
☐ Proximity To Crime Location
☐ Other (Describe)
☐ Evasive, False Or Inconsistent Response To Officer's Questions
☐ Changing Direction At Sight Of Officer/Flight
☐ Ongoing Investigations, e.g., Robbery Pattern
☐ Sights And Sounds Of Criminal Activity, e.g., Bloodstains, Ringing Alarms

Pct. Serial No. ____ | Additional Reports Prepared: Complaint Rpt.No. ____ Juvenile Rpt. No. ____ Aided Rpt. No. ____ Other Rpt. (Specify) ____

REPORTED BY: Rank, Name (Last, First, M.I.)
Print ____ Tax# ____
Signature ____ Command ____

REVIEWED BY: Rank, Name (Last, First, M.I.)
Print ____ Tax# ____
Signature ____ Command ____

These data represent each individual stop that was conducted in the given year. See Figure1.5 for a picture of a blank UF-250 form used by police to document each SQF stop. They provide information on the individuals stopped, the circumstances of the stops, and the locational context of the stops. For instance, the data document the race, gender, approximate age, approximate height and weight, eye color, hair color, and approximate build of the person who was stopped. They provide the location of the stop with geolocation in the form of latitude and longitude. They describe the reason for the stop, such as “furtive movement,” “fits description,” “actions indicative of ‘casing’ victim or location,” or “actions indicative of acting as a lookout.” The data also document if the stopped individual was frisked, searched, arrested, and/or given a summons, whether force was used in the stop and what kind, and other details about the circumstances of the encounter.

### Complaints

Data on complaints made to the city come from the 311 database available through NYC Open Data. This data set contains information on all complaints made via the 311 system since 2010. For comparability with the analysis of stops, I analyze complaints made in 2011. In addition, I run the same analysis on complaints made in 2019 to determine whether patterns of association between neighborhood change and rates of complaints are consistent across both years.

For each complaint, the data set provides a time and date the complaint was made, the means by which the complaint was registered, the category and description of the complaint, the agency that was designated to respond, the location of the complaint (if applicable), and the end date and resolution of the complaint if available. The location provided refers to the location of the behavior or violation that the complainant is complaining about. This is provided as a geolocation with latitude and longitude. Unfortunately, these data do not provide the location of the complainant or any individual information about who made the complaint or who the complaint was about, such as race, age, and gender. This limits analysis to types of complaints made about types of neighborhoods rather than providing the ability to analyze the type of people who complain and are complained about.

### Crimes

In studying certain kinds of social control, such as those enacted by the police, it is necessary to control for underlying crime rates. We expect that crime rates account for a substantial amount of the variability in where police direct their time and attention since it is their job to respond to criminal activity. Crime data for this study come from the NYPD historical incident reports, which are available on NYC Open Data. These data provide information about individual incidents of crime from every criminal complaint filed with the NYPD since 2006. Complaints may be generated from individuals who complain to the police about a crime they witnessed or were a victim of, or by police who stop individuals in the process of a criminal act or in response to a call for service. These data provide information on the age, race, and sex of both the suspect and the victim. They provide a description of the offense and the category of law that was violated. They provide the exact location of the crime including geolocation with latitude and longitude, as well as jurisdiction, precinct, and other characteristics of the location. I use the crime complaints for 2011 and 2019 to control for crime contemporaneous to the stops and complaints of interest.

### Socioeconomic, Demographic, and Other Tract Characteristics

To investigate changes in neighborhood composition, I need data on the socioeconomic and demographic makeup of tracts from two time points, separated by a period of years, that are divided into comparable geographic units. In order to get the most accurate estimates of neighborhood change, I use data from the 2000 and 2010 census. This eliminates the problem of trying to measure change between rolling estimates, as would be necessary if I were to use data from the American Community Survey estimates between the decennial censuses. In order to solve the problem of changing tract boundaries, I use the Longitudinal Tract Data Base (LTDB), which is made available by the US2010 Project (2012) hosted at Brown University. The LTDB takes census counts from 1970 through 2000 and uses a geographic crosswalk to harmonize them to 2010 census tract boundaries so that all the years are directly, geographically comparable.

For the analysis of complaints in 2019, I use the 2007-2011 and 2014-2018 five-year estimates from the American Community Survey (ACS) in place of the census data. The ACS uses a sample to get detailed demographic and socioeconomic information on the population in between the decennial censuses. Five consecutive waves are averaged to create estimates. There is variation in how researchers apply five-year estimates: sometimes a window, such as 2007-2011 is used as an estimate for the midpoint year of 2009; sometimes that window would be used as the estimate for the final year, 2011. In this case, 2014-2018 is the latest available five-year estimate so I use the 2007-2011 and 2014-2018 estimates to find the change in neighborhoods over the time period just prior to the latest available 311 complaint data while ensuring that the five-year estimate representing the first time point does not overlap at all with the five-year estimate representing the second time point.

In order to control for the potential effect of public housing locations on both types of social control, I use data from the NYC Housing Authority (NYCHA).[8] The NYCHA provides data on the location of public housing complexes, as well as the number of buildings and residents. The main footprints of NYCHA complexes have not changed measurably in the last decade, therefore, I use the 2010 map for both the 2011 and 2019 analysis.

Additionally, in order to control for residential versus commercial land use in tracts, I use the 2011 and 2019 Public Land Use Take Lot Output (PLUTO) data provided by the NYC Department of Finance.[9] These data are updated multiple times a year and provide information on each individual tax lot in the city, including location by tract, and land use from among 11 possible categories. I recode these 11 categories into three categories – purely residential (coded as 1); mixed land use (coded as 2); and purely non-residential (coded as 3). I create an indicator of average land use by recoding all tax lots with my three-category system and then average the values for all tax lots in a tract. The value of the indicator for a particular tract ranges from one to three – the closer the value is to one the closer the tract is to purely residential land use, and the closer it is to three the closer the tract is to purely non-residential.

Finally, in order to account for the possibility that patterns of policing are reactive to either political pressure or higher level directives related to investment that precipitates socioeconomic and demographic change in the composition of residents, I use data on building permits from the NYC Department of Buildings to control for

[8]NYCHA data sets are available for download here: https://data.cityofnewyork.us/Housing-Development/NYCHA/n3uv-djd2

[9]PLUTO data sets are available here: https://www1.nyc.gov/site/planning/data-maps/open-data/dwn-pluto-mappluto.page

commercial and real estate investment in tracts.[10] This type of investment may signal impending change to the police and implicitly influence how they patrol, or this type of investment may be accompanied by requests from developers that influence policing at a higher level. The data on building permits provide information on all permits issued in the city. I use data on permits issued for new buildings, major renovations, and demolitions. These categories are most likely to represent new investment in an area. I pull counts of these kinds of permits for 2011 and 2019.

**Putting it all together**

In order to create a master data set for analysis for 2011 and one for 2019, I harmonize data from all the sources described above. Using R, I use the x-y coordinates provided in the stop, complaint, and crime data to assign the individual incidents to the 2010 census tracts in which they occurred. I then aggregate stops, complaints, and crimes by census tract. I merge these aggregated data sets together with the data from the 2000 and 2010 census from the LTDB, which was standardized to 2010 tract boundaries. Additionally, I merge aggregated counts of public housing buildings, the total number of major building permits, and the average landuse by tract. This results in a data set of 2,167 total tracts in NYC, each with 2011 counts of stops, complaints, crimes, NYCHA buildings, major building permits, average landuse, and tract level demographic and socioeconomic characteristics from 2000 and 2010. I create change variables to capture the change in White population, median household income, and other neighborhood characteristics. Finally, I drop all tracts

[10]NYC Department of Buildings permit issuance data set is available for download here: https://data.cityofnewyork.us/Housing-Development/DOB-Permit-Issuance/ipu4-2q9a

with no residential population, those that are fully taken up by parks and cemeteries, a tract in Staten Island that is a combination of parkland and coast guard base, and Riker's Island, NYC's largest jail. This results in an analytic sample of 2,099 tracts for 2011. I do the same for the data for 2019 and additionally drop four tracts that are missing average building age, resulting in an analytic sample of 2,095 tracts for 2019.

### Measuring Neighborhood Change

In this dissertation, I extend previous gentrification typologies that divide neighborhoods geographically into places that were already well off (not-gentrifiable), places that were not well off and had room to move up socioeconomically but maybe had not started the process yet (gentrifiable), and places that were not well off to begin with but had started gaining in socioeconomic status (gentrifying), by adding an additional parameter to capture racial change, resulting in a new classification system with 5 categories: not-gentrifiable, gentrifiable tracts that did not whiten or gentrify, gentrifiable tracts that whitened but did not gentrify, gentrifying tracts that did not whiten, and gentrifying tracts that did whiten. Following Hwang (2019), which builds on these prior approaches to measuring gentrification (Freeman, 2009; Hammel and Wyly, 1996; Wyly and Hammel, 1999), I construct a measure indicating if tracts were gentrifiable or not at time one and if those tracts that were gentrifiable had started gentrifying between time one and time two. Gentrifiable tracts are defined as those with a median household income below the city median at time one.[11] Gentrifying

[11] I use the average median household income across all tracts in the city that had median household income reported even though the analytic sample has slightly fewer tracts due to data limitations of

tracts are those gentrifiable tracts that had an increase in median home value or median rent greater than the average increase for the city and an increase in college educated residents or an increase in median household income greater than the average increase for the city (Hwang, 2019).[12]

Table 1.1: Summary of tracts by type in 2011 and 2019

| | **2011** | | **2019** | |
|---|---|---|---|---|
| | Frequency | Percent | Frequency | Percent |
| Prosperous | 1047 | 49.88 | 893 | 42.63 |
| Persistently poor and not Whitening | 479 | 22.82 | 564 | 26.92 |
| Persistently poor and Whitening | 303 | 14.44 | 440 | 21.00 |
| Gentrifying but not Whitening | 86 | 4.10 | 82 | 3.91 |
| Gentrifying and Whitening | 184 | 8.77 | 116 | 5.54 |

I take this tract typology one step further by considering an additional parameter of neighborhood change: increase in White population, which I refer to as whitening. I consider a tract to be whitening if it had an increase in the percentage of the population that was White between time one and time two,[13] and then exclude

other variables. The difference between the average median household income with and without those tracts is minimal. Using the average for the larger number of tracts is a better reflection of where each individual tract stands in contrast to the city as a whole.

[12]In order to create the tract typology, first I create variables to capture the change in median home value, median rent, median household income, percent college educated, and White population. For home values, rent, and income, I adjust the amounts for the year 2000 to 2010 dollars. Similarly for the 2019 data set, I adjust the amounts to 2018 dollars.

[13]I chose to count any increase in White population as whitening for several reason. First, while socioeconomic factors increased on average across the whole city, on average White population decreased from 2000 to 2010 and from 2011 to 2018, therefore any increase is a deviation from the city trend during both time periods. Second, changes in demographics are likely noticed with smaller scale shifts than changes in socioeconomic factors where an increase of a few dollars in median income will not be noticed but an increase of a few White residents in a neighborhood that has been predominantly Black and Hispanic will likely be a salient change noticed by the people in the neighborhood. There were some tracts in the city where the white population percentage decreased although the white population increased numerically due to greater increases in members of other groups. I do not choose to consider these tracts as whitening because increases in white population are not the predominant type of racial/ethnic demographic change, therefore whitening would be not the salient demographic shift, and the majority of those tracts were already prosperous.

Figure 1.6: Tracts by Type 2000-2010

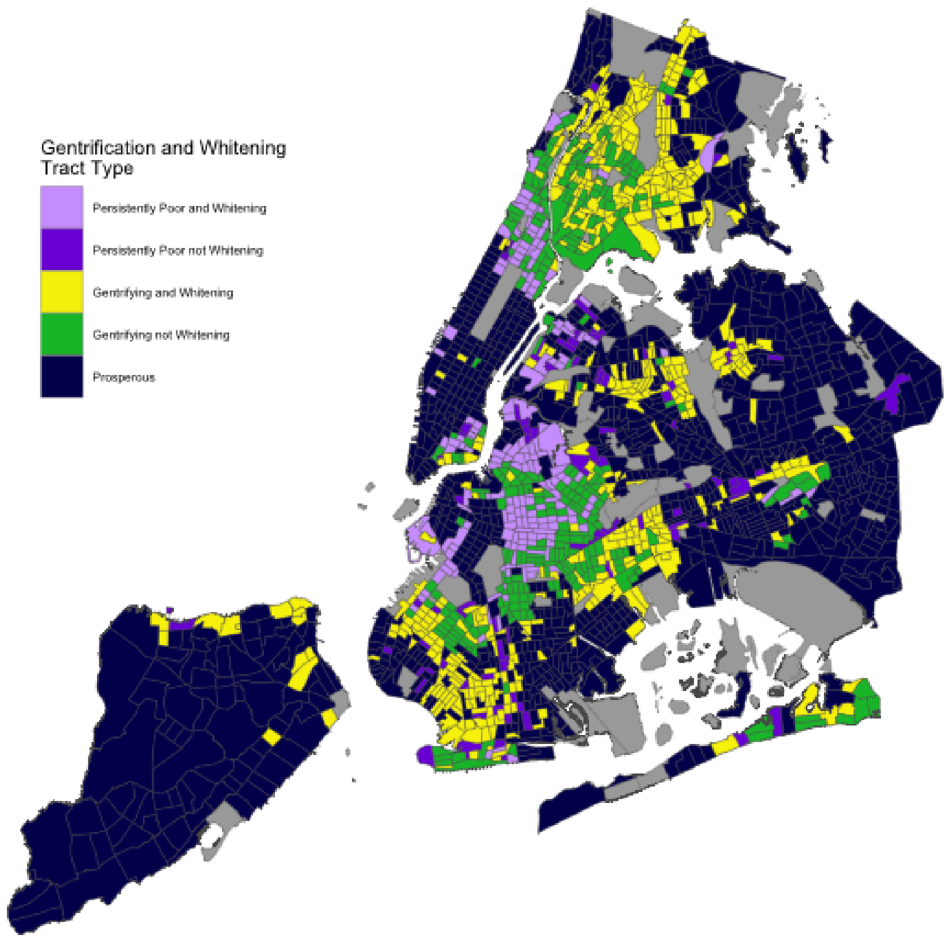
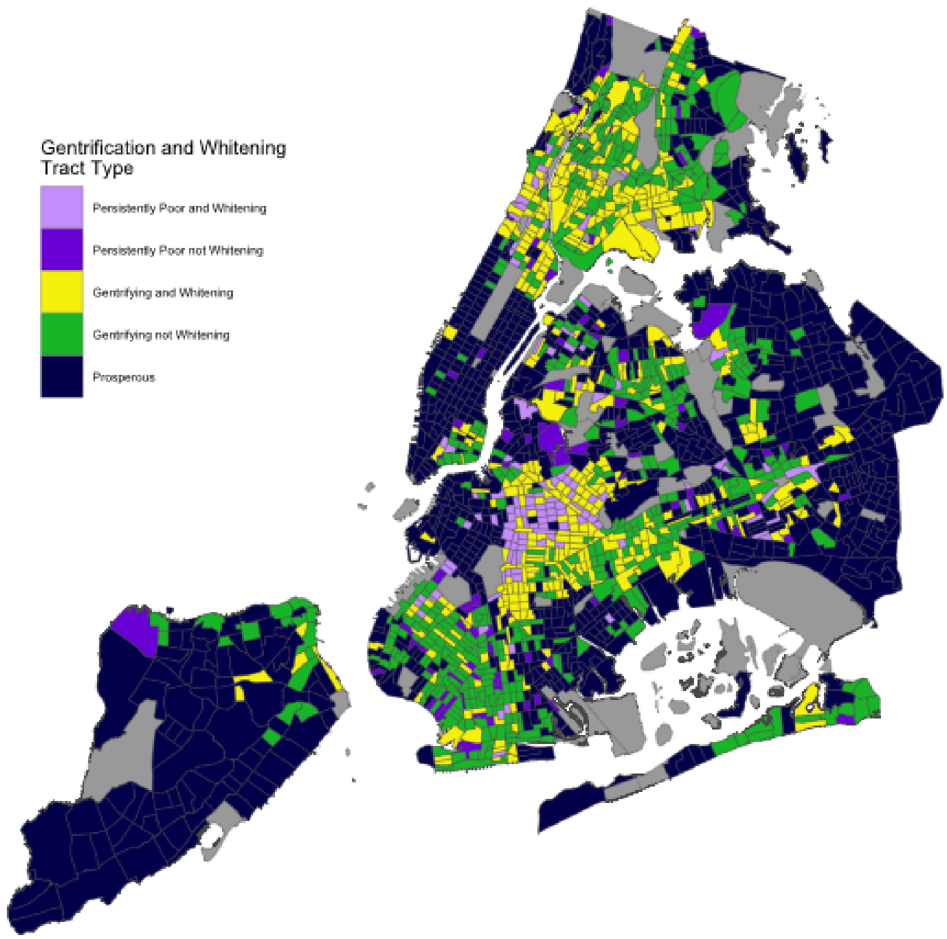


Figure 1.7: Tracts by Type 2011-2018



those tracts in which the number of White residents declined – i.e. those where the White percentage grew due to outmigration of non-White residents. Incorporating this additional parameter into the gentrification tract typology results in a new classification with five categories: not-gentrifiable, which I will call prosperous tracts; gentrifiable but not whitening or gentrifying, which I will call poor and not whitening tracts; gentrifiable and whitening but not gentrifying, which I will call poor and whitening tracts; gentrifying but not whitening tracts; and gentrifying and whitening tracts. I classify tracts into these five categories in 2011 using the 2000 census for time one and the 2010 census for time two. I do the same for 2019 using the 2007-2011 ACS estimates for time one and the 2014-2018 ACS estimates for time two. See Figure 1.6 for a map of the tracts by type in 2011 and Figure 1.7 for tracts by type in 2019 (tracts left blank are those that encompass parks, cemeteries, a coast guard base, and Riker's Island, which are excluded from the analytic sample) and Table 1.1 for a summary of tracts by type in both years. The maps demonstrate the change in tracts over time. Many tracts that were poor in 2010 are gentrifying by 2018.

### 1.3.2 Methods

The outcome variables for all three studies in this dissertation are counts – counts of stops and counts of complaints. For each of the outcomes, the data are overdispersed, meaning their variance is greater than their mean. Rather than a mean and variance both equal to $\mu$, as is assumed by the Poisson model, the negative binomial model assumes a mean of $\mu$ and a variance of $\mu + \alpha\mu^2$. When there is no overdispersion and, therefore, $\alpha = 0$, the negative binomial distribution reduces to the Poisson distribution. All models are run in Stata 2015. Alpha is significant in all the full models (the log of alpha is reported in all regression tables as lnalpha), indicating that negative binomial regression is indeed preferable to Poisson for modeling these data.

Each model includes a logged population at risk for each outcome. The population at risk is the population that is at risk for whatever is being counted. For 311 complaints that result in the NYPD taking some action against the subject of the complaint, the population at risk is the total number of 311 complaints responded to by the NYPD. In the case of police stops, if we are counting all stops in a tract then the population at risk would be the full population in that tract. In the case of stops of Black individuals, the population at risk is the Black population of the tract. The most accurate population at risk would be the count of how many people were actually at risk at any given time when a stop or complaint was made. However, due to data limitations, we have to make do with the residential population of the tract.[14]

I include the logged population at risk in the negative binomial models as both a predictor and an offset[15] with the coefficient constrained to one, which effectively

[14]For some parts of the city, this will mean that the population at risk is too small, thereby inflating the rate. This would happen for neighborhoods where there is a small residential population but a lot of daily foot traffic and a lot of opportunity for individuals to be stopped. In other parts of the city, the population at risk may be inflated making the rate look smaller than it should. This might be in residential tracts where fewer people are out on the street during the day so there is less opportunity for the police to make stops than implied by the size of the residential population. I attempt to control for this through the inclusion of the measure of average land use, which takes into account those commercial areas where there may be more foot traffic than there is residential population.

[15]The offset is necessary when modeling count outcomes that do not have the same baseline for each unit of analysis in the data set. For example, for each tract in the data set there are a number of stops and a number of total people who have the potential to be stopped. The offset essentially acts as a denominator so that the outcome can be interpreted as a rate that is scaled by the relevant population. Because the Poisson and negative binomial regression models log the outcome variable,

allows the count outcome to be interpreted as a rate or count per capita while separately predicting the effect the number of people of the relevant group has on stops of people in that group beyond mere risk.

Following Osgood (2000), the log of the population at risk can be added as a predictor rather than as an offset. When added as an offset, Stata automatically constrains the coefficient to 1, which means we lose any information about the effect of the size of the population at risk on the outcome. Osgoode suggests we include the logged population at risk as a predictor instead, and then interpret the coefficient compared to 1 rather than 0. We can understand the magnitude of the effect by subtracting the coefficient from 1. A coefficient greater than 1 indicates that areas with larger populations at risk have higher per capita stop rates. A coefficient smaller than 1 indicates that areas with larger populations at risk have lower per capita stop rates. By including the logged population at risk as both an offset and as a predictor variable, we effectively decompose the effect into the part that accounts for rate, for which Stata constrains the coefficient to 1, and the part that accounts for the effect the size of the relevant population has on the rate, for which we can interpret the coefficient.

In the findings sections in each of the following three empirical chapters, I will report effect sizes and p-values from my regression models. The data I use in this dissertation comprise the known population of stops in 2011 and the known population of 311 complaints in 2011 and 2019. Given that, the reader may wonder why I include

the variable for the population at risk must also be logged. Stata provides two options for the negative binomial regression command, the expsoure option that accepts an unlogged variable and then logs it for the user, and the offset option that accepts an already logged variable.

the results of the automatically generated significance tests. I do so because, while the findings are descriptive of the relationships in the known population of stops and complaints, those populations are subject to measurement error and the results can also be interpreted as predictions for relationships in other populations of stops and complaints, for example in years that I do not include in this study due to data limitations, in which case the p-values are a useful, if imperfect, benchmark.

## 1.4 Roadmap

In chapters that follow, I will present three empirical studies of social control and neighborhood change. In Chapter 2, I investigate the relationship between gentrification and neighborhood whitening and direct social control enacted by the NYPD in the form of street stops as part of the SQF program. I demonstrate that increases in White population are associated with subsequently higher per capita stops of Black individuals in poor and gentrifying neighborhoods and higher per capita stops of Hispanic individuals in gentrifying neighborhoods, compared to non-whitening neighborhoods of the same socioeconomic status. Increases in White population are not associated with the number of stops of White individuals, however.

In Chapter 3, I investigate the relationship between gentrification and whitening and 311 complaints that are sent to the NYPD. Beyond the substantive reason for the complaint, these complaints represent attempts by individuals to bring the NYPD to the neighborhood to exert social control over others. In this chapter, I look separately at complaints that the NYPD receives, actually responds to, and those complaints that result in corrective action by the police. I find that gentrifying and whitening tracts had the highest per capita number of complaints sent to the NYPD, with rates significantly higher than their non-whitening, gentrifying counterparts. I also find that whitening in both poor and gentrifying neighborhoods is associated with significantly more per capita complaints that result in informal police action than in poor and gentrifying tracts that did not whiten, but whitening in gentrifying tracts is associated with significantly fewer per capita complaints that result in formal police action compared to their non-whitening counterparts.

Chapter 4 presents an investigation of the relationship between neighborhood change and the kind of complaints that make up the largest proportion of those sent to the NYPD – residential noise complaints. Although these complaints are folded into the complaints analyzed in the previous chapter, I single them out here because they represent complaints made about behavior that occurs in the privacy of one's own home, norms around which can differ by background and culture. Complaints about residential noise represent attempts by individuals to change the private behavior of their neighbors through intervention from local officials. Whereas in Chapter 3 the focus is on NYPD response and action, in this Chapter, I focus on complaints about specific behavior, which carry cultural implications, the details of which are lost in analysis of bigger aggregate categories of complaint. I demonstrate that the combination of gentrification and whitening is associated with significantly higher rates of calls for service regarding loud music/parties and loud talking compared to all other neighborhood types. In the conclusion, I discuss the findings and their implications, limitations of the research, and avenues for future work.

# Chapter 2

# "Hands where I can see them":

## Neighborhood change and social control through Stop, Question, and Frisk

## 2.1 Introduction

Recent events have drawn increased attention to interactions between the police and people of color (Smith, 2020; Restuccia and Li, 2020). Discriminatory patterns of policing have led to lawsuits and consent decrees aimed at police departments across the country. The spotlight has illuminated stark differences in patterns of policing in richer whiter neighborhoods compared to poorer neighborhoods with more residents of color (Gordon, 2018). Simultaneously, there has been extensive socioeconomic and demographic shifts within cities over the past several decades (Richardson et al., 2019; Angel and Lamson-Hall, 2014). Existing literature on neighborhood change focuses primarily on how influxes of commercial and residential investment and higher-income residents affect housing prices, displacement of poorer residents, and crime rates (Atkinson, 2000; Guerrieri et al., 2013; Kirk and Laub, 2010; Papachristos et al., 2011). Qualitative literature provides anecdotal evidence of the impact of neighborhood change on culture, social ties, and social control (DeSena, 2012; Freeman, 2006; Kasinitz, 1988), but there is not yet a systematic account of patterns of formal social control in changing neighborhoods across a city. In this chapter, I seek to fill that gap with an investigation of the effect of neighborhood racial and socioeconomic change on patterns of street stops made by police.

To investigate this issue, I ask to what extent increases in members of a privileged group, especially in spaces previously dominated by members of a less privileged group, affect racial patterns in police stops. In other words, to what extent does the increased presence of such new residents adversely affect old residents by subjecting them, directly or indirectly, to increased social control? Additionally, I ask to what extent increases in socioeconomically privileged residents versus increases in racially privileged residents differ in their association with patterns of social control. To that end, I analyze how gentrification and increases in white population from 2000 to 2010 affected rates of police stops by race in 2011, controlling for contemporary neighborhood characteristics.

I hypothesize that (1) there will be a higher rate of policing in poor and gentrifying neighborhoods previously inhabited predominantly by members of less privileged groups that whitened (gained white population) and (2) the additional policing will disproportionately burden people of color, in other words, there will be more stops of Black and Hispanic residents but not of white residents despite increases in white share of the population. I argue that, in spite of potentially positive outcomes for neighborhoods resulting from socioeconomic change and increased residential integration, there are negative consequences for the less privileged group when more socially privileged residents move into spatial proximity. One potential mechanism linking demographic and socioeconomic change to increased social control may be that as new residents pull the social norms of their neighborhoods towards white, middle-to-upper-class norms, Black and Hispanic residents could receive greater police attention due to suspicion triggered by bias. It may be that officers begin to perceive these residents as out of place as the context changes around them.

Ongoing processes of neighborhood change and urban residential churning[1] that many cities are experiencing makes understanding these consequences extremely important. The implications of discrimination that local residents may face as more racially and socioeconomically privileged residents move into their neighborhoods represents an understudied phenomenon with potentially life-altering consequences. Understanding these patterns can inform public policy on housing and zoning, community organizing, community policing, police training, and the implementation of police practices related to suspicion and low-level offenses.

[1] Residential churning refers to the constant movement of residents into and out of neighborhoods by analogy with churn rate used to describe the movement of individuals into and out of groups usually with regard to employment or customer base. Residential churning is usually related to residential and economic instability and rapid neighborhood change (See (Kingsley et al., 2012; Thomas et al., 2016; Schachter and Besbris, 2017).

## 2.2 Background and Literature

### 2.2.1 Policing Race and Space

As representatives of a local government institution, the police are essentially armed civil servants, tasked with putting themselves on the line to enforce laws, provide aid, and protect citizens from harm. However, a substantial body of research has demonstrated the ways in which policing is not evenly distributed, spatially or socially. The law-enforcement part of policing seems to fall disproportionately on people and communities of color, while those communities simultaneously feel deprived of protection and aid.

On average, white individuals have lower rates of contact with the police than people of color, despite evidence that rates of criminal offending are generally comparable across racial groups (Berger et al., 2015; Crutchfield et al., 2012b). People of color are more likely than white people to be subject to drug arrests though there is no evidence that they use drugs more or commit more drug related offenses (Mitchell and Caudy, 2015). Black drivers are more likely to experience traffic stops than white drivers (Engel and Calnon, 2004b). People of color are more likely to experience street stops than white people, despite the fact that when people of color are stopped on the street they are less likely to have any contraband confiscated and less likely to receive a summons or be arrested, suggesting that stops of people of color are more likely to be prejudicial while stops of white people are more likely to be based on accurate suspicion (Fagan, 2012). In other words, when police stop white individuals, the suspicion that led to the stops is more often proven accurate, resulting in higher rates of arrest, summons, and/or seizure of illegal items.

Just as individual people of color are more likely to have negative encounters with the police in the latter's law enforcement capacity, there is corresponding evidence of an overpolicing[2] of places associated with people of color, poverty, and disadvantage (Alexander, 2010; Gelman et al., 2007; Goffman, 2009). Smith and Holmes (2014) found evidence to suggest that "disadvantaged minority neighborhoods may trigger myriad social psychological responses among police officers that make the gratuitous use of force more likely" and that police are more likely to use excessive force against people of color in particular spatial and social contexts.

The fact that policing imposes social control disproportionately on Black Americans in the United States stems, in part, from the slave catcher origins of police in parts of the country (Barkan and Bryjak, 2011; Bass, 2001a). Police historically played a role in maintaining spatial boundaries through the enforcement of laws related to the "Black Codes",[3] "Sundown Towns" (i.e. towns in which people of color were only allowed before sundown and therefore places where they could work but not live), and through participating in racialized violence aimed at intimidating Black people who integrated previously white spaces (Bass, 2001b; Hirsch, 1998; Loewen, 2005; Sugrue, 2014; Blackmon, 2009; DuBois, 1935).

[2]Overpolicing (otherwise over policing or over-policing) has come to refer to the criminalization of and enforcement against everyday behaviors, generally in communities of color, as well as the militarization of the police. See (ACLU, 2007; Madar, 2017) and #overpolicing on Twitter: https://twitter.com/hashtag/overpolicing

[3]"Black Codes," were the precursor to Jim Crow Laws. They were enacted following the end of the Civil War and were intended to control the behavior and movement of Black individuals, particularly in the South. They included prohibitions against vagrancy and other behaviors very similar to contemporary "quality of life" infractions, and they were explicitly intended to be used against Black people (Blackmon, 2009; DuBois, 1935).

While communities of color experience overpolicing in the form of disproportionate law and boundary enforcement,[4] communities of color simultaneously experience underpolicing in terms of aid and protection that police are supposed to provide. Evidence suggests that people of color are less likely to call the police for help in an emergency especially following high profile, local incidents of police violence (Desmond et al., 2016) and people of color tend to see police more negatively than white people do because of negative experiences both at the individual and network level (Lee and Gibbs, 2015; Rosenbaum et al., 2005) These negative experiences contextualize the sentiment ethnographers have noted among members of communities of color that police are not adequately balancing their range of responsibilities, but are harassing local youth while ignoring community needs (Brownlow, 2017; Freeman, 2006; Gau and Brunson, 2015; Goffman, 2009; Sugrue, 2014).

### 2.2.2 Policing Changing Neighborhoods

Less research exists on patterns of policing in changing neighborhoods. Anecdotal evidence suggests that policing, or at least residents' perceptions of levels of policing, increases in neighborhoods with incoming white and higher-SES residents. Some residents perceive increases in city attention and police protection in response to more white residents (Coscarelli, 2014). Many residents who see their neighborhoods changing around them in New York believe the police force to be mostly white[5] and,

[4]Here I refer to disproportionalities in law enforcement as overpolicing. By this I mean that when police are more likely to enforce laws against one group of people and not another despite no differences in underlying rates at which people do illegal things, then it is overpolicing of one group and underpolicing of another.

[5]In fact, based on a report done in 2007, the NYPD was 54% white. However, that is significantly more white than the city as a whole which was about 33% white in 2007. At the time of the study,

therefore, naturally "more responsive" to white residents and areas where the white population is increasing (Freeman, 2006, 103) because they are "more protective of their own kind" and also in part because white residents may demand more from the police than their non-white neighbors (Freeman, 2006, 102).

Another mechanism linking racial and socioeconomic change to policing may be that, just as higher-SES white residents are salient signals of change to the residents of Black and Latino neighborhoods, they may also be particularly salient to police officers. Police rely on available, perceivable cues for evaluating situations, forming suspicion, and making decisions (Alpert et al., 2005). Therefore, visually salient cues are likely important in shaping patterns of low-level policing in the form of Terry Stops,[6] often called Stop, Question, and Frisk (SQF) in New York, which requires officers to make quick decisions to initiate interaction based on their observations. The history of police enacting social control over communities of color in order to maintain a racialized spatial order, where police enforcement kept Black citizens from venturing out of place, combined with new types of neighborhood change that include increases in white higher-SES residents, may result in Black and Hispanic residents appearing more and more out of place where they were previously unremarkable (Bass, 2001b). Perhaps, when white residents move in, their presence is a visual cue of the beginning of a shift in that neighborhood towards a "white space" (Anderson,

Hispanics in the NYPD were at approximate parity with their share of the city population, Asians were overrepresented, and Blacks were underrepresented (Cohen and Fredericks, 2014)

[6] Terry Stops refer to a type of police stop. They are named Terry Stops after the 1968 Supreme Court ruling in Terry v. Ohio, which established that police officers could briefly detain someone based on a reasonable suspicion that the individual was in the process of or about to commit a crime and that the officer could conduct a pat down of the outer garments if there was a reasonable suspicion that the person was armed and a danger to the officer and/or others.

2015).

Research has shown that the interaction between race and place is important in understanding patterns of policing. Black drivers are more likely to be stopped when driving through white neighborhoods despite lower levels of offending in those areas (Meehan and Ponder, 2002) and they are more likely to be frisked once stopped when they appear out of place in predominantly white neighborhoods (Carroll and Gonzalez, 2014). When space that has been associated with one group is, suddenly or slowly, inhabited by members of a group with greater social privileged and power, it is likely there will be corresponding changes in patterns of social control in that neighborhood. As the demographic and socioeconomic landscape changes, people and behaviors that were once the norm may begin to seem deviant or out of place, inviting suspicion and higher rates of formal social control.

## 2.3 Models

For this analysis, I use the master data set for 2011 described in Chapter 1. My outcomes of interest are the total number of stops for each tract in 2011, broken down by the recorded race/ethnicity of the person stopped.[7] My predictor of interest is my gentrification and whitening tract typology. I hypothesized that poor and gentrifying neighborhoods that whitened would have higher rates of policing that

[7]Here race/ethnicity are determined by what the officer chose to write on the UF-250 form for the stop. It may be that the individuals would self-identify in other ways. The analysis is capturing the association between neighborhood change and stops of people perceived by officers to be of each different racial/ethnic group. For our purpose, this is preferable to self-identified race/ethnicity. The argument that neighborhood whitening is a salient cue of neighborhood change that is associated with more policing of people of color suggests that police will pay more attention to people they perceive to be of color, which is what the race variable in the UF-250 actually measures.

would disproportionately affect Black and Hispanic residents compared to white residents. To investigate this hypothesis, I conduct separate analyses for all stops and for stops broken down by race of the person stopped for Black, Hispanic, and white residents (see Table 2.1 for descriptive statistics). I use the same base models to investigate each outcome and to compare across outcomes. While I cannot make causal claims, I have fixed the temporal order by predicting 2011 stops with the change in tracts from 2000 to 2010.

Table 2.1: Descriptive statistics by tract (n=2,099)

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Total Stops | 311.03 | 400.50 | 0 | 3453 |
| Black Stops | 160.04 | 274.99 | 0 | 3066 |
| Hispanic Stops | 101.22 | 167.17 | 0 | 1610 |
| White Stops | 27.39 | 37.19 | 0 | 468 |
| White Population % in 2000 | 25.75 | 32.51 | 0.11 | 99.00 |
| White Population % in 2010 | 33.51 | 30.95 | 0.07 | 99.60 |
| Crime Rate/1,000 pop | 19.16 | 99.06 | 1.17 | 3470.09 |
| Violent Crime Rate/1,000 pop | 5.99 | 19.01 | 0 | 619.05 |
| Property Crime Rate/1,000 pop | 13.17 | 82.95 | 0.58 | 2974.36 |
| Median Household Income 2000 in 2010$ | 40803.36 | 18919.07 | 6771.00 | 188697.00 |
| Median Household Income 2010 | 57068.22 | 27622.64 | 9675.00 | 250001.00 |
| Building Permits in 2011 | 12.47 | 19.13 | 0 | 385 |
| # NYCHA Buildings | 4.92 | 17.32 | 0 | 193 |
| Average Landuse | 1.42 | 0.40 | 1 | 3 |
| Population | 3884.54 | 2105.34 | 73 | 26588 |

Equation 2.1 represents the simplest form of my conceptual model, which predicts the number of police stops in tract $i$ in year $t$, where $t$ is 2011, with the tract typology I described above ($TractType$) and the logged population at risk:

$$stops_{it} = \beta_{i0} + \beta_{i1} TractType_{i(t-1)} + \beta_{i2} LoggedRiskPopulation_{i(t-1)} + u_{it} \qquad (2.1)$$

The stated official policy for the implementation of SQF in NYC was to focus attention on areas with high crime rates. To account for this, I control for crime with a rate of all violent crimes (non-negligent homicide, aggravated assault, and robbery) and a rate of all property crimes (burglary, larceny, and motor vehicle theft) in 2011 per 1,000 population. I additionally include the non-Hispanic white population percent in 2000 to account for the baseline white population in the tracts.

I include a control for the number of public housing project buildings in each tract due to the possibility that their reputation as crime hotspots will lead to increased policing (Fagan et al., 2012b; Ryley et al., 2014). I also control for land use to account for possible differences in stop patterns in residential and non-residential spaces. For this I use the previously described average land use scale. I control for building permits that represent new investment in a tract by including a sum of all permits issued in 2011 for new buildings, major renovations, and demolitions. Additionally, I include dummy variables for each borough (Manhattan is the omitted category) to capture possible borough-specific effects.[8]

[8] I chose not to use police precinct fixed effects to account for difference in policy and practice across precincts for several reasons. First, tracts do not fall neatly into precincts in NYC. Many tracts fall across precinct boundaries and, therefore, are policed by officers who report to different precincts – sometimes this is a case of a tract that belongs to two different precincts, but there are also many instances where tracts fall across boundaries for three, four, or more precincts. This creates a difficult situation of deciding which precinct to assign a tract to for the sake of fixed effects. One potential solution to this geographic problem is to use census blocks rather than tracks for the unit of analysis. I chose not to do this because census blocks are geographically small for capturing meaningful change in neighborhood demographics. Another problem with using police precinct fixed effects stems from issues related to fixed effects estimation in count data methods. Allison and Waterman (2002) demonstrate the problems of using statistical software commands for negative binomial fixed effects estimation, which produces conditional fixed effects. They suggest including dummy variables in the regression equation, rather than using the pre-coded commands, to create unconditional fixed effects estimation, but this can produce estimates with standard errors that are too small and must be corrected, and while there is evidence that this solves the problem of bias from incidental parameters it is likely that any problems of bias will be compounded by the issue of tract assignment to precincts. For these reasons, I have chosen not to use precinct fixed effects. I did, however, perform robustness checks with precinct dummy variables for unconditional fixed

There are several controls for markers of poverty and tract socioeconomic status that I did not include in the final models whose exclusion should be noted. I ran the models both with and without the percent female-headed households, the percent unemployed, and the percent of housing units that were vacant. Likelihood ratio testing indicated that these controls did not significantly improve the model either individually or in combination; therefore, I left them out of the final models for the sake of parsimony.

To achieve linear bivariate relationships with the outcomes, I log the crime rates. I estimate robust standard errors clustered on Neighborhood Tabulation Area (NTA) to address the possibility of a violation of the assumption of independent errors due to the spatial relationship of tracts within NTAs and boroughs.[9] I choose to cluster on NTA rather than borough because any spatial effects are more likely to be seen at a smaller distance than borough, which are large and internally heterogeneous

effects. To do this, I use the publicly available shapefile for police precincts. In QGIS, I map tracts to precincts and calculate the percentage of the tract area that falls in each precinct. I then assign a tract to the precinct in which the majority (or in a small number of tracts, the plurality) of its area falls. Sensitivity checks indicate that the results are substantively the same when tracts that fall about evenly between precincts are assigned to either precinct. Predicted counts of stops with the precinct fixed effects produce a pattern similar to those produced by the analysis without fixed effects presented in this chapter.

[9]Neighborhood Tabulation Areas are geographic units that were created by the NYC Department of Planning. While they do not represent exact historical neighborhood boundaries, they are useful because they encompass whole census tracts. https://data.cityofnewyork.us/City-Government/Neighborhood-Tabulation-Areas-NTA-/cpf4-rkhq

geographic areas. Equation 2.2 shows the full model:

$$
\begin{aligned}
stops_{it} = \beta_{i0} + \beta_{i1} TractType_{i(t-1)} + \beta_{i2} PercentNonHispanicWhite_{i(t-11)} + \\
\beta_{i3} LoggedViolentCrimeRate_{it} + \beta_{i4} LoggedPropertyCrimeRate_{it} + \\
\beta_{i5}[\mathbf{Z}_{i(t-1)}] + LoggedRiskPopulation_{i(t-1)} + u_{it}
\end{aligned} \tag{2.2}
$$

where $\mathbf{Z}$ is a matrix of spatial characteristics: total public housing buildings, total building permits, average land use, and borough.

### 2.3.1 Methods

I use the full model described above for all outcomes, except to predict white stops. To predict white stops, it is necessary to alter the model in two ways. First, I exclude the baseline measure of non-Hispanic white population percent in 2000 as it is multicollinear with the logged population at risk, which is the white population when predicting white stops. In its place, I include the not-white population in 2000. Additionally, postestimation link tests[10] show that the model predicting white stops is properly specified when borough dummies are excluded and tract type is interacted with the Non-Hispanic white population percent in 2000.[11] Additionally, according to

[10] The link test, based on Tukey (1949), tests if the link between the dependent and independent variables is appropriate or if the dependent variable should be transformed in order to appropriately relate to the independent variables. The test in Stata adds the squared independent variables to the model and then tests for significance when compared to the unsquared model. If the t-test for the squared model versus the unsquared model is not significant then there is no link error. If the t-test is significant, then the dependent variable should be transformed or, as is commonly done, although it is a misinterpretation of the test, additional independent variables and/or transformations of independent variables can be added to achieve proper model specification.

[11] I suspect this may be due to a combination of factors. First, overall Staten Island has many more white stops on average than the other boroughs. Second, there are a handful of outlier tracts with substantially more stops of white individuals than average in Brooklyn, Manhattan, and Staten

the link test, the full model predicting all stops is not properly specified unless it also has an interaction between tract type and Non-Hispanic white population percent in 2000. Predicted counts from the final models indicate they provide good fit of the observed data. I run the models both with and without standard errors clustered on the Neighborhood Tabulation Area – the results are the same. Below I present the results from the models with the clustered standard errors.

## 2.4 Findings

### 2.4.1 Total Stops

To test my first hypothesis, that whitening in poor and gentrifying neighborhoods was associated with higher rates of stops, I run my models predicting all stops in 2011. Table 2.2 shows results from the full and constrained models. Likelihood ratio testing indicates that the full model is preferable to the constrained models and results of the postestimation link test show that the full interaction model is properly specified, so I will limit my discussion to Models 3 and 4.

Stops per capita were very different depending on tract type, as demonstrated by the predicted counts for Model 4 shown in Figure 2.1. The plots of predicted counts presented in this dissertation were created using the -margins- and -marginsplot- commands in Stata. They show counts predicted for each tract type holding the covariates at their means for the full sample using the -atmeans- option – in other words, they represent net effects of tract type holding all else constant.

Island.

Table 2.2: Models predicting stops per capita in 2011

| | All Stops | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| ***Tract Type*** | | | | |
| Prosperous | 0.427*** | 0.771*** | 0.727*** | 0.498*** |
| | (0.04) | (0.05) | (0.04) | (0.04) |
| Poor and not Whitening (reference) | | | | |
| Poor and Whitening | 1.450*** | 1.134 | 1.070 | 1.023 |
| | (0.15) | (0.08) | (0.07) | (0.07) |
| Gentrifying but not Whitening | 0.539*** | 0.789*** | 0.794** | 0.635*** |
| | (0.10) | (0.06) | (0.06) | (0.07) |
| Gentrifying and Whitening | 1.180 | 0.945 | 0.858* | 0.832* |
| | (0.14) | (0.07) | (0.06) | (0.07) |
| ***Controls*** | | | | |
| Non-Hispanic White Pop % 2000 | | 0.990*** | 0.988*** | 0.982*** |
| | | (0.00) | (0.00) | (0.00) |
| Log of Violent Crime Rate | | 1.327*** | 1.281*** | 1.293*** |
| | | (0.04) | (0.04) | (0.04) |
| Log of Property Crime Rate | | 1.501*** | 1.449*** | 1.441*** |
| | | (0.08) | (0.07) | (0.06) |
| # of Issued Building Permits | | | 1.001 | 1.001 |
| | | | (0.00) | (0.00) |
| # of Public Housing Buildings | | | 1.003 | 1.003* |
| | | | (0.00) | (0.00) |
| Average Landuse | | | 1.430*** | 1.407*** |
| | | | (0.11) | (0.10) |
| Logged Pop at Risk (Total Pop) | 0.477*** | 0.892* | 0.876** | 0.850*** |
| | (0.07) | (0.05) | (0.04) | (0.04) |
| ***Borough*** | | | | |
| Manhattan (reference) | | | | |
| The Bronx | | | 0.695*** | 0.688*** |
| | | | (0.07) | (0.07) |
| Brooklyn | | | 0.898 | 0.966 |
| | | | (0.08) | (0.08) |
| Queens | | | 0.941 | 1.036 |
| | | | (0.09) | (0.09) |
| Staten Island | | | 1.992*** | 1.948*** |
| | | | (0.21) | (0.19) |
| ***Interaction*** | | | | |
| Prosperous*Non-Hispanic White Pop % 2000 | | | | 1.010*** |
| | | | | (0.00) |
| Poor & Whitening*Non-Hispanic White Pop % 2000 | | | | 0.998 |
| | | | | (0.00) |
| Gentrifying & not Whitening*Non-Hispanic White Pop % 2000 | | | | 1.007** |
| | | | | (0.00) |
| Gentrifying & Whitening*Non-Hispanic White Pop % 2000 | | | | 0.999 |
| | | | | (0.00) |
| lnalpha | 0.816* | 0.438*** | 0.381*** | 0.364*** |
| | (0.06) | (0.02) | (0.02) | (0.02) |
| BIC | 27593.790 | 26104.470 | 25837.242 | 25766.154 |

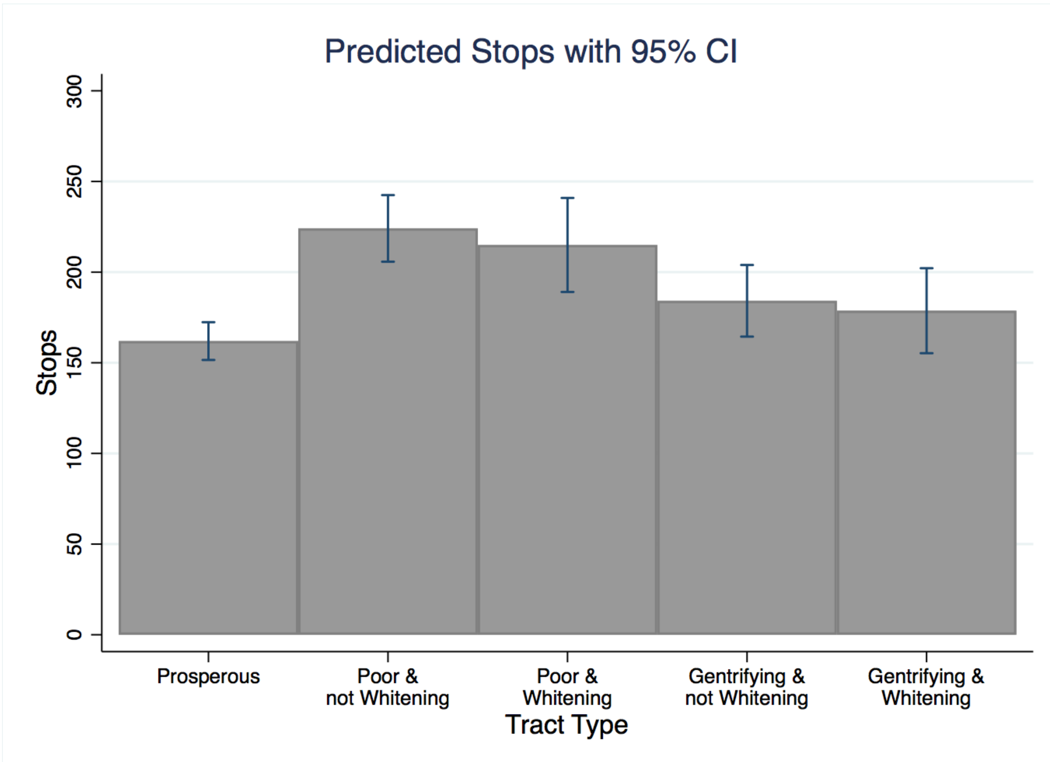
Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Looking at Table 2.2, the coefficient estimates for the covariates in Models 3 and 4 are consistent, with similar magnitude, direction, and significance. In tracts that were prosperous in 2000, there were fewer stops per capita than in all other tract types, all else held constant. There were not statistically significant differences in total stops per capita between poor tracts that did and did not whiten. Neither were there significant differences in total stops per capita between gentrifying tracts that did and did not whiten. The violent and property crime rates were both associated with stops in a predictable way – the more of each type of crime the more per capita stops there were. Given the police department's rhetoric regarding deployment of police to places with higher crime rates, we might also expect there to be a nonlinear relationship between crime and stops (Bloomberg, 2013; Bratton, 2015). To test this, I ran the models with a square term for the violent crime rate, for the property crime rate, and also ran the model with a combined crime rate and crime rate squared. Each model with a squared crime rate term did not pass the link test for specification, but the coefficients for the main predictors and other covariates stayed substantially the same. Even when controlling for crime rate, which the police department says is the main basis of their deployment decision making, the effect of tract type remains significant. Land use is also significantly associated with approximately 40% more stops per capita in tracts that are mixed residential and non-residential compared to fully residential tracts.

Figure 2.2 shows contrast plots with each tract type as reference. The contrast plots show the net difference in predicted stops for each tract type compared to the reference tract type, holding all covariates at their means. The contrast plots

Figure 2.1: Predicted number of stops by tract type

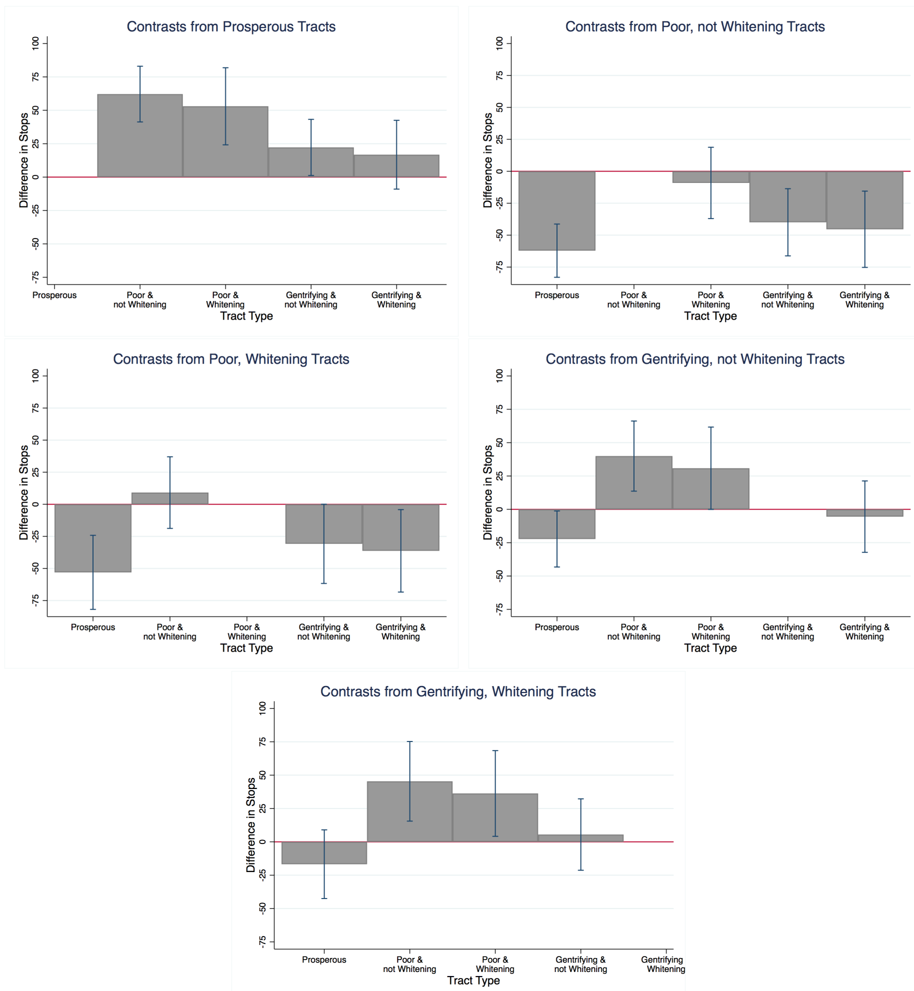
*Note: Figure shows stops predicted by the model by tract type holding all other covariates at their means.*




show that there were more stops per capita in both types of poor tracts compared to all other tract types. This is confirmed by a Wald test, which demonstrates that in poor tracts, both whitening and not, stops per capita were significantly higher than in tracts that were gentrifying but not whitening. We might expect higher levels of social control in poor neighborhoods due to documented inequalities in the distribution of policing across NYC, with more policing occurring in lower income neighborhoods with larger non-white populations (Fagan and Davies, 2000; Fagan et al., 2016; Lautenschlager and Omori, 2019). Gentrification, on the other hand,

Figure 2.2: Contrast plots for model predicting all stops

*Note: Figures show predicted net differences in counts for each tract type compared to the omitted reference category holding all other covariates at their means.*



seems to decrease the amount of police initiated social control. So far, whitening does not seem to impact this kind of social control, although that picture will change when we examine stops separated by the race/ethnicity of the people being stopped.

Figure 2.3: Predicted stops by tract type and Non-Hispanic white pop % in 2000

*Note: Figure shows counts predicted by the model by tract type across the distribution of non-Hispanic white population % holding all other covariates at their means*

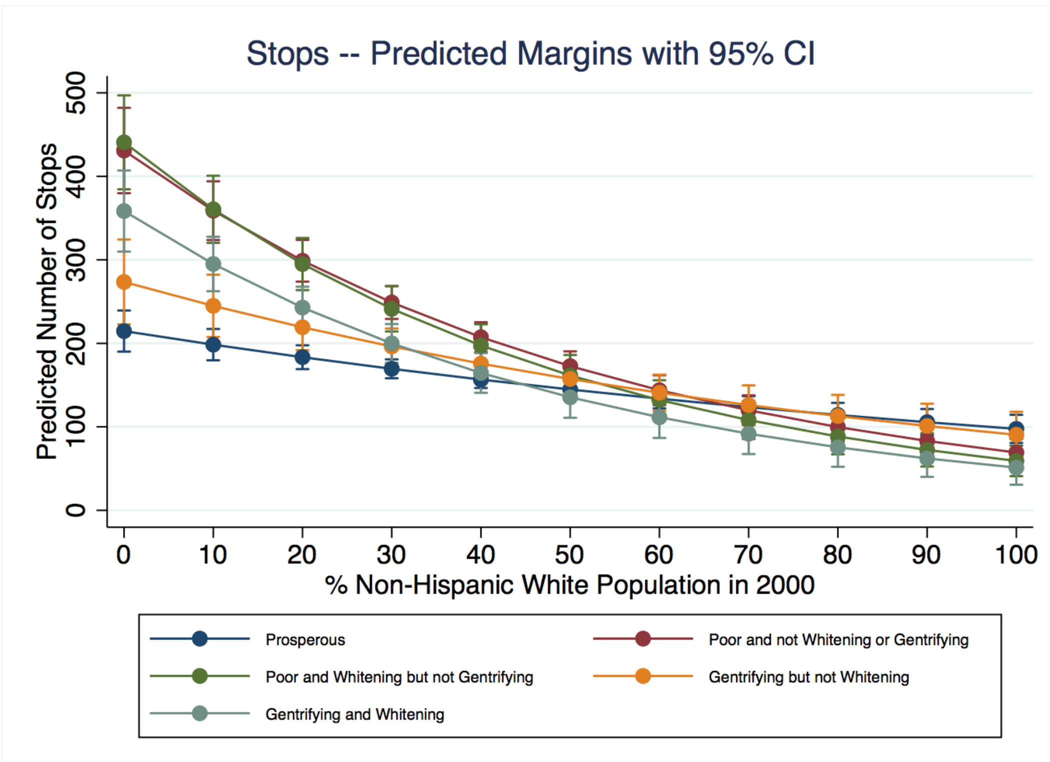



Figure 2.3 shows predicted stops by tract type and across the distribution of Non-Hispanic white population percent in 2000 from Model 4. Overall, across all tract types, there are fewer stops in tracts that started off whiter in 2000. Baseline whiteness of the tract has a greater effect in both types of poor tracts and in gentrifying and

whitening tracts than it has in prosperous tracts and gentrifying tracts that did not whiten. These findings suggest that the less white the neighborhood was to begin with in 2000, the more stops there were in poor neighborhoods and in gentrifying and whitening neighborhoods compared to prosperous tracts and gentrifying tracts that did not whiten. Prosperity and economic gentrification, therefore, seem to be somewhat protective, whereas poverty, in combination with a larger population of color, is associated with more social control in the form of street stops by the police.

### 2.4.2 Stops by race/ethnicity

When we modeled all stops together, we saw that poverty is associated with the highest levels of social control from the police compared to the other tract types. Whitening did not appear to be associated with street stops. However, aggregating all stops together, regardless of the race/ethnicity of the people being stopped, may have obscured certain relationships. Modeling stops by race/ethnicity separately, along with the tract typology that decouples socioeconomic and demographic changes, reveals patterns where whitening, specifically in poor tracts, is associated with more stops per capita of Black individuals, all else equal, but not with stops of Hispanic or white individuals. If there were higher levels of stops related with whitening tracts for all three race/ethnicity categories, then we might assume there is something in particular about whitening neighborhoods that draws more police attention, which may be indicative of systemic discrimination against particular types of places, but it would not necessarily represent discrimination against particular types of people. But, my analysis reveals a pattern in which whitening in poor tracts is associated with more stops of one group of people but not more stops of the others.

See Table 2.3 for comparison of the results across the three race/ethnicity models and Figure 2.4 for counts predicted by the models versus counts observed in the data for model fit.[12] Notice that the final model for white stops includes the baseline not-white population in 2000 as a control, rather than the Non-Hispanic white population baseline, which I include in the models of Black and Hispanic stops. This is for the same reason stated above – I include the logged white population in 2010 to control for the population at risk, and as an offset to make the predictions from the model interpretable as per capita counts, which means I cannot include the non-Hispanic white population percent in 2000 as an additional control due to multicollinearity. The model of white stops also includes an interaction to achieve proper model specification as detailed in the Methods section above.

Figure 2.5 shows predicted counts by tract type for the three race outcomes, holding covariates at their means. For all three groups, there are fewer stops per capita in prosperous tracts than poor tracts. However, in those poor tracts that whitened, there were 19.5% more stops of Black individuals per capita than in poor tracts that did not whiten. There were not significantly more Hispanic or white stops in poor tracts that whitened compared to poor tracts that did not whiten. In the case of Hispanic stops per capita, a Wald test confirms that there was not a significant difference in Hispanic stops per capita between the whitening and not whitening poor

[12]There are few postestimation tools available for evaluating negative binomial regression models. One option is to compare counts predicted by the model to counts observed in the data. The predicted versus observed plots used throughout this dissertation show the probability distribution of the observed counts and the probability distribution of the predicted counts plotted together. The more the predicted count probability distribution matches the observed probability distribution, the better the model fit.

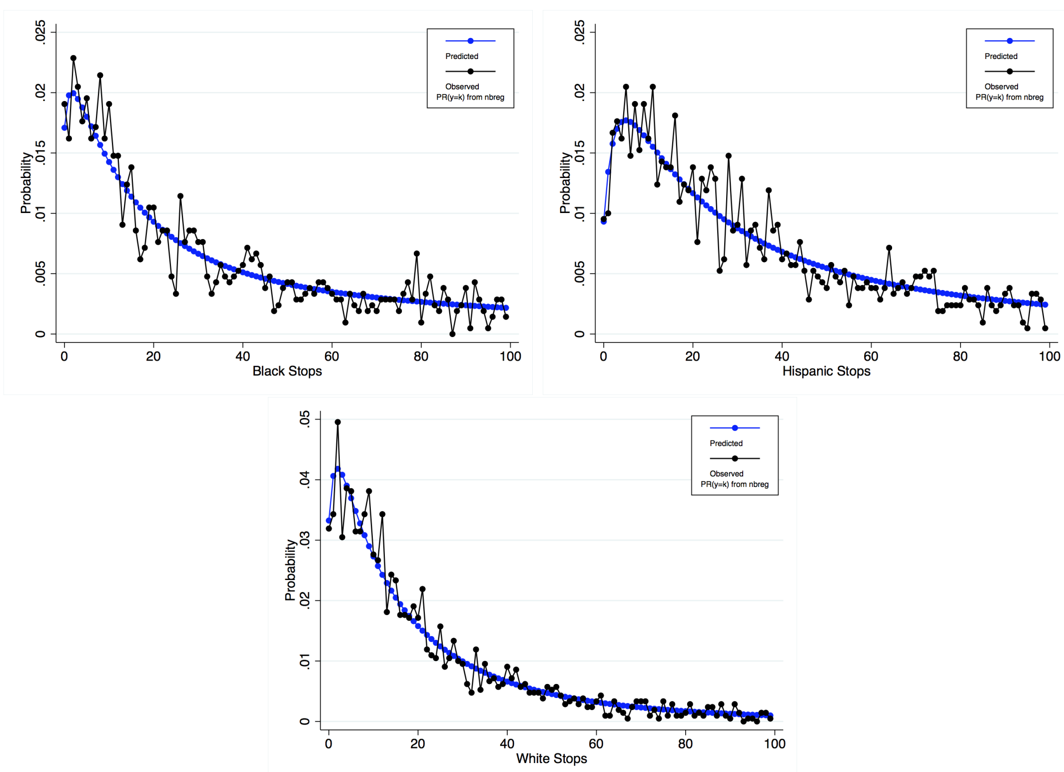
Table 2.3: Comparing Model 3 Across Race/Ethnicity

| | Stops | | |
|---|---|---|---|
| | **Black** | **Hispanic** | **White** |
| ***Tract Type*** | | | |
| Prosperous | 0.680*** | 0.661*** | 0.938 |
| | (0.07) | (0.05) | (0.16) |
| Poor and not Whitening (reference) | | | |
| Poor and Whitening | 1.195* | 0.947 | 0.339** |
| | (0.11) | (0.07) | (0.12) |
| Gentrifying but not Whitening | 0.695*** | 0.775** | 0.763 |
| | (0.07) | (0.08) | (0.15) |
| Gentrifying and Whitening | 0.862 | 0.812* | 0.464*** |
| | (0.09) | (0.07) | (0.12) |
| ***Interaction*** | | | |
| Non-White Pop %2000 * Prosperous | | | 0.995* |
| | | | (0.00) |
| Non-White Pop % 2000 * Poor not Whitening (reference) | | | |
| Non-White Pop % 2000 * Poor and Whitening | | | 1.010** |
| | | | (0.00) |
| Non-White Pop % 2000 * Gentrifying not Whitening | | | 1.002 |
| | | | (0.00) |
| Non-White Pop % 2000 * Gentrifying and Whitening | | | 1.005 |
| | | | (0.00) |
| ***Controls*** | | | |
| Not-White Pop % 2000 | | | 1.000 |
| | | | (0.00) |
| Non-Hispanic White Pop % 2000 | 1.001 | 1.002 | |
| | (0.00) | (0.00) | |
| Log of Violent Crime Rate | 1.432*** | 1.187*** | 1.298*** |
| | (0.05) | (0.04) | (0.04) |
| Log of Property Crime Rate | 1.293*** | 1.440*** | 1.140** |
| | (0.07) | (0.09) | (0.06) |
| # of Issued Building Permits | 1.007** | 1.004* | 1.008*** |
| | (0.00) | (0.00) | (0.00) |
| # of Public Housing Buildings | 1.004* | 1.000 | 1.008*** |
| | (0.00) | (0.00) | (0.00) |
| Average Landuse | 1.552*** | 1.648*** | 1.405*** |
| | (0.16) | (0.15) | (0.15) |
| ***Borough*** | | | |
| Manhattan (reference) | | | |
| The Bronx | 0.499*** | 0.554*** | |
| | (0.07) | (0.07) | |
| Brooklyn | 0.646*** | 0.767* | |
| | (0.08) | (0.08) | |
| Queens | 0.618** | 0.924 | |
| | (0.10) | (0.11) | |
| Staten Island | 0.875 | 0880 | |
| | (0.14) | (0.11) | |
| Logged Pop at Risk | 0.651*** | 0.871** | 0.632*** |
| | (0.02) | (0.04) | (0.02) |
| lnalpha | 0.599*** | 0.492*** | 0.632*** |
| | (0.03) | (0.03) | (0.04) |
| BIC | 21911.736 | 20663.707 | 16827.210 |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure 2.4: Predicted vs observed stop frequencies by race/ethnicity in 2011

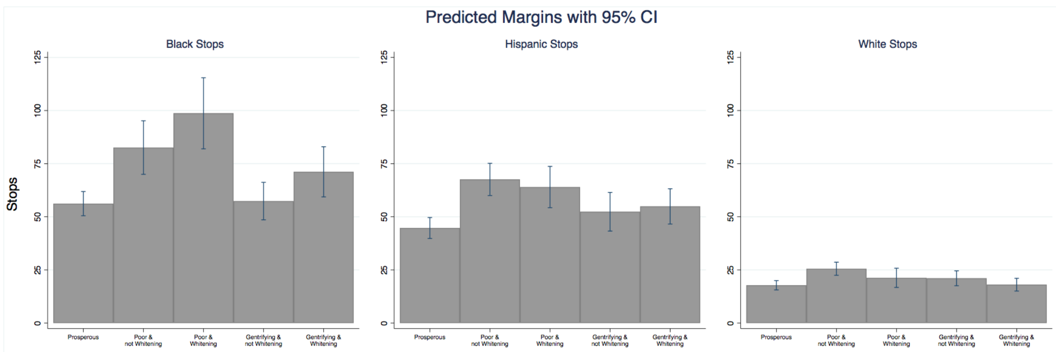
*Note: Figures show the probability distribution of the counts of stops predicted by the models plotted against the observed probability distribution from one stop through 99 stops, which is a maximum count limit imposed by the user generated -prcounts- Stata command that predicts count probabilities*



tracts. Tables 2.4, 2.5, and 2.6 show the effects for Model 3 with different tract type reference groups: prosperous tracts, poor tracts that did not whiten, and gentrifying tracts that did not whiten.

Figure 2.5: Predicted number of stops by tract type across three race/ethnicity groups

*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means*




For Black individuals, the number stops per capita in gentrifying tracts that did not whiten was statistically indistinguishable from the number of stops per capita in prosperous tracts. There were significantly more stops per capita of Black individuals in both types of poor tracts and in gentrifying tracts that whitened compared to prosperous tracts, all else equal. Compared to poor tracts that did not whiten, there were significantly fewer stops of Black individuals per capita in prosperous tracts and in gentrifying tracts that did not whiten. Gentrifying and whitening tracts were statistically indistinguishable from poor tracts that did not whiten, while whitening in poor tracts was associated with 19.5% more Black stops per capita compared to poor tracts that didn't whiten. With gentrifying tracts that did not whiten as the reference category, the coefficient for gentrifying tracts that did whiten is positive,

Table 2.4: Comparison of effects with different tract type reference groups for per capita stops of Black individuals in 2011

*Note: The first column holds out prosperous tracts as the reference. The second column holds out poor tracts that did not whiten as the reference. The third column holds out gentrifying tracts that did not whiten as the reference.*

| | **Stops of Black Individuals** | | |
|---|---|---|---|
| ***Tract Type*** | | | |
| Prosperous | | 0.680*** | 0.979 |
| | | (0.07) | (0.09) |
| Poor and not Whitening | 1.470*** | | 1.439*** |
| | (0.14) | | (0.15) |
| Poor and Whitening | 1.757*** | 1.195* | 1.720*** |
| | (0.19) | (0.11) | (0.20) |
| Gentrifying but not Whitening | 1.021 | 0.695*** | |
| | (0.09) | (0.07) | |
| Gentrifying and Whitening | 1.267* | 0.862 | 1.240 |
| | (0.13) | (0.09) | (0.14) |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 2.5: Comparison of effects with different tract type reference groups for per capita stops of Hispanic individuals in 2011

*Note: The first column holds out prosperous tracts as the reference. The second column holds out poor tracts that did not whiten as the reference. The third column holds out gentrifying tracts that did not whiten as the reference.*

| | **Stops of Hispanic Individuals** | | |
|---|---|---|---|
| ***Tract Type*** | | | |
| Prosperous | | 0.661*** | 0.854 |
| | | (0.05) | (0.09) |
| Poor and not Whitening | 1.512*** | | 1.291*** |
| | (0.12) | | (0.13) |
| Poor and Whitening | 1.432*** | 0.947 | 1.222 |
| | (0.15) | (0.07) | (0.14) |
| Gentrifying but not Whitening | 1.172 | 0.775*** | |
| | (0.12) | (0.08) | |
| Gentrifying and Whitening | 1.228* | 0.812* | 1.048 |
| | (0.13) | (0.07) | (0.12) |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 2.6: Comparison of effects with different tract type reference groups for per capita stops of white individuals in 2011

*Note: The first column holds out prosperous tracts as the reference. The second column holds out poor tracts that did not whiten as the reference. The third column holds out gentrifying tracts that did not whiten as the reference.*

| | Stops of White Individuals | | |
|---|---|---|---|
| ***Tract Type*** | | | |
| Prosperous | | 0.938 | 1.229 |
| | | (0.16) | (0.289) |
| Poor and not Whitening | 1.066 | | 1.311 |
| | (0.19) | | (0.26) |
| Poor and Whitening | 0.361** | 0.339** | 0.444 |
| | (0.13) | (0.12) | (0.19) |
| Gentrifying but not Whitening | 0.814 | 0.763 | |
| | (0.19) | (0.15) | |
| Gentrifying and Whitening | 0.495** | 0.464** | 0.609 |
| | (0.11) | (0.12) | (0.18) |
| ***Interaction*** | | | |
| Not-White Pop % 2000 | 0.995* | 1.000 | 1.002 |
| | (0.00) | (0.00) | (0.00) |
| Not-White Pop % 2000 * Prosperous | | 0.995* | 0.993 * |
| | | (0.00) | (0.00) |
| Not-White Pop % 2000 * Poor not Whitening | 1.005* | | 0.998 |
| | (0.00) | | (0.00) |
| Not-White Pop % 2000 * Poor and Whitening | 1.015*** | 1.010** | 1.008 |
| | (0.00) | (0.00) | (0.00) |
| Not-White Pop % 2000 * Gentrifying not Whitening | 1.007* | 1.002 | |
| | (0.00) | (0.00) | |
| Not-White Pop % 2000 * Gentrifying and Whitening | 1.010** | 1.005 | 1.003 |
| | (0.00) | (0.00) | (0.00) |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

although not significant at the p¡0.05 level (24% more stops per capita with p=0.061), and suggests the same pattern shown in poor tracts: whitening associated with more stops per capita of Black individuals compared, all else equal.

For Hispanic individuals, the number of stops per capita in gentrifying tracts that did not whiten was not statistically different from the number of stops per capita in prosperous tracts, as was the case with stops of Black individuals. There were more stops per capita of Hispanic individuals in both types of poor tracts and in gentrifying tracts that whitened compared to prosperous tracts. Unlike the pattern for Black stops, Hispanic stops per capita were not significantly different between poor tracts that whitened and poor tracts that did not whiten. There were fewer stops per capita of Hispanic individuals in prosperous tracts and both types of gentrifying tracts compared to poor tracts that did not whiten. For stops of Hispanic individuals, whitening does not appear to have an association with social control in the form of police stops, although gentrification may be somewhat protective with more stops happening in poor tracts regardless of whitening status, all else equal.

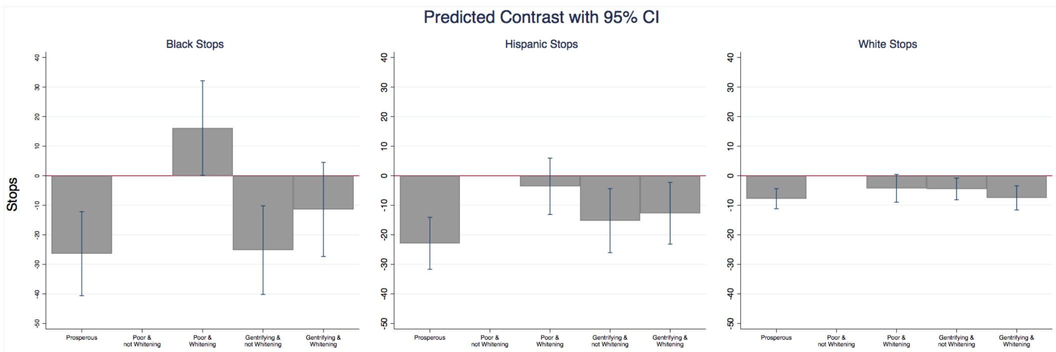
There were more stops per capita of white individuals in poor and not whitening tracts compared to prosperous tracts and compared to gentrifying tracts that also whitened. The interaction with tract type and the not-white baseline population shows that there were significantly fewer stops of white individuals in poor tracts that whitened compared to those that did not, but that the more not-white the tract was to begin with the smaller the difference between whitening and not whitening poor tracts. In other words, the effect of being a poor tract that whitened compared to one that did not becomes less negative the bigger the baseline not-white population percent.

The findings from the white stops model suggest that gentrification has a protective effect for white individuals. Gentrifying tracts that did not whiten tend to be whiter to begin with than gentrifying tracts that did whiten but, even controlling for baseline white population in 2000 for Black and Hispanic stops and controlling for not-white population in 2000 for white stops, gentrification without whitening appears to lower the burden of policing compared to poor tracts that neither whitened nor gentrified, while whitening appears to particularly increase the burden for Black individuals but not for white individuals in both poor and gentrifying tracts.

Figure 2.6 shows contrast plots for stops of each group with poor tracts that did not whiten as the reference category. The plots show the net differences in per capita stops for each tract type compared to the reference, holding all covariates at their means. The first panel shows the contrasts for Black stops. Compared to poor tracts that did not whiten, prosperous tracts and gentrifying tracts that did not whiten had approximately the same number fewer stops per capita of Black individuals. Gentrifying tracts that whitened had a lower predicted number of stops per capita, all else equal, but the 95% confidence interval includes zero so the difference does not reach the threshold of statistical significance. Poor tracts that whitened are the only type that had more predicted stops than poor tracts that did not whiten, all else equal. Per capita stops of Black individuals were comparable in both the most disadvantaged tracts – those that remained poor and did not whiten – and tracts that gained residents with two kinds of privilege – those that both gentrified and whitened. Comparing the next two panels for Hispanic and white stops, it is clear that there is not a statistically significant difference between poor tracts that whitened and those that did not.

Figure 2.6: Contrasts by tract type across race/ethnicity

*Note: Figures show predicted net differences in counts for each tract type compared to the omitted reference category (poor tracts that did not whiten) holding all other covariates at their means*



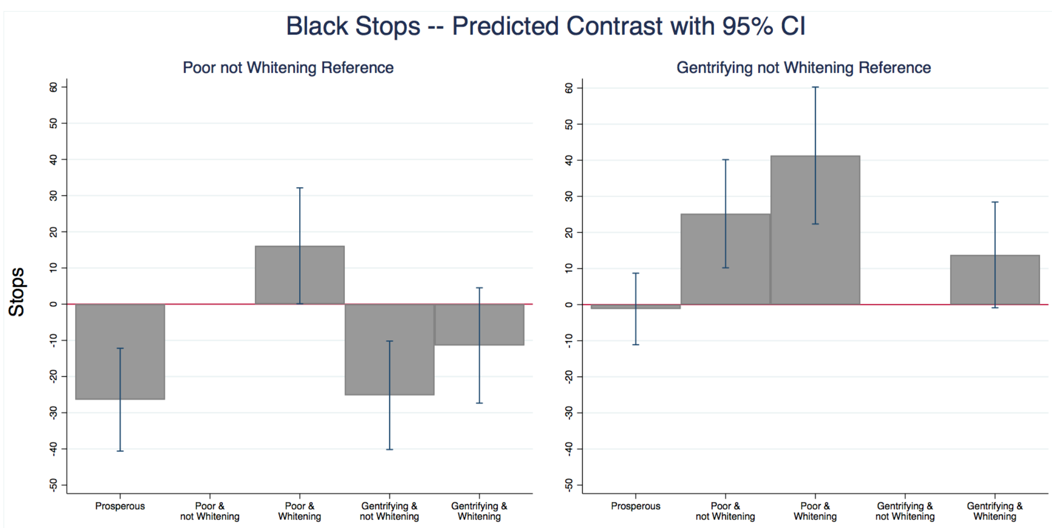

Gentrifying tracts that did not whiten had fewer stops per capita than poor and not whitening tracts across all three groups. Taking all the evidence together, a pattern emerges that was previously obscured by aggregating all stops together in the initial analysis. For the most part, tract type is not associated with the patterns of white stops – except in poor and not whitening tracts where there are the most stops of white individuals compared to all other tract types.[13] Tract type is weakly

[13]There are several reasons that might explain this. First, it maybe that poor tracts that are not whitening are predominantly white tracts and that people get stopped more in poor neighborhoods, regardless of their race/ethnicity. It could also be that poor tracts that did not whiten have predominantly not white population and therefore white individuals are stopped there because they seem out of place. The evidence does not provide much support for either hypothesis. The model accounts for the size of the white population, so that rules out more opportunity for white people to be stopped as an explanation. In 2000, poor tracts that would not whiten were 23.5% non-Hispanic white, compared to 12.5% in poor tracts that would whiten. By 2010, the poor tracts that did not whiten had lost white population (19% non-Hispanic white) while the poor tracts that did whiten

associated with Hispanic stops, with more stops in poor tracts of both types per capita, all else equal, compared to gentrifying and prosperous tracts. On the other hand, both economic status and whitening are associated with stops of Black individuals. Economic gentrification on its own appears to be protective, making the number of stops in those tracts look more like stops in prosperous tracts. Whitening appears to work in the opposite direction with gentrifying tracts that whitened looking like poor tracts that did not whiten and poor tracts that whitened looking worst of all (see Figure 2.7 for contrast with two reference groups).

Figure 2.7: Predicted difference in Black stops by tract type comparing two reference groups

*Note: Figures show the predicted net differences in the number of stops of Black individuals, holding all covariates at their means, for each tract type compared to poor tracts that did not whiten in the first panel and compared to gentrifying tracts that did not whiten in the second panel.*




were up to 16% non-Hispanic white. If there were a out-of-place argument to be made, we would expect it in poor tracts that whitened from 2000 to 2010 because those persistently had the smallest white population, but those are not the tracts with the most per capita stops of white individuals. More research is necessary to determine why exactly the most stops of white individuals occurred in poor tracts that did not whiten.

Across all three groups, higher violent and property crime rates are associated with more stops per capita. The number of public housing units in a tract is associated with slightly more stops of Black and white individuals but not Hispanic individuals. Mixed land use is associated with more stops per capita for members of each group compared to tracts that are fully residential. Finally, the number of major building permits issued in a tract in 2011 is associated with between 0.4 and 0.8% more per capita stops across the three groups. It may be that major building permits, as a proxy for residential and commercial investment, have a nonlinear effect on stops depending on the tract and who the investment is meant to serve. To investigate that, I ran the models for each group including an interaction between the baseline population (non-Hispanic white population in 2000 for the models of Black and Hispanic stops and not-white population in 2000 for the model of white stops) and the number of major building permits. There was no difference in the effect of building permits on per capita stops for Hispanic or white individuals. There was however a difference for stops of Black individuals with major building permits having a greater effect on per capita stop counts the whiter the tract was to begin with in 2000. The magnitude of the effect was exceedingly small, however: a one percentage point larger white population in 2000 was associated with a 0.01 percentage point increase in the effect of permits on stops.

In the model of all stops made in 2011, I included an interaction between tract type and baseline white population. Similarly, in the model of white stops, I included an interaction between tract type and the baseline not-white tract population. Including a similar interaction in the analysis of Black and Hispanic stops, although the

Table 2.7: Comparing Model 4 Across Race/Ethnicity

| | Stops | | |
|---|---|---|---|
| | Black | Hispanic | White |
| ***Tract Type*** | | | |
| Prosperous | 0.415*** | 0.502*** | 0.938 |
| | (0.05) | (0.05) | (0.16) |
| Poor and not Whitening (reference) | | | |
| Poor and Whitening | 1.003 | 0.808* | 0.339** |
| | (0.09) | (0.07) | (0.12) |
| Gentrifying but not Whitening | 0.574*** | 0.672* | 0.763 |
| | (0.09) | (0.12) | (0.15) |
| Gentrifying and Whitening | 0.774* | 0.735** | 0.464** |
| | (0.09) | (0.09) | (0.12) |
| ***Controls*** | | | |
| Non-Hispanic White Pop % 2000 | 0.990*** | 0.995* | |
| | (0.00) | (0.00) | |
| Not-White Pop % 2000 | | | 1.000 |
| | | | (0.00) |
| Log of Violent Crime Rate | 1.446*** | 1.196*** | 1.298*** |
| | (0.05) | (0.04) | (0.04) |
| Log of Property Crime Rate | 1.300*** | 1.430*** | 1.140* |
| | (0.07) | (0.09) | (0.06) |
| # of Issued Building Permits | 1.006** | 1.004* | 1.008*** |
| | (0.00) | (0.00) | (0.00) |
| # of Public Housing Buildings | 1.006*** | 1.001 | 1.008*** |
| | (0.00) | (0.00) | (0.00) |
| Average Landuse | 1.521*** | 1.649*** | 1.405** |
| | (0.14) | (0.15) | (0.15) |
| Logged Pop at Risk | 0.646*** | 0.859*** | 0.632*** |
| | (0.02) | (0.04) | (0.02) |
| ***Borough*** | | | |
| Manhattan (reference) | | | |
| The Bronx | 0.501*** | 0.554*** | |
| | (0.07) | (0.06) | |
| Brooklyn | 0.733** | 0.807* | |
| | (0.09) | (0.08) | |
| Queens | 0.703* | 0.979 | |
| | (0.11) | (0.12) | |
| Staten Island | 0.885 | 0.880 | |
| | (0.13) | (0.11) | |
| ***Interaction*** | | | |
| Prosperous*Non-Hispanic White Pop % 2000 | 1.016*** | 1.009*** | |
| | (0.00) | (0.00) | |
| Poor & Whitening*Non-Hispanic White Pop % 2000 | 1.008 | 1.008** | |
| | (0.00) | (0.00) | |
| Gentrifying & not Whitening*Non-Hispanic White Pop % 2000 | 1.009** | 1.006 | |
| | (0.00) | (0.00) | |
| Gentrifying & Whitening*Non-Hispanic White Pop % 2000 | 1.003 | 1.004 | |
| | (0.00) | (0.00) | |
| Prosperous*Not-White Pop % 2000 | | | 0.995* |
| | | | (0.00) |
| Poor & Whitening*Not-White Pop % 2000 | | | 1.010** |
| | | | (0.00) |
| Gentrifying & not Whitening*Not-White Pop % 2000 | | | 1.002 |
| | | | (0.00) |
| Gentrifying & Whitening*Not-White Pop % 2000 | | | 1.005 |
| | | | (0.00) |
| lnalpha | 0.570*** | 0.484*** | 0.632*** |
| | (0.03) | (0.03) | (0.04) |
| BIC | 21835.457 | 20658.892 | 16827.210 |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

interaction is not necessary for model specification, provides insight into where that interaction most plays out and who it most affects. Table 2.7 shows the results of Model 4 with the interaction for stops of Black individuals, Hispanic individuals, and white individuals. For the stops of Black and Hispanic individuals, the interaction is between tract type and the non-Hispanic white population percentage for each tract in 2000, at the beginning of the study period. For stops of white individuals, Table 2.7 reproduces the final model shown in Table 2.2 with interactions between tract type and the not-white population percentage for each tract in 2000.

Figure 2.8: Predicted number of stops by race/ethnicity, tract type, and demographic distribution in 2000

*Note: Figures show number of stops predicted by the model by tract type across the distribution of baseline population holding all other covariates at their means*

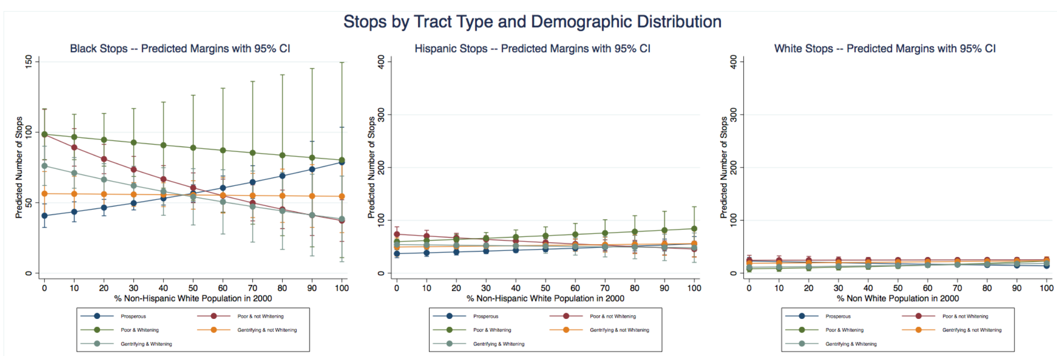


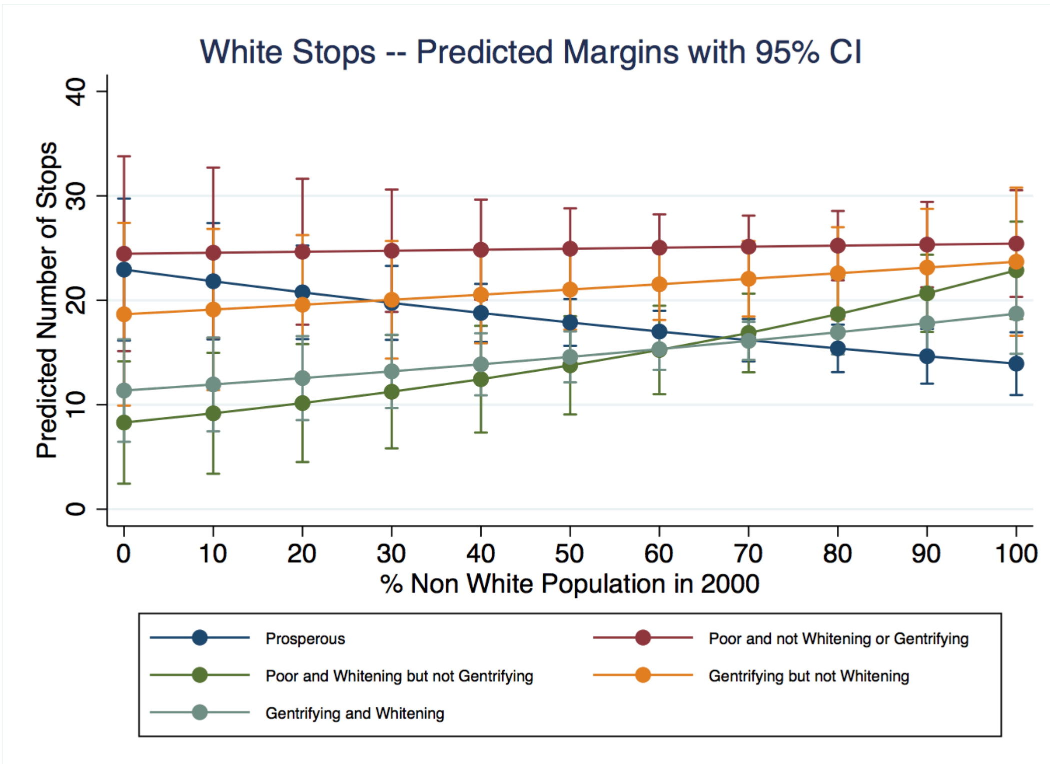

Figure 2.8 shows the predicted number of stops per capita for stops of Black individuals, Hispanic individuals, and white individuals, respectively, by tract type and across the distribution of non-Hispanic white population in 2000 for Black and Hispanic stops and across the distribution of not-white population in 2000 for white stops. For stops of Black individuals, graphed in the first panel, non-Hispanic white

population percent at the beginning of the period of study had a different association with each tract type, although those differences are not always statistically significant. A greater percentage non-Hispanic white population in 2000 is associated with fewer stops per capita of Black individuals in gentrifying neighborhoods that whitened and poor tracts that both did not whiten. The smaller the share of the population that was non-Hispanic white, the more stops of Black individuals in these three track types. The non-Hispanic white population percent in 2000 is not associated with the number of stops of Black individuals per capita in gentrifying tracts that did not whiten and poor tracts that did whiten. Non-Hispanic white population in 2000 is associated with more stops of Black individuals in prosperous tracts, so the whiter the prosperous neighborhood was to begin with the more Black stops per capita in 2011.

For stops of Hispanic individuals, depicted in the middle panel of Figure 2.8, there is not a significant effect of non-Hispanic white population in 2000 on stops per capita in 2010, and that is consistent across tract type. The slopes all go in the same directions as those for Black stops, suggesting a similar pattern on a much smaller scale, except for poor tracts that whitened. For these tracts, the slope goes in the opposite direction suggesting that there were more stops of Hispanic individuals in poor tracts that started off whiter in 2000 and whitened more between 2000 and 2010. The third panel depicts stops of white individuals in 2010. There is no association between the not-white population of the tract in 2000 and the stops of white individuals in 2010. Figure 2.9 shows the predicted counts of stops of white individuals by tract type across the distribution of baseline not-white population

Figure 2.9: Predicted number of stops by race/ethnicity, tract type, and demographic distribution in 2000

*Note: Figure shows counts of white stops predicted by the model by tract type across the distribution of the baseline not-white population holding all other covariates at their means*




percent in 2000 with a more appropriate scale. The figure demonstrates that the differences between poor and gentrifying tracts that whitened and their non-whitening counterparts are greater in tracts with the smallest baseline not-white population in 2000 compared to tracts with the biggest baseline not-white population. This suggests that whitening in tracts is protective for white individuals against police stops, but that the protective power is less the less white the tract was to begin with.

## 2.5 Supplementary Analyses

### 2.5.1 Stops of Asian Individuals

Despite the fact that there are more stops of Asian individuals on average than stops of white individuals, I did not focus on stops of Asian New Yorkers in the main analysis. This is primarily because the Asian population in New York is highly concentrated in particular areas of the city. While this can be said, to a certain extent, of the other groups, there are generally much higher numbers of Black, white, and Hispanic individuals in the city as a whole and they are geographically much more dispersed than Asian New Yorkers.

Figure 2.10: Stops of Asian Individuals in 2011 by quintile

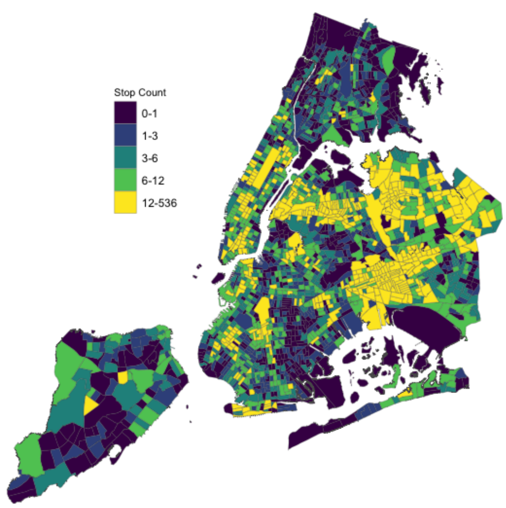
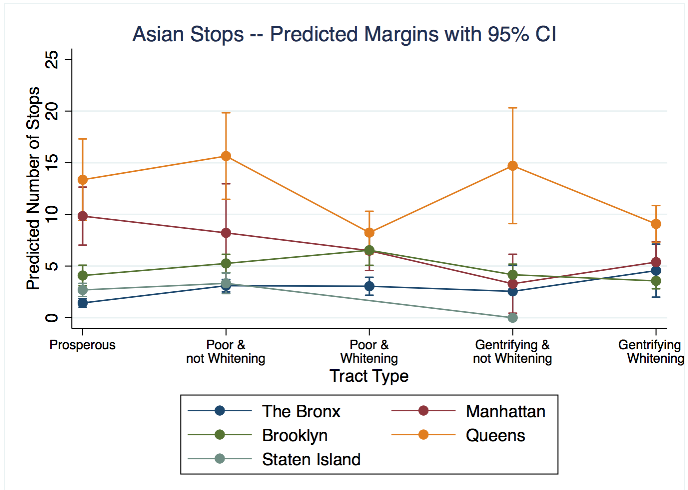



Figure 2.10 shows the distribution of stops of Asian individuals in 2011. The majority of stops were in midtown and Chinatown in Manhattan, in Sunset Park in

Figure 2.11: Predicted number of stops of Asian Individuals by tract type and borough

*Note: Figure shows number of stops predicted by the model by borough and tract type holding all other covariates at their means*



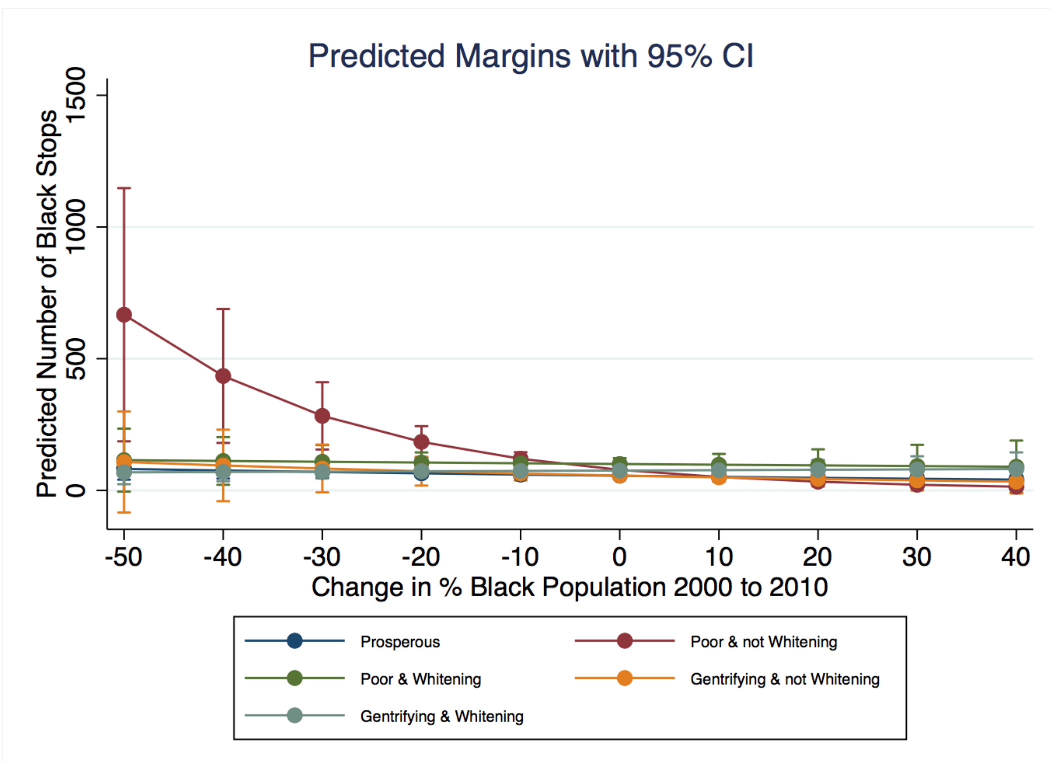

Brooklyn, and in the broader area around Flushing and Jamaica in Queens. Findings from the model interacting tract type with borough, depicted in Figure 2.11, show that in Queens, there are more stops in both poor and gentrifying tracts that were also whitening compared to their non-whitening socioeconomic counterparts.

### 2.5.2 Racial Threat Theory

Among other things, Racial Threat Theory posits that as Black population increases in an area, there will be subsequent increases in social control against Black individuals there (King and Wheelock, 2007). It is possible that changes in Black population correlate with tract type and are responsible for the patterns of stops of Black individuals demonstrated above. To test this theory, I run the model predicting Black stops and include an interaction between the tract typology and the change in Black population between 2000 and 2010. Racial Threat Theory would predict that increases in the percentage of the population that is Black would be associated with higher rates of stops of Black individuals across all tracts, regardless of their gentrification and whitening status. Figure 2.12 shows the marginal predictions from

Figure 2.12: Predicted number of stops by tract type across range of change in percent Black population

*Note: Figure shows number of stops predicted by the model by tract type across the distribution of change in the percent Black population holding all other covariates at their means*




the model interacting tract type with the change in the percentage of the population that was Black from 2000 to 2010. There is no increase in stops of Black individuals with larger increases in Black population percent. In poor tracts that did not gentrify or whiten, loss of Black population at the extreme end of the distribution appears to be associated with an increase in Black stops, which is the opposite of what we would expect with racial threat theory. The predictions for any loss of Black population larger than 24 percentage points, however, should be taken with a grain of salt given that largest loss of Black population in a tract that was poor and didn't gentrify or whiten is a loss of 23.8 percentage points. There is no evidence that Racial Threat Theory explains the patterns of stops in NYC in 2011.

### 2.5.3 Counting Stops in Buffer Zones

There is a potential estimation problem inherent to analyses of events aggregated within small spatially defined units, such as tracts. The exact outlines of tracts are relatively arbitrary spatial boundaries. Stops that fall at or near the borders could arguably be influenced by the characteristics of and events in the tracts on either side of the border. Following Zhang et al. (2012), one solution to this issue is to create buffers zones around tract borders, aggregate stops within those buffers, and compare model results for counts within tracts and counts including those in the buffer zones around tract boundaries. Using QGIS, I created buffer zones of 100 meters, 250 meters, and 500 meters around each tract and then aggregated stops by race/ethnicity within each of these new sets of boundaries. Table 2.8 shows the results from the buffer analysis for stops of Black individuals, Table 2.9 shows the results from the buffer analysis for stops of Hispanic individuals, and Table 2.10 shows the results from the buffer analysis for stops of white individuals.

Table 2.8: Results modeling counts of Black stops in tracts, 100m, 250m, and 500m buffers

| | Black Stops | | | |
|---|---|---|---|---|
| | **Tract** | **100m** | **250m** | **500m** |
| ***Tract Type*** | | | | |
| Prosperous | 0.680*** | 0.743** | 0.801* | 0.876 |
| | (0.07) | (0.08) | (0.08) | (0.09) |
| Poor and not Whitening (reference) | | | | |
| Poor and Whitening | 1.195* | 1.175 | 1.230* | 1.220* |
| | (0.11) | (0.11) | (0.11) | (0.11) |
| Gentrifying but not Whitening | 0.695*** | 0.838 | 0.839 | 0.984 |
| | (0.07) | (0.10) | (0.09) | (0.09) |
| Gentrifying and Whitening | 0.862 | 0.944 | 1.017 | 1.055 |
| | (0.09) | (0.10) | (0.11) | (0.12) |
| ***Controls*** | | | | |
| Non-Hispanic White Pop % 2000 | 1.001 | 0.996 | 0.993** | 0.990*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Log of Violent Crime Rate | 1.432*** | 1.266*** | 1.203*** | 1.124*** |
| | (0.05) | (0.05) | (0.04) | (0.04) |
| Log of Property Crime Rate | 1.293*** | 1.368*** | 1.340*** | 1.327*** |
| | (0.07) | (0.07) | (0.06) | (0.07) |
| # of Issued Building Permits | 1.007** | 1.003 | 1.002 | 1.001 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| # of Public Housing Buildings | 1.004* | 1.003* | 1.002 | 1.001 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Average Landuse | 1.552*** | 1.605*** | 1.541*** | 1.480*** |
| | (0.16) | (0.15) | (0.13) | (0.11) |
| ***Borough*** | | | | |
| Manhattan (reference) | | | | |
| The Bronx | 0.499*** | 0.508*** | 0.448*** | 0.453*** |
| | (0.07) | (0.08) | (0.07) | (0.07) |
| Brooklyn | 0.646*** | 0.654** | 0.615*** | 0.625*** |
| | (0.08) | (0.09) | (0.09) | (0.09) |
| Queens | 0.618** | 0.518*** | 0.384*** | 0.329*** |
| | (0.10) | (0.08) | (0.06) | (0.05) |
| Staten Island | 0.875 | 0.706* | 0.491*** | 0.378*** |
| | (0.14) | (0.11) | (0.08) | (0.07) |
| Logged Pop at Risk | 0.651*** | 0.601*** | 0.569*** | 0.538*** |
| | (0.02) | (0.02) | (0.02) | (0.02) |
| lnalpha | 0.599*** | 0.539*** | 0.527*** | 0.520*** |
| | (0.03) | (0.03) | (0.04) | (0.04) |
| BIC | 21911.736 | 25619.063 | 28393.638 | 31734.973 |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 2.9: Results modeling counts of Hispanic stops in tracts, 100m, 250m, and 500m buffers

| | Hispanic Stops | | | |
|---|---|---|---|---|
| | **Tract** | **100m** | **250m** | **500m** |
| ***Tract Type*** | | | | |
| Prosperous | 0.661*** | 0.645*** | 0.648*** | 0.642*** |
| | (0.05) | (0.05) | (0.06) | (0.06) |
| Poor and not Whitening (reference) | | | | |
| Poor and Whitening | 0.947 | 0.919 | 0.971 | 0.985 |
| | (0.07) | (0.07) | (0.08) | (0.08) |
| Gentrifying but not Whitening | 0.775** | 0.821* | 0.776** | 0.818* |
| | (0.08) | (0.08) | (0.07) | (0.08) |
| Gentrifying and Whitening | 0.812* | 0.848 | 0.885 | 0.904 |
| | (0.07) | (0.08) | (0.10) | (0.11) |
| ***Controls*** | | | | |
| Non-Hispanic White Pop % 2000 | 1.002 | 1.000 | 0.998 | 0.996 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Log of Violent Crime Rate | 1.187*** | 1.142*** | 1.078** | 1.033 |
| | (0.04) | (0.03) | (0.03) | (0.03) |
| Log of Property Crime Rate | 1.440*** | 1.349*** | 1.298*** | 1.268*** |
| | (0.09) | (0.08) | (0.06) | (0.06) |
| # of Issued Building Permits | 1.004* | 1.001 | 1.000 | 0.999 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| # of Public Housing Buildings | 1.000 | 0.997 | 0.996** | 0.993*** |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Average Landuse | 1.648*** | 1.776*** | 1.737*** | 1.675*** |
| | (0.15) | (0.17) | (0.16) | (0.15) |
| ***Borough*** | | | | |
| Manhattan (reference) | | | | |
| The Bronx | 0.554*** | 0.584*** | 0.552*** | 0.588*** |
| | (0.07) | (0.08) | (0.08) | (0.09) |
| Brooklyn | 0.767* | 0.714** | 0.656** | 0.636*** |
| | (0.08) | (0.08) | (0.09) | (0.08) |
| Queens | 0.924 | 0.864 | 0.706* | 0.650** |
| | (0.11) | (0.11) | (0.11) | (0.09) |
| Staten Island | 0.880 | 0.687** | 0.439*** | 0.321*** |
| | (0.11) | (0.08) | (0.06) | (0.04) |
| Logged Pop at Risk | 0.871** | 0.784*** | 0.737*** | 0.676*** |
| | (0.04) | (0.04) | (0.04) | (0.04) |
| lnalpha | 0.492*** | 0.473*** | 0.492*** | 0.493*** |
| | (0.03) | (0.03) | (0.03) | (0.03) |
| BIC | 20663.707 | 24375.114 | 27293.669 | 30609.408 |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 2.10: Results modeling counts of white stops in tracts, 100m, 250m, and 500m buffers

| | White Stops | | | |
|---|---|---|---|---|
| | **Tract** | **100m** | **250m** | **500m** |
| ***Tract Type*** | | | | |
| Prosperous | 0.696*** | 0.700*** | 0.693*** | 0.698*** |
| | (0.05) | (0.05) | (0.05) | (0.04) |
| Poor and not Whitening (reference) | | | | |
| Poor and Whitening | 0.833 | 0.838 | 0.918 | 0.915 |
| | (0.09) | (0.08) | (0.09) | (0.08) |
| Gentrifying but not Whitening | 0.824* | 0.923 | 0.900 | 0.981 |
| | (0.07) | (0.06) | (0.06) | (0.06) |
| Gentrifying and Whitening | 0.706*** | 0.814* | 0.929 | 0.995 |
| | (0.07) | (0.08) | (0.08) | (0.08) |
| ***Controls*** | | | | |
| Not-White Pop % 2000 | 0.998 | 0.997 | 0.997 | 0.997 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Log of Violent Crime Rate | 1.300*** | 1.220*** | 1.166*** | 1.125*** |
| | (0.04) | (0.03) | (0.03) | (0.02) |
| Log of Property Crime Rate | 1.117* | 1.154** | 1.157*** | 1.155*** |
| | (0.06) | (0.06) | (0.05) | (0.04) |
| # of Issued Building Permits | 1.009*** | 1.004** | 1.002 | 1.000 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| # of Public Housing Buildings | 1.007*** | 1.004** | 1.003* | 1.000 |
| | (0.00) | (0.00) | (0.00) | (0.00) |
| Average Landuse | 1.453*** | 1.509*** | 1.517*** | 1.562*** |
| | (0.15) | (0.14) | (0.12) | (0.11) |
| Logged Pop at Risk | 0.624*** | 0.578*** | 0.560*** | 0.539*** |
| | (0.02) | (0.02) | (0.02) | 0.02) |
| lnalpha | 0.647*** | 0.489*** | 0.420*** | 0.361*** |
| | (0.04) | (0.03) | (0.03) | (0.02) |
| BIC | 16846.187 | 19975.923 | 22341.101 | 25138.362 |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

The models using counts from the three new sets of geographic boundaries made of tracts and buffer zones produce results with coefficients that are generally of the same direction and similar magnitude as the models with counts from within tract boundaries alone. The overall patterns from the buffer models match those from the tract analysis. There were generally many fewer stops per capita of individuals from all three racial groups in prosperous tracts than in poor tracts that did not whiten. There were generally more stops in poor tracts that did whiten compared to poor tracts that did not whiten for Black individuals but not for Hispanic or white individuals.

### 2.5.4 Prosperous Tracts

The gentrification tract typology, as implemented by Hwang (2019) and Wyly and Hammel (1999) defined tracts as not gentrifiable if they had higher than average median household income at the beginning of a period of change. This typology considers these tracts too prosperous to gentrify and doesn't consider the ways in which they might also change over the course of the period of study. It may be that tracts that were considered too prosperous to be gentrifiable in 2000 were no longer so prosperous in 2010. If this is the case, then it may be unwise to keep all the not gentrifiable tracts from 2000 together in a group for the purposes of modeling stops in 2011 based on the change in tracts over the prior 10 year period. To test this, I create a new division of tracts with an additional two categories. First, I divide the prosperous tracts into those that stayed prosperous and those that were prosperous but did not remain that way. I consider tracts no longer prosperous if their median household income was below the city average for 2010. That is, they had a median household income above the city average in 2000 but below the city average in 2010. Then I divide those tracts that were prosperous but did not remain so into those that had increases in white population and those that did not have increases. Adding this to my gentrification and whitening typology creates a total of 7 categories. Table 2.11 shows a summary of tracts in this new typology.

Table 2.11: Summary of tracts by type 2000-2010 including disaggregation of prosperous tracts

| | Frequency | Percent |
|---|---|---|
| Persistently Prosperous | 818 | 38.97 |
| Was Prosperous and not whitening | 202 | 9.62 |
| Was Prosperous and whitening | 27 | 1.29 |
| Persistently poor and not whitening | 479 | 22.82 |
| Persistently poor and whitening | 303 | 14.44 |
| Gentrifying but not whitening | 86 | 4.10 |
| Gentrifying and whitening | 184 | 8.77 |

Figure 2.13: Predicted number of stops by tract type by race/ethnicity

*Note: Figure shows number of stops predicted by the model by tract type, including additional tract types split from the prosperous category, for each race/ethnic group holding all covariates at their means*

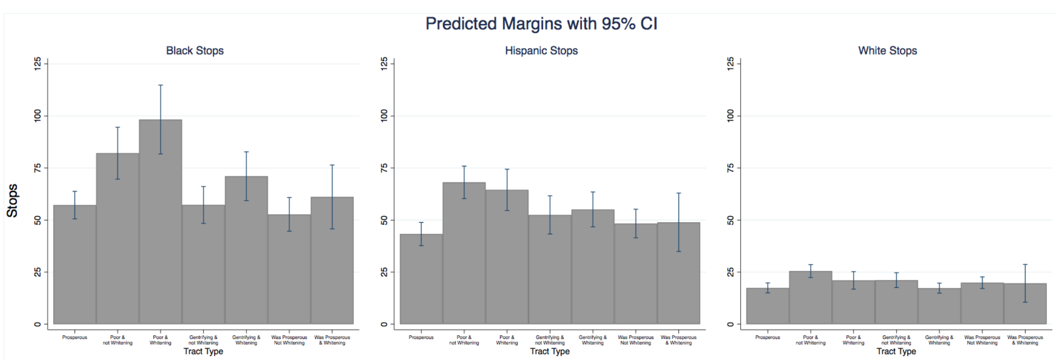


Figure 2.13 shows predictions of stops across the new tract typology for the three racial/ethnic groups, holding covariates at their means. It is clear from this figure that across all groups stops in the formerly prosperous tracts are quite similar to stops in the tracts that remained prosperous. There is evidence to support a broader pattern when we compare predicted counts for Black stops in formerly prosperous tracts that had increases in white population with stops in formerly prosperous tracts that *did not* gain white population. Whitening is predictive of stops of Black individuals controlling for the baseline white population with the effect diminishing the higher the socioeconomic status of the tract.

## 2.6 Discussion

To what extent are increases in the prevalence of members of a privileged group in spaces previously dominated by members of less privileged groups associated with increases in police stops, and to what extent do these associations vary by race and ethnicity? To what extent do gentrification and neighborhood whitening adversely affect residents of color by subjecting them to increased social control in the form of police stops? I found that whitening and gentrification have different and interacting associations with patterns of stops by race/ethnicity.

Per capita rates of all stops aggregated together showed that poverty was associated with the highest rates of stops, followed by gentrification, with the lowest rates of stops in the prosperous tracts. This analysis alone seems to disprove my hypothesis that whitening would be associated with increased social control. However, when the outcome is disaggregated by the race/ethnicity of the people being stopped, a different pattern emerges.

The results of the by race/ethnicity analysis are partially consistent with my hypothesis, that higher number of stops per capita in both poor and gentrifying neighborhoods that experienced neighborhood whitening would affect Black and Hispanic residents but not white residents. The evidence supports this hypothesis with respect to stops of Black individuals. There are more stops per capita of Black individuals associated with tracts that whitened, regardless of their socioeconomic status, compared to their same socioeconomic status counterparts. The findings for Hispanic stops do not support my hypothesis. There is little evidence that whitening is associated with higher per capita stops of Hispanic individuals in either poor or gentrifying tracts. There are more stops of Hispanic individuals in both types of poor tracts compared to prosperous tracts. There are also more stops of Hispanic individuals in gentrifying tracts that whitened compared to prosperous tracts, while gentrifying tracts that did not whiten have statistically equivalent per capita stops as prosperous tracts. While this would seem to indicate that there are more stops per capita of Hispanics in gentrifying tracts that whitened compared to their non whitening counterparts, tests do not show a statistically significant difference in per capita stops between the two types of gentrifying tracts. White stops per capita are substantively the same across all tract types.

While more investigation is necessary to determine why there are these differences across groups, the results are consistent with the idea of a three-tiered racial hierarchy in the United States. In this system, individuals are "white," "honorary white," or “collectively black,” and the assignment of individuals to “honorary white” or “collectively black” is dependent on threat assessment based on the social context (Bonilla-Silva, 2004; Dixon, 2006). In this case, it may be that Hispanic individuals are categorized as “honorary white” in the context of a poor neighborhood with increasing white population but as “collectively black” in a gentrifying neighborhood with increasing white population. This is also supported by the suggestion of more Hispanic stops in poor tracts that whitened and that started out whiter in 2000, seen in Figure 2.8. Additionally, the findings from the analysis of stops of Asian individuals supports this interpretation. It may be that there was little association between neighborhood type and stops of Asian individuals except in Queens because in Queens there is a large concentration of Asian New Yorkers who are lower income immigrants and are less likely to be afforded honorary whiteness. It may be that in the other boroughs, Asian immigrants and Asian Americans are more dispersed, have higher average income or education, and be contextually afforded honorary whiteness.

These findings are consistent with the idea, proposed earlier, that white residents are a salient visual signal to the police about the neighborhood that may cast Black and “collectively black” residents as suspicious or out of place in their newly changed context. This is borne out in the results depicted in Figure 2.8, showing higher per capita rates of Black stops in gentrifying neighborhoods that started off with minimal white population in 2000 and whitened by 2010. In neighborhoods that are poor or gentrifying and also gaining white population, the increase in white residents may signal to the police that change is taking place, although this appears to be most pronounced in poor neighborhoods. As these areas become more white and white social norms for public behavior become expected, Black and Hispanic individuals who don't conform to those norms, or because of stereotypes are assumed not to conform, may appear out of place. Gains in socioeconomic status may be a subtler indication of change and would, therefore, be less likely to make certain people in the neighborhood seem more out of place than before.

We know from both scholarly and anecdotal evidence that racial and socioeconomic change can precipitate racial tensions in urban neighborhoods (Doering, 2020; Kirkland, 2008; Carlisle, 2020). This chapter contributes to our knowledge of how these kinds of change are related to patterns of social control. Neighborhood whitening in poor and gentrifying neighborhoods is associated with more stops per capita of Black individuals – but not of white individuals. This demonstrates one way in which neighborhood change contributes to racial disparities in social control.

Higher rates of policing of Black individuals in poor and gentrifying neighborhoods that also whitened in the prior decade might be explained through several mechanisms. Police may believe that new white residents in a previously non-white neighborhood are potential victims of petty crime at the hands of a population that is regularly under suspicion. Thus police may act to protect the new residents from their potential victimizers. Or white residents may be more vocal about demanding service from the police and more politically connected, thus effectively inducing more intensive policing of their neighbors of color. This would be consistent with the finding that in multiethnic communities the majority of sanctions related to social norm violations are imposed by high status individuals against lower status individuals (Winter and Zhang, 2018). We can imagine that these same patterns apply to perceived social norm violations based on culturally different ideas of acceptable behavior in public space. Or there may be more police to begin with in changing neighborhoods that start out with lower incomes and few white residents; the increased presence of white residents may trigger stereotypes of Black criminality and white victimhood for police officers patrolling those areas, and they may begin to see Black residents as more suspicious and out of place (Russell-Brown, 1998; Welch, 2007). My results may be generated by some combination of these mechanisms or by something altogether different and unmeasured. Whatever the mechanism, understanding the effect is essential if public policy hopes to find ways to mitigate the negative consequences so that neighborhoods can benefit from the positive aspects of increased racial and socioeconomic integration.

There are several limitations to this study. There may be unobserved factors contributing to stop patterns that cannot be captured by available administrative data, such as officer bias.[14] Additionally, there are factors that the police do measure, such as deployment numbers and race of the officers, but do not make available to the public that may further explain the patterns. Future work should include analysis of individual stops, looking at the impact of neighborhood change on escalation of stops to frisks, searches, and use of force.

Finally, the work presented here is necessarily descriptive – it presents suggestive associations that warrant further study through multiple modes of research. Fieldwork

[14]Officer bias would only be an issue if it was not evenly distributed across census tracts. We have no strong reason to believe that there is a systematic pattern to officer bias based on assigned precinct. However, it is possible that there is some mechanism through which officers can request precincts, which makes it possible that officers biases are not randomly distributed, although we cannot assume that biased officers would all request to police areas full of people they are biased against.

can help to illuminate heterogeneous processes that generate unequal outcomes in different neighborhoods. Interviews with police officers, residents, and local policy makers can help determine how police and residents perceive neighborhood change and elicit mechanisms linking those perceptions to actions.

# Chapter 3

# "I'm Calling the Cops": Policing the neighborhood through calls to the NYPD via 311

## 3.1 Introduction

In the previous chapter, I looked at patterns of street stops that the NYPD made across different types of changing neighborhoods. Direct police action is, however, only one form of social control that can be exerted over a neighborhood and its residents. In this chapter, I will investigate social control that individuals initiate by making formal complaints to the city via the 311 system.

The NYC 311 system launched in 2003. It was the second 311 system to be established in the United States, following a similar system in Baltimore. When it launched, individuals could place a call to 311 and, just like with a call to 911, an operator would pick up and take your complaint and then direct it to the appropriate agency for response. Online service was added in 2009 so that complaints could be made via the internet in addition to over the phone. Mobile service was added in 2011 so that people could text their complaints to 311, making the service even more accessible and immediate. Phone remains the predominate means of lodging a complaint or taking advantage of other 311 services, followed by the online forms, and then mobile devices via texting and the 311 app. In the first full year of service, there were about 4.5 million citizen interactions with the 311 system. That number was up to 22 million for the year 2011 and in 2018 there were 44 million total interactions.[1]

After a complaint or request is made, it is allocated to the appropriate agency for response. When that agency is the NYPD, the NYPD then has the option to respond or decline to respond, depending on the details in the complaint. When the NYPD does choose to respond, the officers may take action based on the circumstances they find at the address to which they were directed via the complaint. Sometimes, when a complaint is called in and the operator deems it an urgent issue, they will pass the caller over to the 911 system so that the 911 operator can determine if an emergency response is necessary.[2] Calls to 311 in which the caller is redirected to 911 are not recorded in the 311 data (Mulligan et al., 2019).

When an individual contacts 311 to make a complaint about their neighborhood or about their neighbors, whether they realize it or not, they are making a specific request to the city to have an official city agency respond to their complaint on their behalf. In this chapter, I will focus specifically on all the complaints that are sent to

[1]See https://www1.nyc.gov/311/311-sets-new-record-in-2018.page for 311 usage reporting for 2018.

[2]Mulligan et al. (2019) confirms that this is the case. Additionally, this has been my experience using the 311 system to report trespassers climbing precariously on the roof of an abandoned building behind my apartment. The operator decided it was an urgent issue and transferred the call to a 911 operator who immediately dispatched officers to the scene.

the NYPD.[3] I will then break it down further and analyze the subset of complaints that result in the police "taking action" after they respond, which I will refer to as informal action, and the subset that result in the police issuing a summons or making an arrest after they respond, which I will refer to as formal action. Here, rather than focusing on the content of the complaint, I will focus on the intent and outcome – individuals invoking an official agency of social control, which entails the possibility of police response and police action against the people about whom the complaint was made. Below I will show that, all else equal, in 2011 there were more complaints sent to the NYPD in gentrifying tracts that whitened compared to gentrifying tracts that did not whiten. In 2019, all else equal, there were more complaints sent to to the NYPD in both gentrifying tracts that whitened and poor tracts that whitened compared to their non-whitening counterparts. For complaints to which the NYPD took informal action, there were more in both gentrifying tracts that whitened and poor tracts that whitened compared to their non-whitening counterparts, all else equal. For the complaints that resulted in the NYPD taking formal action, there were fewer in neighborhoods that whitened, especially gentrifying neighborhoods, compared to their non-whitening, same socioeconomic status counterparts.

[3] When I refer to complaints sent to the NYPD, I mean complaints that were made by an individual, which the 311 operator, or the online 311 algorithm, determines fall under the NYPD's jurisdiction. Those complaints are sent via the 311 system to the NYPD for response.

## 3.2 Background and Literature

### 3.2.1 Claiming the Neighborhood

Gentrification and neighborhood whitening are processes of demographic movement over time. These processes involve the shift of people in space, but they also involve negotiations of differing social norms and expectations as groups from different intersectional racial, ethnic, and socioeconomic backgrounds become neighbors and occupy the same social space. With these social changes and ensuing negotiations, comes the potential for conflict over social norms, expectations of appropriate neighborhood behavior, and appropriate means through which neighbors will resolve their issues.

In Chapter 1, I described what the research says about social control in changing neighborhoods. Residents of gentrifying and whitening neighborhoods express feeling as if the newcomers are taking over (Freeman, 2006; Kirkland, 2008). There is a sense that long term residents who were previously at home in their neighborhoods are suddenly out of place as the new richer, whiter residents make the neighborhood their home (Langegger, 2016; Cresswell, 1996). Shifts in social norms through contestation and negotiation can change not only what behaviors are considered acceptable, but also the times at which certain behaviors are acceptable (Langegger, 2016; Edensor, 2010; Lefebvre, 2004). For example, social norms may differ over the time of night at which loud noise should cease. Fireworks may be acceptable on the Fourth of July but not other days of the year.

White and higher SES residents are more likely to think behaviors associated with poverty and small apartments – such as socializing outside a building rather than inside private spaces that may be cramped and overheated – are unacceptable, nuisance behaviors that either portend violence or threaten their property values, and which should be censured in some way (Chaskin and Joseph, 2013, 2010; Pattillo, 2010; Freeman, 2006; Fischer, 1982). Given these differences in expectations, and the idea that certain behaviors are normal for one group and nuisances or threats to another group, conflict in neighborhoods with changing populations are to be expected. The question then becomes how residents deal with this kind of neighborhood conflict, especially when the contested or undesirable behavior is not severe enough to warrant calling 911.

### 3.2.2 Making Complaints, Requesting NYPD Service

In general, in the United States, there are group based differences in who is likely to trust the local government and police and to call them for services even when it is not an emergency. Studies have shown that Black Americans have less trust in the local government than white Americans do, especially in areas where there are higher levels of race based discrimination (Heideman, 2020; Giulietti et al., 2019). Lack of trust is associated with lower levels of use. Cavallo et al. (2014) found that tracts with larger low income populations and with more Black and Hispanic residents were less likely to call 311 to report problems than other areas of NYC. Similarly, Kontokosta et al. (2017) found that, controlling for building conditions, areas with higher Black and Hispanic population were more likely to underreport building issues to 311 while areas with higher SES and more white residents were likely to overreport building issues to 311. While we do not know who specifically is making the complaints, we can infer from this previous literature that lower income, Black and Hispanic individuals are less likely to contact the city government for help than are higher SES white individuals.

In addition to lack of trust in local government services, Black Americans are more likely to view the police as illegitimate and unable to adequately ensure public safety (Kirk and Matsuda, 2011; Kirk and Papachristos, 2011). This does not mean that Black Americans are less likely to care about sanctions for criminal rule breaking, just that they are less likely than white Americans to trust the police to handle their duty to sanction and maintain public safety appropriately (Garofalo, 1977; Hindelang, 1974; Huang and Vaughn, 1996; Schuman et al., 1997). This means they may be more likely to rely on community or individual solutions rather than calling the police for help (Sampson and Bartusch, 1998; Anderson, 1999; Baumer, 2002; Kirk and Papachristos, 2011; Sampson, 2012). White Americans, on the other hand, report the highest levels of trust in and willingness to cooperate with the police (Tyler, 2005).

Given generalized differences in trust in local government, trust in the police, and willingness to contact or cooperate with the police, I hypothesize that there will be higher rates of complaints of the type sent to the NYPD in tracts that have gained residents with both socioeconomic and racial privilege relative to recent historical makeup of that tract. In other words, I hypothesize that there will be higher rates of complaints sent to the NYPD in gentrifying tracts that also whitened compared to other tract types, and that additionally, given racial differences in likelihood to trust and call local authorities, that there will be higher rates of these complaints in whitening tracts compared to their non-whitening socioeconomically similar counterparts. Furthermore, I hypothesize that, given the patterns of policing demonstrated in Chapter 2, there will be more actions taken by the NYPD in response to complaints in tracts that whitened compared to tracts that did not.

## 3.3 Data and Models

To model the relationship between neighborhood change and complaints that are received by the NYPD, and to test my hypotheses, I look at complaints made in 2011 and 2019 using the data sets that are described in Chapter 1. As in Chapter 2, the predictor of interest is my gentrification and whitening tract typology. I hypothesized that gentrification and whitening would predict higher rates of complaints that are sent to the NYPD. I also hypothesized that gentrification and whitening would be associated with higher rates of complaints resulting in the NYPD taking action and issuing summons and arrests following an NYPD response.[4] Table 3.9 shows the different kinds of complaints that were sent to the NYPD in 2011 and 2019. Once the NYPD receives a complaint from the 311 system, the agency can either respond, refer the complaint to a different agency, or decline any response. Of those complaints to which the NYPD responds, they only take action against those for which the complained about behavior is ongoing or there is some other condition that prompts a response. Most complaints responded to by the NYPD result in no corrective action

[4] A note on terminology: The NYPD responds to a complaint by sending officers to investigate. Once the NYPD has responded to the scene, they can choose to take action if there is ongoing evidence of the behavior detailed in the complaint. Hereafter, I will use "response" to mean the NYPD showed up. Taking action of some kind is a further step beyond merely showing up.

because the behavior has stopped or there is no evidence of the offense. However, once the NYPD has arrived at the address of the complaint, they can react by "taking action," "writing a report," issuing a summons, or even executing an arrest. The 311 data do not further specify what constitutes "taking action," and when asked by a local reporter, an NYPD officer said that "police actions vary depending on the situation" (Song, 2020). Based on personally observed anecdotal evidence, one type of action that could fall in this category is the police talking with the subject(s) of the complaint and requesting that they cease the offending behavior.

Here, I analyze complaints received by the NYPD and complaints resulting in the NYPD officers "taking action" or issuing a summons or arrest after responding to the scene. I use the same underlying model to investigate each outcome, with minor differences by outcome, which I will describe in detail below. Similar to the analysis of stops in Chapter 2, I have fixed the temporal ordering by predicting complaints made in 2011 with neighborhood change occurring between 2000 and 2010 and predicting complaints made in 2019 with neighborhood change occurring between 2011 and 2018. Tables 3.2 and 3.3 show a summary of complaints in 2011 and 2019, respectively. There were many more complaints overall in 2019 than in 2011. For example, where there were an average of about 21 complaints resulting in police action per tract in 2011, there were 78 such complaints on average in 2019.

Table 3.2: Summary of NYPD and neighborhood noise complaints in 2011

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Complaints sent to NYPD | 132.40 | 94.22 | 0 | 904 |
| Complaints Resulting in NYPD "Taking Action" | 20.32 | 20.98 | 0 | 174 |
| Complaints Resulting in Summons or Arrest | 7.59 | 6.98 | 0 | 59 |

Table 3.3: Summary of NYPD complaints in 2019

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| Complaints sent to NYPD | 392.88 | 326.95 | 7 | 6,938 |
| Complaints Resulting in NYPD "Taking Action" | 76.65 | 71.44 | 1 | 678 |
| Complaints Resulting in Summons or Arrest | 23.37 | 23.86 | 0 | 247 |

In order to model complaints that result in some corrective action, I determine the number of complaints that the NYPD actually responds to. To do this, I follow the method described by the Community Service Society (2019) to separate out complaints sent to the NYPD that do not receive an NYPD response and then work backwards to determine the total for each tract that did get a response. Complaints designated for the NYPD that did not get an NYPD response are those with the following information in the description of the complaint resolution: 1) "The Police Department reviewed your complaint and provided additional information below," 2) "This complaint does not fall under the Police Department's jurisdiction," 3) "Your complaint has been forwarded to the New York Police Department for a non-emergency response," 4) "Your complaint has been received by the Police Department and additional information will be available later," 5) "Your complaint has been received by the Police Department and it has been determined that a long-term investigation may be necessary," and 6) "Your request can not be processed at this time because of insufficient contact information." Those complaints that were sent to the NYPD and did not have one of those six descriptions in the complaint resolution were actually responded to by the police.

There are four possible actions the NYPD can take once they have responded to a complaint: take action, write a report, issue a summons, or make an arrest. A response without action would consist of the NYPD showing up to the address in the complaint, taking no action, and leaving. This type of response is recorded as "The Police Department responded and upon arrival those responsible for the condition were gone," "The Police Department responded to the complaint and determined that police action was not necessary," "The Police Department responded to the complaint and with the information available observed no evidence of the violation at that time," and "The Police Department responded to the complaint but officers were unable to gain entry into the premises." In my analysis of complaints resulting in action, I look at complaints that resulted in the NYPD taking informal action to fix the conditions of the complaint and separately consider complaints that result in the NYPD taking formal action in the form of issuing a summons or making an arrest.

Table 3.4: Descriptive statistics by tract for analysis of 2011 complaints (n=2,099)

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| White Population % in 2000 | 35.75 | 32.51 | 0.11 | 99.00 |
| White Population % in 2010 | 33.51 | 30.95 | 0.07 | 99.60 |
| Crime Rate/1,000 pop | 19.16 | 99.06 | 1.17 | 3470.09 |
| Violent Crime Rate/1,000 pop | 5.99 | 19.01 | 0 | 619.05 |
| Property Crime Rate/1,000 pop | 13.17 | 82.95 | 0.57 | 2974.36 |
| Median Household Income 2000 in 2010$ | 40,803.36 | 18,919.07 | 6,771 | 188,697 |
| Median Household Income 2010 | 57,068.22 | 27,622.64 | 9,675 | 250,001 |
| # NYCHA Buildings | 4.92 | 17.32 | 0 | 193 |
| # of Building Permits Issued | 12.47 | 19.13 | 0 | 385 |
| Average Land Use | 1.42 | 0.40 | 1 | 3 |
| Population | 3,884.54 | 2,105.34 | 73 | 26,588 |

Tables 3.4 and 3.5 show descriptive statistics for the relevant covariates for the analyses of 2011 and 2019, respectively. As in Chapter 2, I begin with a simple conceptual model and add theoretically motivated controls to build the full model.

Table 3.5: Descriptive statistics by tract for analysis of 2019 complaints (n=2,095)

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| White Population % in 2011 | 33.89 | 31.33 | 0 | 100 |
| White Population % in 2018 | 32.32 | 29.34 | 0 | 99.59 |
| Crime Rate/1,000 pop | 0.70 | 3.62 | 0 | 118.18 |
| Violent Crime Rate/1,000 pop | 0.25 | 1.09 | 0 | 45.45 |
| Property Crime Rate/1,000 pop | 0.46 | 2.80 | 0 | 72.73 |
| Median Household Income 2011 in 2018$ | 54,577.76 | 26,283.17 | 9,212 | 239,614 |
| Median Household Income 2018 | 58,286.86 | 28,652.66 | 8,611 | 216,604 |
| # NYCHA Buildings | 4.93 | 17.33 | 0 | 193 |
| # of Building Permits Issued | 16.72 | 19.37 | 0 | 247 |
| Average Land Use | 1.40 | 0.38 | 1 | 3 |
| Population | 4,014.52 | 2,178.53 | 60 | 28,272 |

Equation 3.1 represents the model in its simplest form, using the tract typology to predict the number of complaints in tract $i$ in year $t$, where $t$ is either 2011 or 2019.

$$complaints_{it} = \beta_{i0} + \beta_{i1} TractType_{i(t-1)} + \beta_{i2} LoggedRiskPopulation_{i(t-1)} + u_{it} \quad (3.1)$$

Since the negative binomial model logs the outcome, the logged population at risk is included to make the outcome interpretable as a count per capita. In the case of complaints sent to the NYPD, I use the total population of the tract as the population at risk. For both models of complaints resulting in NYPD action, I use the total number of complaints responded to by the NYPD as the population at risk, as there can only be action for complaints to which the NYPD actually responds.

Racial and ethnically correlated differences in cultural norms may influence the likelihood of residents to make complaints or the prevalence of behaviors likely to induce some residents to complain about others. Given the evidence cited above that white residents move into neighborhoods with particular expectations of normal, acceptable behavior, I include a control for the percentage of the population of the tract that is not non-Hispanic white in 2010 and the percentage in 2018, for the 2011 and 2019 complaints analyses, respectively. This allows me to control for the percentage of the population that new white residents might expect to deviate from their expectations of acceptable neighborhood behavior.

Residents may be more likely to resort to using the 311 system to make complaints in neighborhoods with higher crime rates. Higher crime rates may make residents reluctant to confront their neighbors personally for fear of creating conflict. I control for the violent and property crime rates in the same year as the complaints to account for this possibility. I also include a control for the number of public housing buildings in the tract. Additionally, I include controls for the average land use in a tract, ranging from 1 (completely residential) to 3 (completely non-residential) due to the competing possibilities that more complaints that fall under the NYPD's purview may occur in commercial areas where there is more likely to be outside noise or that there may be more complaints about illegal parking and blocked driveways in residential areas. In the analysis of complaints resulting in action by the NYPD, I include a count of building permits issued for major demolition, construction, and renovations in the year of the complaints. This is based on the logic used in Chapter 2, that major investment in neighborhoods may exert some influence, either official or unofficial, on the practices of the police in those areas. In this way, building permits are unlikely to influence individuals' decisions to complain to the 311 about things that the police may respond to, but it may influence police decisions to take action in response to complaints once they have been made.[5] Finally, I include borough dummy variables to capture possible borough-specific differences in the tendency to complain.

To achieve linear bivariate relationships with the outcomes, I log both the property and violent crime rates. In addition, for the analysis of complaints sent to and complaints responded to by the NYPD, I include a square of the logged property crime rate. As with the analyses in Chapter 2, I estimate robust standard errors clustered on Neighborhood Tabulation Area (NTA) to address possible violations of the assumption of independence of errors due to the spatial relationship of census tracts within larger spatial units. Equation 3.2 shows the full model including the additional measures, where **Z** is a matrix of tract characteristics such as total public housing buildings, total building permits issued for major construction and major renovations, average land use, and borough.

$$\begin{aligned} complaints_{it} = \beta_{i0} + \beta_{i1} TractType_{i(t-1)} + \beta_{i2} PercentNotWhite_{i(t-11)} + \\ \beta_{i3} LoggedViolentCrimeRate_{it} + \beta_{i4} LoggedPropertyCrimeRate_{it} + \\ \beta_{i5} [\mathbf{Z}_{i(t-1)}] + LoggedRiskPopulation_{i(t-1)} + u_{it} \end{aligned} \tag{3.2}$$

[5] It could be that major building permits come with more noise, more driveways blocked by construction vehicles, and therefore more things to complaint about. I ran the model of complaints sent to the NYPD including the measure of building permits and it was not significantly associated with those complaints in either year.

## 3.4 Findings

### 3.4.1 Complaints sent to the NYPD

To test my hypothesis that there will be higher rates of complaints that engage the NYPD in neighborhoods that are gentrifying and whitening than in other neighborhoods, I run the full and constrained models predicting total complaints sent to the NYPD in 2011 and 2019. Table 3.6 shows the results for 2011 from the simplest model, predicting the number of complaints sent to the NYPD with the tract typology and the logged population at risk, the same model adding in crime rates and not-white population percentage, and the full model with additional controls to account for tract characteristics. Figure 3.1 shows the predicted counts versus the observed counts as a measure of model fit. While there is some variation in the distribution of observed complaints, the prediction from the full model mirrors the overall shape of the distribution. The *lnalpha* parameter is significant across all three models, indicating that the negative binomial model is necessary to properly model these data and account for the overdispersion in the distributions of the outcomes. Comparing the three models, gentrifying and whitening tracts had significantly higher per capita complaints sent to the police than gentrifying and not whitening tracts. The magnitude of the effect reduces slightly as more covariates are added to the model, but the association holds in the full model. Model comparison using likelihood ratio testing and comparison of BIC confirm that the full model (Model 3) is preferable to the constrained models, so I will primarily limit my discussion to the results from the full model.

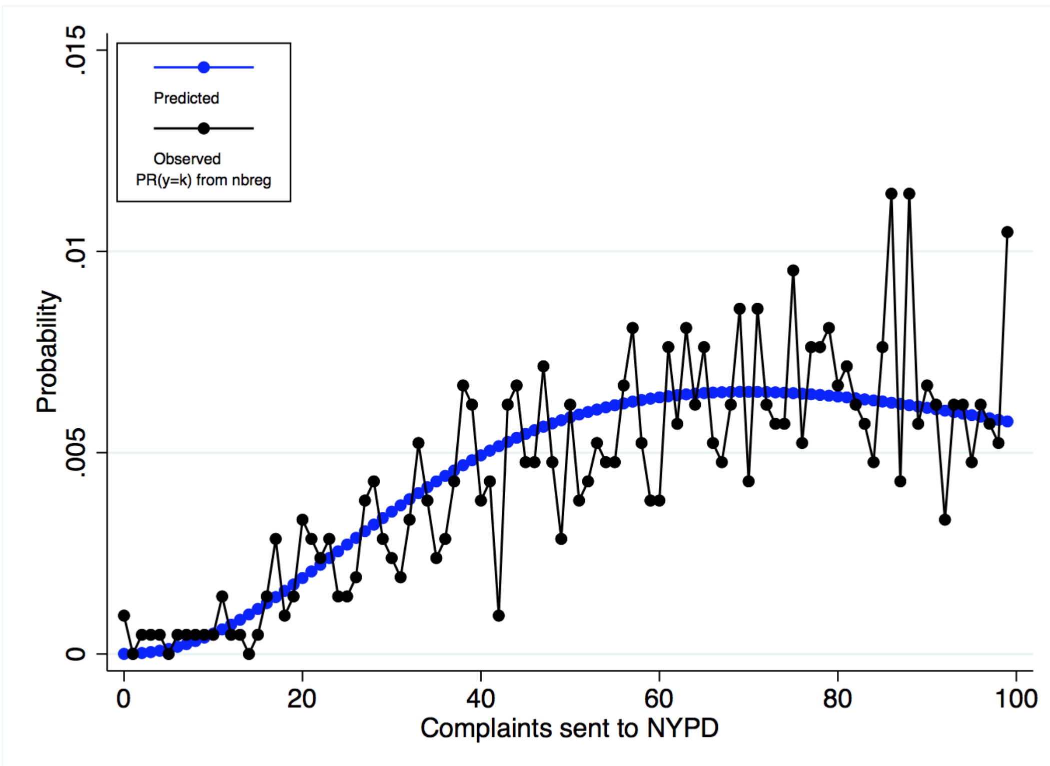
Table 3.6: Models predicting complaints sent to the NYPD in 2011

| | Complaints sent to the NYPD | | |
|---|---|---|---|
| | **(1)** | **(2)** | **(3)** |
| ***Tract Type*** | | | |
| Gentrifying but not Whitening (reference) | | | |
| Prosperous | 0.917 | 0.905 | 0.898 |
| | (0.07) | (0.06) | (0.06) |
| Poor and not Whitening | 1.076 | 1.004 | 0.998 |
| | (0.08) | (0.06) | (0.06) |
| Poor and Whitening | 1.105 | 0.942 | 0.931 |
| | (0.11) | (0.07) | (0.07) |
| Gentrifying and Whitening | 1.433*** | 1.174* | 1.190** |
| | (0.11) | (0.08) | (0.085) |
| ***Controls*** | | | |
| Not White Pop % 2010 | | 1.000 | 1.000 |
| | | (0.00) | (0.00) |
| Log of Violent Crime Rate | | 1.114*** | 1.110*** |
| | | (0.02) | (0.02) |
| Log of Property Crime Rate | | 1.291** | 0.995 |
| | | (0.04) | (0.05) |
| Log of Property Crime Rate$^2$ | | | 1.049*** |
| | | | (0.01) |
| # of Public Housing Buildings | | | 0.998** |
| | | | (0.00) |
| Average Land Use | | | 0.943 |
| | | | (0.05) |
| ***Borough*** | | | |
| Manhattan (reference) | | | |
| The Bronx | | | 0.877 |
| | | | (0.06) |
| Brooklyn | | | 0.831* |
| | | | (0.06) |
| Queens | | | 0.876 |
| | | | (0.07) |
| Staten Island | | | 0.785** |
| | | | (0.06) |
| Logged Pop at Risk (Total Pop) | 0.646*** | 0.825*** | 0.831*** |
| | (0.07) | (0.03) | (0.03) |
| lnalpha | 0.275*** | 0.211*** | 0.202*** |
| | (0.02) | (0.01) | (0.01) |
| BIC | 23168.666 | 22616.441 | 22576.322 |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure 3.1: Predicted versus observed complaints send to the NYPD in 2011

*Note: Figure shows the probability distribution of counts predicted by the model plotted against the observed probability distribution from one complaint through 99 complaints, which is a maximum count limit imposed by the user-generated -prcounts- Stata command that predicts count probabilities.*




Model 2 adds the not-white population and the two logged crime rates. Not-white population percentage is not associated with the number of complaints per capita sent to the NYPD. Both violent crime and property crime rates are associated with higher numbers of complaints per capita. Model 3 includes additional covariates, as well as the square of the logged property crime rate. When the additional covariates are added to to the model, the positive significant coefficient for logged property crime rate remains, however, the link test indicates that the model is not properly specified.

Table 3.7: Comparison of effects with different tract type reference groups for per capita complaints sent to the NYPD in 2011

*Note: The first column holds out prosperous tracts as the reference. The second column holds out poor tracts that did not whiten as the reference. The third column holds out gentrifying tracts that did not whiten as the reference.*

| | **Complaints sent to NYPD** | | |
|---|---|---|---|
| ***Tract Type*** | | | |
| Prosperous | | 0.900** | 0.898 |
| | | (0.03) | (0.06) |
| Poor and not Whitening | 1.112** | | 0.998 |
| | (0.04) | | (0.06) |
| Poor and Whitening | 1.037 | 0.933 | 0.931 |
| | (0.05) | (0.04) | (0.07) |
| Gentrifying but not Whitening | 1.114 | 1.002 | |
| | (0.07) | (0.06) | |
| Gentrifying and Whitening | 1.326*** | 1.193*** | 1.190** |
| | (0.07) | (0.06) | (0.08) |

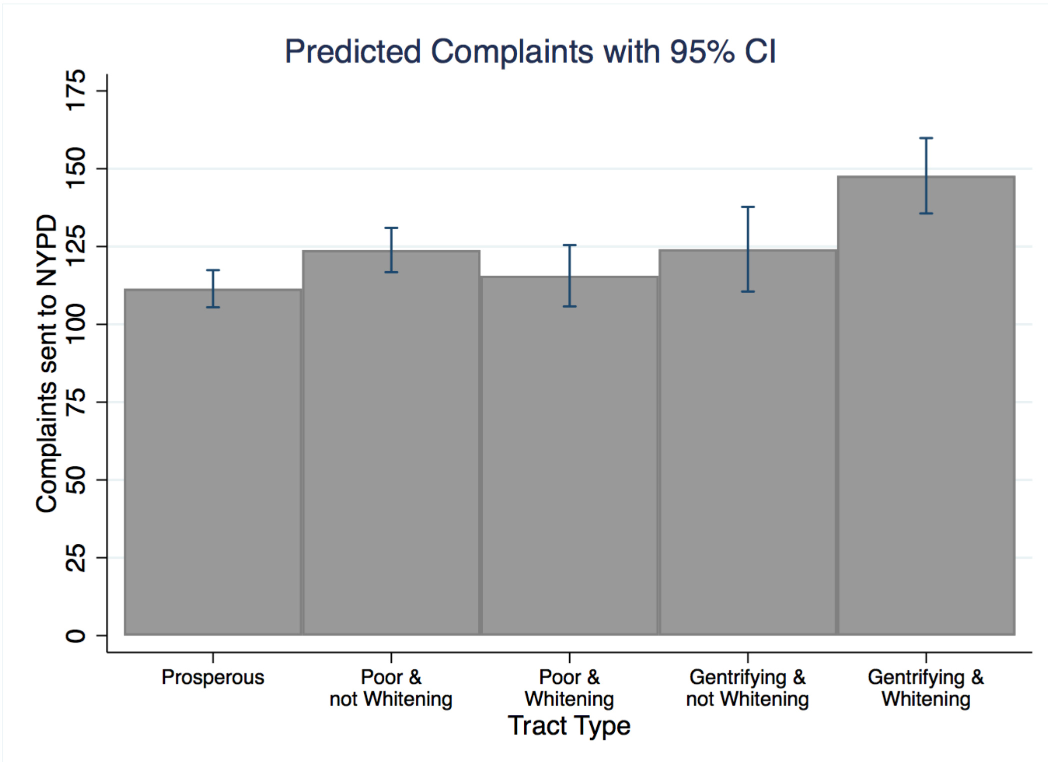
Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Adding the square of the logged property crime rate fixes the specification problem. With the squared term, the logged property crime rate is no longer associated with the complaints sent to the NYPD, but the coefficient for the squared term is significant and positive. The logged property crime rate has a U-shaped relationship with complaints sent to the NYPD, with more complaints at the low and high ends of the distribution of property crime and fewer complaints in the middle of that distribution. It may be that, compared to tracts in the middle of the crime rate distribution, there is more behavior that warrants complaint in areas that also have high crime rate and there are also more complaints where there is low crime but more residents of privilege who are more prone to complain.

With the full model, not-white population percentage remains unassociated with the number of per capita complaints that the 311 system sends to the NYPD. In

Figure 3.2: Predicted number of complaints sent to the NYPD in 2011 by tract type

*Note: Figure shows counts predicted by the model by tract type holding all other covariates at their means.*

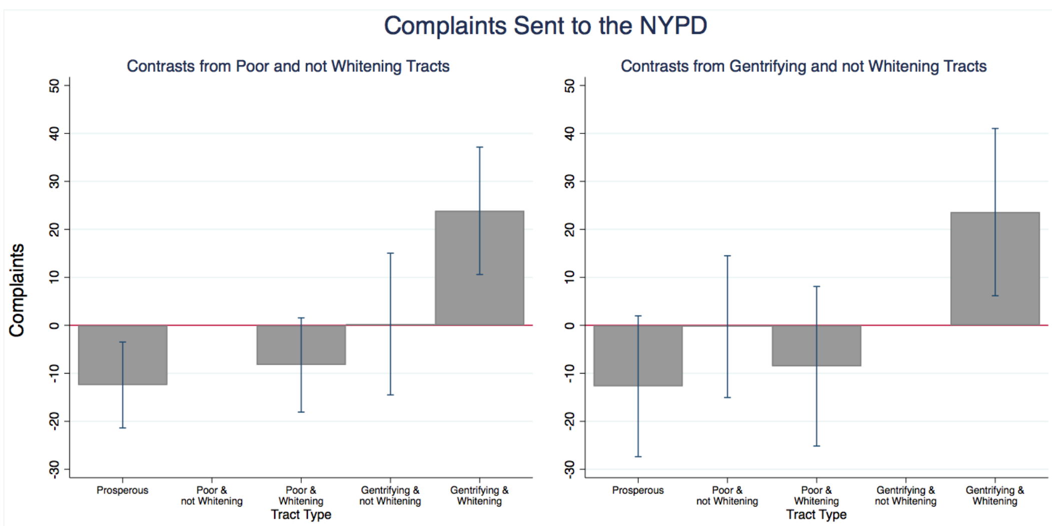



addition to crime rates, the number of public housing buildings in a tract is significantly related to the number of complaints per capita that get sent to the NYPD. The relationship is negative and the magnitude is very small – for each additional public housing building in a tract there are 0.2% fewer complaints per capita that are sent to the NYPD.

Table 3.7 shows the coefficients for the neighborhood typology with three difference reference categories: prosperous tracts, poor tracts that did not gentrify or whiten, and gentrifying tracts that did not whiten. Poor tracts that did not whiten are predicted to have 11.2% more complaints per capita sent to the NYPD on average than prosperous tracts, all else equal. Gentrifying tracts that whitened are predicted to have 32.6% more complaints per capita sent to the NYPD on average than prosperous tracts. Those gentrifying and whitening tracts are also predicted to have 19.3% more complaints per capita than poor tracts that did not whiten and 19% more complaints per capita than gentrifying tracts that did not whiten, all else equal. Figure 3.2

Figure 3.3: Predicted difference in complaints sent to the NYPD in 2011 by tract type from two reference groups: poor tracts that did not whiten and gentrifying tracts that did not whiten

*Note: Figure shows predicted net differences in complaints by tract type compared to a reference category holding all other covariates at their means.*




shows the predicted number of complaints for each tract type, holding the covariates at their sample means. Gentrifying and whitening tracts had 19% more complaints per capita sent to the NYPD than gentrifying tracts that did not whiten, all else equal. Figure 3.3 shows contrast plots for two reference groups: poor tracts that did not whiten and gentrifying tracts that did not whiten. Poor tracts that whitened did not have statistically different per capita counts of complaints that were sent to the NYPD compared to poor tracts that did not whiten. Gentrifying tracts that whitened, though, did have more complaints than gentrifying tracts that did not whiten – just over 20 more complaints in the whitening gentrifying tracts, on average, all else held equal.

Table 3.8 shows the results from the same model predicting complaints in 2019 with neighborhood change from 2011 to 2018 and Figure 3.4 shows the predicted counts versus the observed counts for model fit. Coefficients for the tract typology categories are shown for three reference groups. For 2019 complaints, the not-white population percentage is statistically significant, predicting 0.2% more complaints per capita for each additional percentage point. The less white the tract, the more complaints of the type that get sent to the NYPD, whereas this was not the case in 2011. Violent crime rate is not a statistically significant predictor of complaints sent to the NYPD in 2019, although it was in 2011. Property crime, however, is consistently a predictor of more complaints sent to the NYPD. This could reflect a reluctance on the part of residents to deal with issues themselves because of some fear of interaction with their neighbors (although I would expect violent crime rate to be a better proxy for that than property crime rate) or it could be that places with higher property crime rates are also likely to have more deviant behaviors in general, including the kind of low level behaviors that do not warrant a 911 call but do warrant a 311 call.

Similar to 2011, the number of public housing buildings is associated with slightly

Table 3.8: Modeling per capita complaints sent to the NYPD in 2019

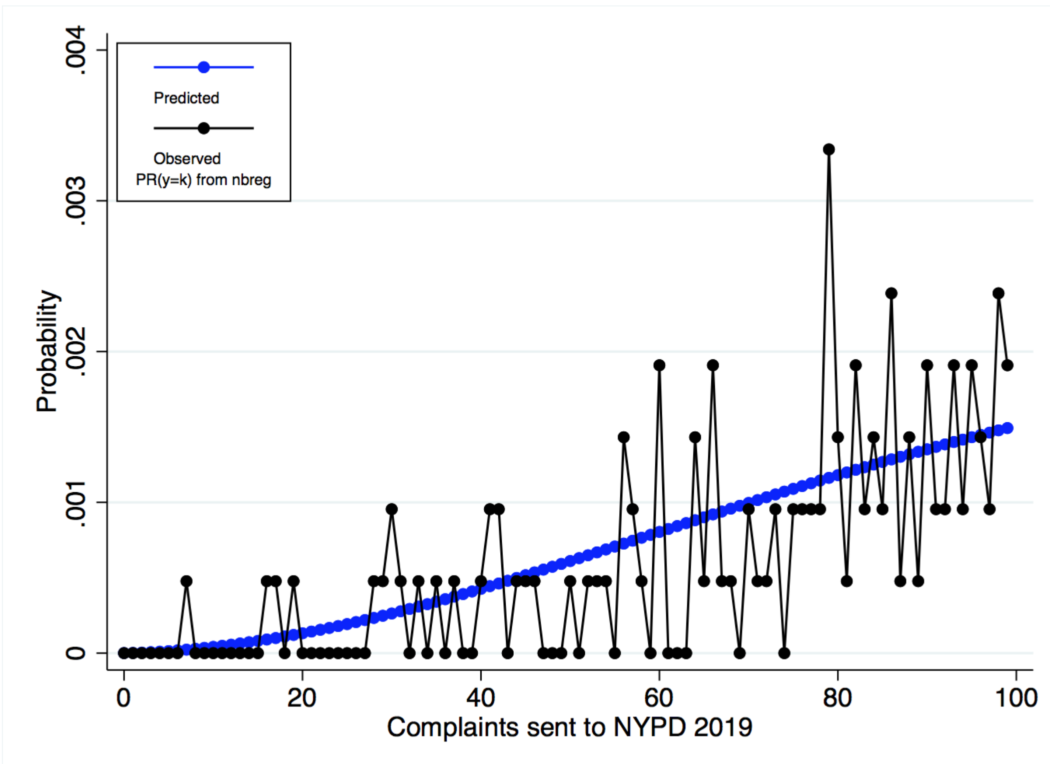
*Note: This table shows the coefficients for the tract typology with three different reference categories: prosperous in the first column, poor but not whitening in the second column, and gentrifying but not whitening in the third column.*

| | **Complaints sent to NYPD** | | |
|---|---|---|---|
| ***Tract Type*** | | | |
| Prosperous | | 0.925 | 0.916 |
| | | (0.05) | (0.06) |
| Poor and not Whitening | 1.081 | | 0.991 |
| | (0.06) | | (0.07) |
| Poor and Whitening | 1.220** | 1.129* | 1.118 |
| | (0.09) | (0.06) | (0.09) |
| Gentrifying but not Whitening | 1.092 | 1.009 | |
| | (0.07) | (0.07) | |
| Gentrifying and Whitening | 1.436*** | 1.328*** | 1.315*** |
| | (0.10) | (0.08) | (0.11) |
| ***Controls*** | | | |
| Not White Pop % 2018 | 1.002* | | |
| | (0.00) | | |
| Log of Violent Crime Rate | 1.015 | | |
| | (0.01) | | |
| Log of Property Crime Rate | 1.180*** | | |
| | (0.04) | | |
| Log of Property Crime Rate $^2$ | 1.029*** | | |
| | (0.01) | | |
| # of Public Housing Buildings | 0.997*** | | |
| | ().00) | | |
| Average Land Use | 1.214* | | |
| | (0.10) | | |
| ***Borough*** | | | |
| Manhattan (reference) | | | |
| The Bronx | 0.962 | | |
| | (0.09) | | |
| Brooklyn | 0.919 | | |
| | (0.09) | | |
| Queens | 1.037 | | |
| | (0.11) | | |
| Staten Island | 0.772* | | |
| | (0.09) | | |
| Logged Pop at Risk (Total Pop) | 0.739*** | | |
| | (0.03) | | |
| lnalpha | 0.287*** | | |
| | (0.03) | | |
| BIC | 27700.380 | | |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure 3.4: Predicted versus observed complaints send to the NYPD in 2019

*Note: Figure shows the probability distribution of counts predicted by the model plotted against the observed probability distribution from one complaint through 99 complaints, which is a maximum count limit imposed by the user-generated -prcounts- Stata command that predicts count probabilities.*

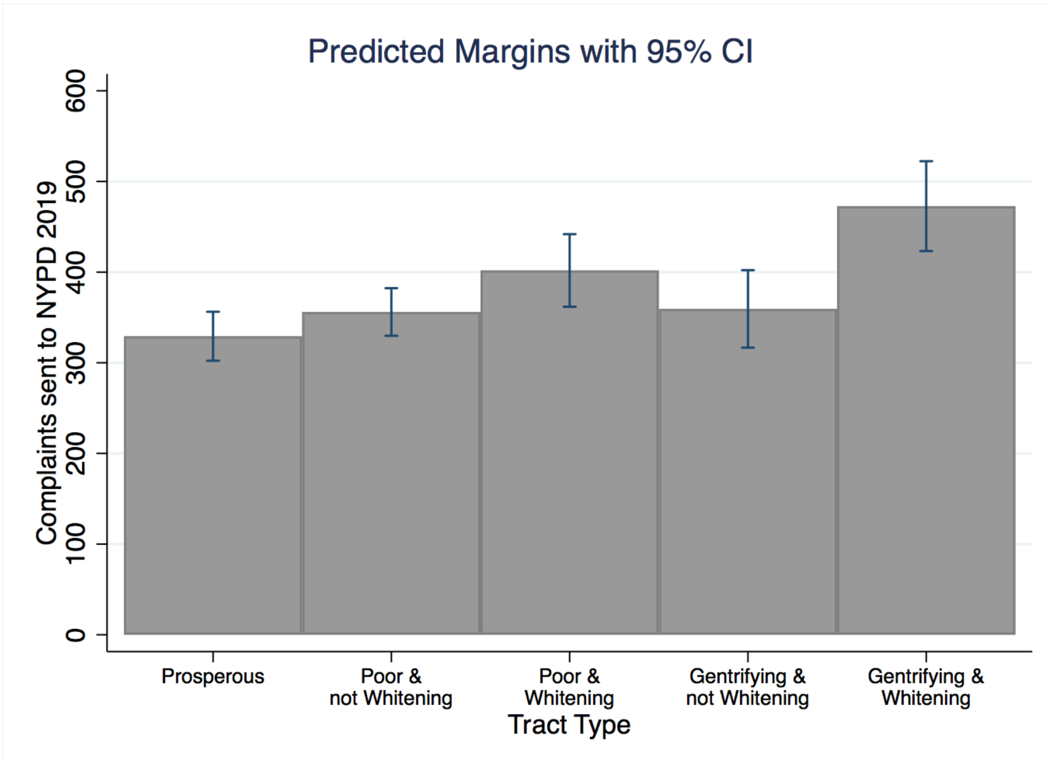



fewer complaints per capita sent to the NYPD. Here, average land use is also significant, with more complaints per capita predicted for tracts with less residential land use.

Figure 3.5 shows the predicted number of complaints by tract type, holding covariates at their sample mean. The difference between gentrifying tracts that whitened and those that did not is a bit more pronounced in 2019 compared to 2011. The differences are made even clearer in Figure 3.6, which shows contrast plots for two reference groups. As in 2011, in 2019 there were more complaints in gentrifying tracts

Figure 3.5: Predicted number of complaints sent to the NYPD in 2019 by tract type

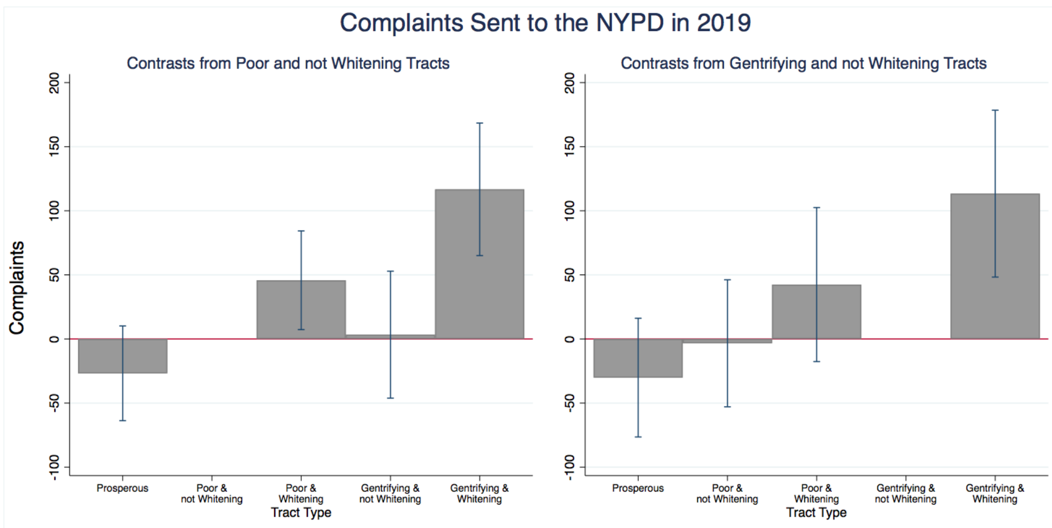
*Note: Figure shows counts predicted by the model by tract type holding all other covariates at their means.*




that whitened than in gentrifying tracts that did not whiten. In 2011, the difference between the two types of gentrifying tracts was just more than 20 complaints per capita on average, in 2019 the difference was more than 100 on average, although given the higher overall number of complaints in 2019, when converted to standard deviations the difference between the two types of gentrifying tracts is about the same size in both years. Unlike in 2011, when poor tracts, both whitening and not, had statistically indistinguishable per capita counts of complaints sent to the NYPD, in 2019 there were more complaints per capita in poor tracts that whitened compared

Figure 3.6: Predicted difference in complaints sent to the NYPD in 2019 by tract type from two reference groups: poor tracts that did not whiten and gentrifying tracts that did not whiten

*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all other covariates at their means.*




to poor tracts that did not whiten, all else equal, with about 50 more complaints per capita on average in whitening poor tracts than non whitening poor tracts.

### 3.4.2 Complaints resulting in NYPD Action

Once the police have responded to a 311 complaint, they have several options about how to react to resolve the complaint. Many complaints to which the NYPD respond end up essentially unresolved. Either there is no evidence of the conditions mentioned in the complaint, the individuals complained about are no longer present, or the circumstance complained about has already been resolved by the time the NYPD arrives. Sometimes, though, the NYPD does take some action to effect a resolution to the complaint. Table 3.9 shows a break down of the types of action the NYPD took to resolve complaints in 2011 and 2019.

Table 3.9: Types of actions taken by NYPD in response to 311 complaints in 2011 and 2019

| | **2011** | **2019** |
|---|---|---|
| | Frequency | Frequency |
| Took action to fix conditions | 42,827 | 164,510 |
| Report made | 1,556 | 3,441 |
| Summons issued | 34,553 | 49,282 |
| Arrests made | 122 | 220 |

The most frequent type of action is the relatively vague resolution of the NYPD "took action" to fix the condition described in the complaint. This indicates that the NYPD did something but that it did not rise to a summons or arrest. The next most frequent action is issuing a summons. This would occur when the police determine that the behavior in the complaint rises to the level of a misdemeanor or a civil infraction. This is followed by "writing a report," and the most infrequent response is making an arrest, which happened 122 times in 2011 and 220 times in 2019. Below I present separate analyses for informal action, which could have psychological consequences for the recipient from the police taking informal action in response to a complaint by a neighbor, and for formal action, which could have more serious legal consequences.

The models of complaints resulting in action differ slightly from the other models presented thus far in this chapter, as discussed in the Data and Models section. I omit the squared term for the logged property crime rate because it does not improve model fit. I add the control variable for the number of major building permits in the tract in 2011. As in Chapter 2, this is to account for the possibility that NYPD

Table 3.10: Modeling per capita complaints resulting in informal NYPD action in 2011

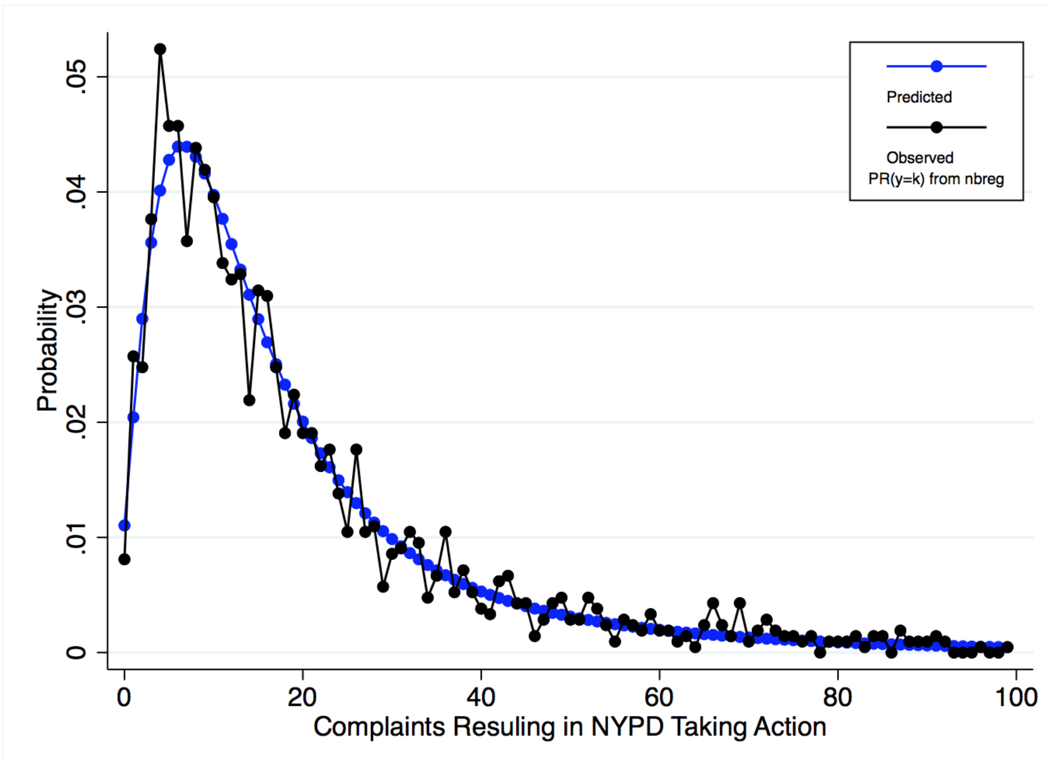
*Note: This table shows the coefficients for the tract typology with three different reference categories: prosperous in the first column, poor but not whitening in the second column, gentrifying but not whitening in the third column.*

| | Complaints Resulting in NYPD 'Taking Action' | | |
|---|---|---|---|
| ***Tract Type*** | | | |
| Prosperous | | 1.088 | 1.013 |
| | | (0.05) | (0.06) |
| Poor and not Whitening | 0.919 | | 0.931 |
| | (0.04) | | (0.06) |
| Poor and Whitening | 1.072 | 1.167** | 1.086 |
| | (0.05) | (0.05) | (0.08) |
| Gentrifying but not Whitening | 0.987 | 1.074 | |
| | (0.06) | (0.07) | |
| Gentrifying and Whitening | 1.123* | 1.222** | 1.138 |
| | (0.06) | (0.07) | (0.08) |
| ***Controls*** | | | |
| Not White Pop % 2010 | 1.002* | | |
| | (0.00) | | |
| Log of Violent Crime Rate | 1.074*** | | |
| | (0.02) | | |
| Log of Property Crime Rate | 0.945* | | |
| | (0.02) | | |
| # of Public Housing Buildings | 1.003*** | | |
| | (0.00) | | |
| Average Land Use | 1.214*** | | |
| | (0.06) | | |
| # Major Building Permits | 0.999 | | |
| | (0.00) | | |
| ***Borough*** | | | |
| Manhattan (reference) | | | |
| The Bronx | 0.891 | | |
| | (0.07) | | |
| Brooklyn | 0.725*** | | |
| | (0.05) | | |
| Queens | 0.630*** | | |
| | (0.05) | | |
| Staten Island | 0.511*** | | |
| | (0.04) | | |
| Logged Pop at Risk | 1.016 | | |
| (Total Complaints Responded to by NYPD) | (0.02) | | |
| lnalpha | 0.119*** | | |
| | (0.01) | | |
| BIC | 13806.354 | | |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure 3.7: Predicted versus observed complaints resulting in NYPD taking informal action in 2011

*Note: Figure shows the probability distribution of counts predicted by the model plotted against the observed probability distribution from one complaint through 99 complaints, which is a maximum count limit imposed by the user-generated -prcounts- Stata command that predicts count probabilities.*



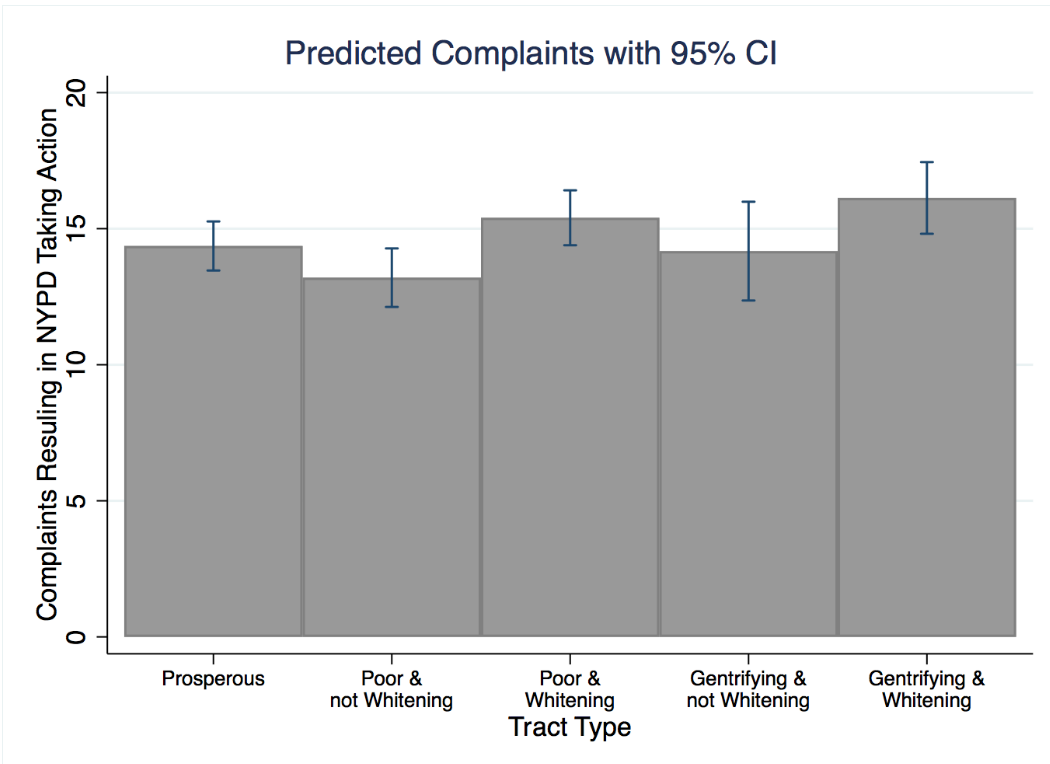

enforcement decisions are somehow influenced by major investment in a tract. Finally, the population at risk for these models is the number of complaints to which the NYPD responded. This makes the results interpretable in relation to the rate of NYPD actions out of total NYPD responses.

Figure 3.7 shows the fit for the model of complaints resulting in police taking informal action in response to a complaint in 2011. Table 3.10 shows the results from that model with coefficients for three reference categories for tract type. A one percentage point increase in not-white population in 2010 is associated with 0.2% more complaints resulting in informal action per capita. The violent crime rate is also associated with more per capita complaints resulting in informal police action. On the other hand, while property crime was associated with more complaints sent to the NYPD, it is associated with *fewer* complaints resulting in the police taking informal action. Conversely, while the number of public housing buildings in a tract was associated with fewer complaints sent to the NYPD, it is associated with *more* instances of informal police action in response to a complaint. This may suggest that the police are more aggressive in their informal actions in areas with more public housing even though those areas get fewer complaints from their neighbors, or it could be that people in public housing are less likely to make frivolous complaints. Average land use is associated with informal action against complaints with more informal action taken in tracts with less residential land use. Finally, all else constant, the number of major building permits is not associated with the number of complaints resulting in informal police action in 2011.

Figure 3.8 shows the predicted number of complaints resulting in informal NYPD action by tract in 2011, holding covariates at their means. Figure 3.9 shows contrast plots visualising the net differences in predicted counts compared to two reference groups, all else held equal. The NYPD taking informal action in response to a 311 complaint is a relatively rare occurrence. The counts per tract are quite low compared to how many complaints are sent to the NYPD. For poor tracts, however, there are significant differences based on whitening, albeit with effects of small magnitude.

Figure 3.8: Predicted number of complaints resulting in NYPD taking informal action in 2011

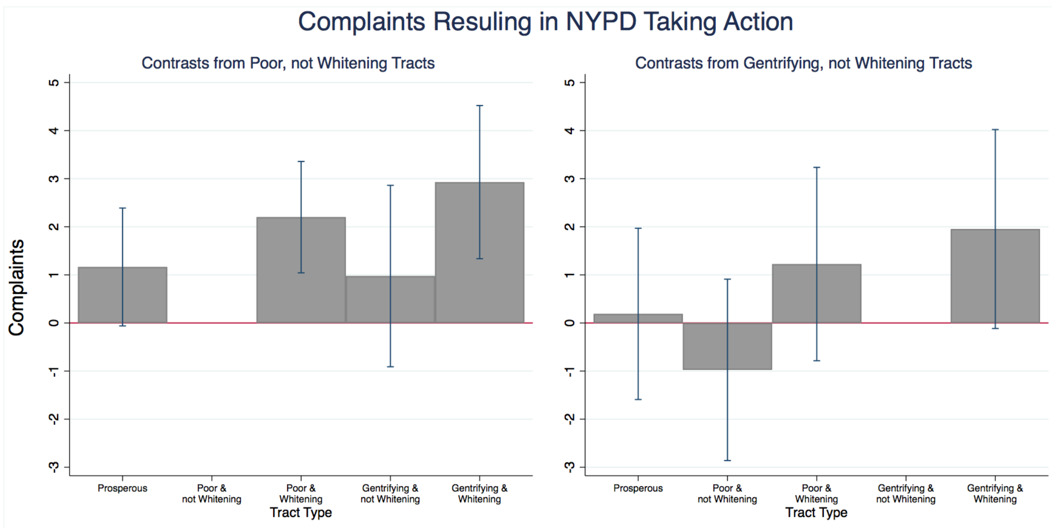
*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*




There were approximately two more complaints per capita resulting in informal police action on average in poor tracts that whitened compared to their non whitening counterparts, all else held equal. Similarly, there were approximately two more complaints per capita resulting in informal police action in gentrifying tracts that whitening compared to their non whitening counterparts, all else equal, although the difference in gentrifying tracts did not pass the conventional threshold of significance ($p = 0.72$). This equates to a 16.7% difference in poor tracts based on whitening and

Figure 3.9: Predicted difference in number of complaints resulting in informal action by the NYPD in 2011 compared to poor and not whitening tracts and gentrifying and not whitening tracts

*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all covariates at their means.*




a 13.8% difference in gentrifying tracts based on whitening, all else equal.

Table 3.11 shows the results from the model of complaints resulting in the NYPD taking informal action in 2019 for each of three reference groups for tract type and Figure 3.10 shows the model fit with the frequency of predicted counts graphed against the frequency of counts observed in the data. For each one percentage point increase in the not-white population in 2018, there are 0.3% more complaints per capita resulting in informal police action in 2019. Violent and property crime rates are not associated with complaints resulting in NYPD action in 2019. This is different than the findings in the 2011 model where violent crime was associated with more informal NYPD action and property crime was associated with less. It is unclear

Table 3.11: Modeling per capita complaints resulting in informal NYPD action in 2019

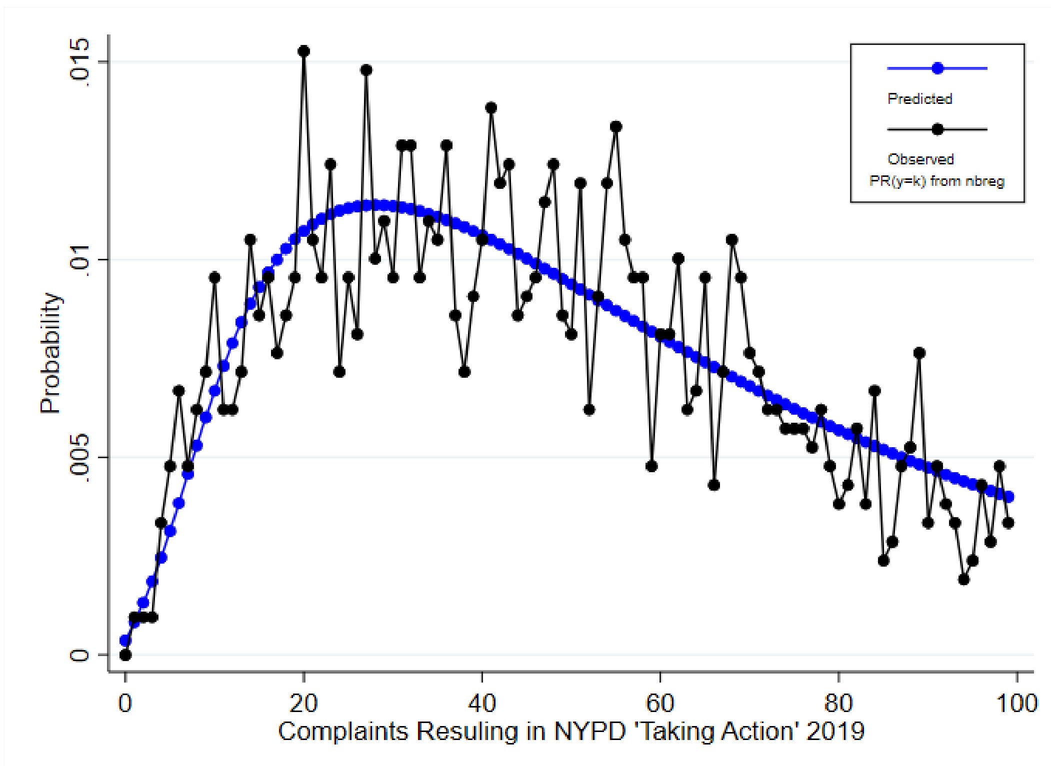
*Note: This table shows the coefficients for the tract typology with three different reference categories: prosperous in the first column, poor but not whitening in the second column, gentrifying but not whitening in the third column.*

| | Complaints Resulting in NYPD 'Taking Action' | | |
|---|---|---|---|
| ***Tract Type*** | | | |
| Prosperous | | 1.101 | 1.121 |
| | | (0.06) | (0.07) |
| Poor and not Whitening | 0.908 | | 1.018 |
| | (0.05) | | (0.05) |
| Poor and Whitening | 0.963 | 1.060 | 1.079 |
| | (0.04) | (0.04) | (0.06) |
| Gentrifying but not Whitening | 0.892 | 0.982 | |
| | (0.06) | (0.05) | |
| Gentrifying and Whitening | 1.017 | 1.119 | 1.139 |
| | (0.05) | (0.07) | (0.08) |
| ***Controls*** | | | |
| Not White Pop % 2018 | 1..003** | | |
| | (0.00) | | |
| Log of Violent Crime Rate | 1.008 | | |
| | (0.01) | | |
| Log of Property Crime Rate | 0.999 | | |
| | (0.01) | | |
| # of Public Housing Buildings | 1.005*** | | |
| | (0.00) | | |
| Average Land Use | 1.169*** | | |
| | (0.06) | | |
| # Major Building Permits | 1.002** | | |
| | (0.00) | | |
| ***Borough*** | | | |
| Manhattan (reference) | | | |
| The Bronx | 1.010 | | |
| | (0.08) | | |
| Brooklyn | 0.964 | | |
| | (0.07) | | |
| Queens | 1.026 | | |
| | (0.08) | | |
| Staten Island | 1.498*** | | |
| | (0.11) | | |
| Logged Pop at Risk | 0.973 | | |
| (Total Complaints Responded to by NYPD) | (0.03) | | |
| lnalpha | 0.149*** | | |
| | (0.01) | | |
| BIC | 19249.586 | | |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure 3.10: Predicted versus observed complaints resulting in NYPD taking action in 2019

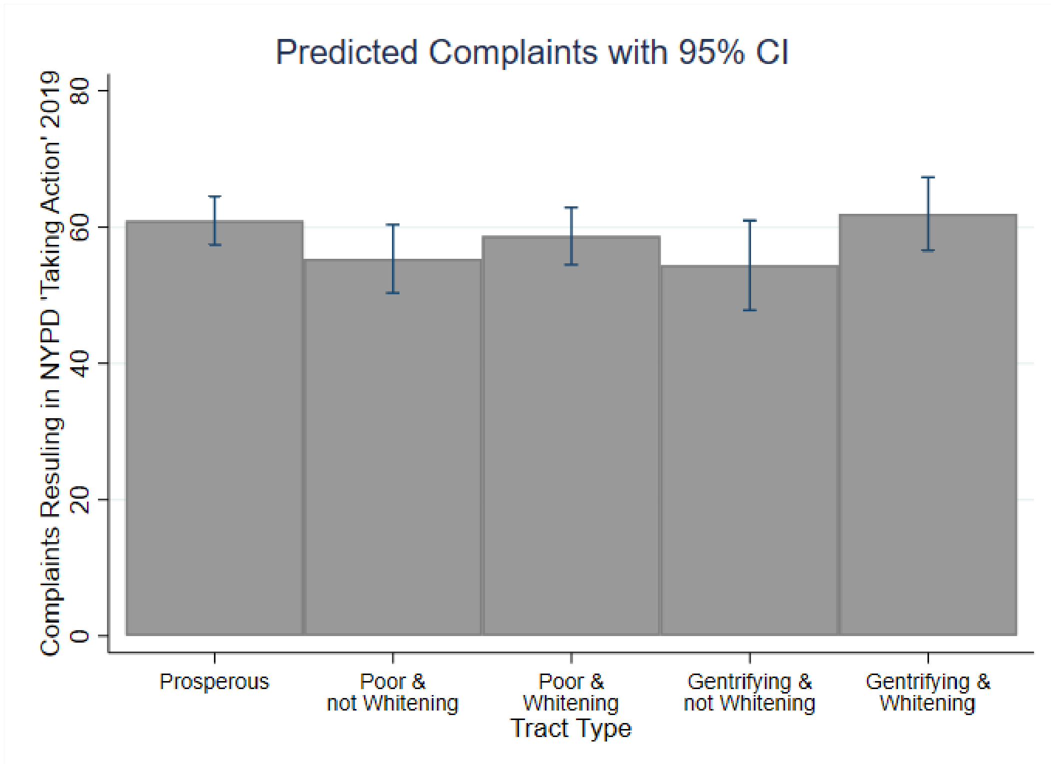
*Note: Figure shows the probability distribution of counts predicted by the model plotted against the observed probability distribution from one complaint through 99 complaints, which is a maximum count limit imposed by the user-generated -prcounts- Stata command that predicts count probabilities.*




why this would be the case except maybe that crime in 2019 was lower than the already low crime rates in 2011 and, therefore, factored much less into NYPD action than it did in earlier years. The number of public housing buildings in a tract is associated with complaints resulting in informal NYPD action – for each additional building there is a corresponding 0.5% higher number of police actions in response to complaints made through 311. Average land use is also associated with more police action in response to complaints. Each step up the land use scale from fully

Figure 3.11: Predicted number of complaints resulting in NYPD taking action in 2019

*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*

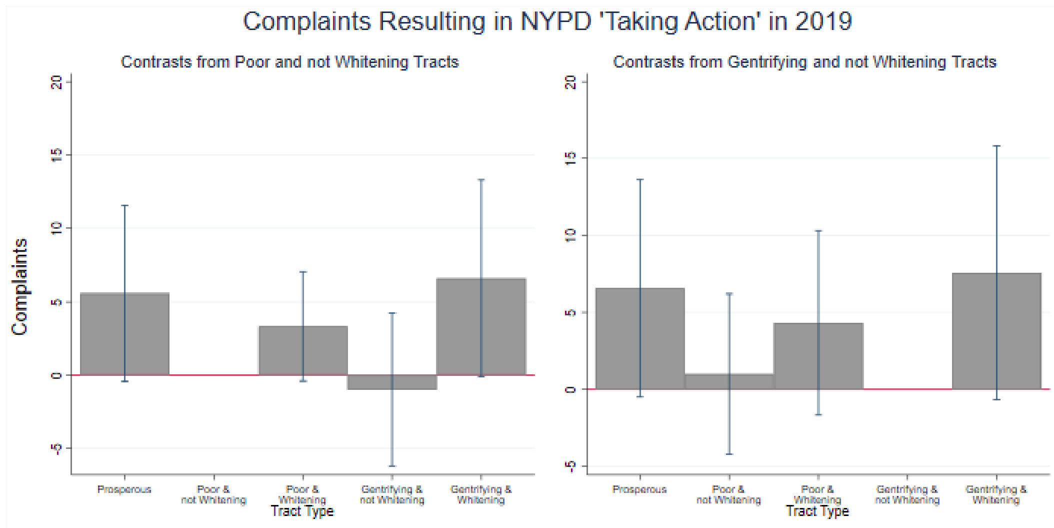



residential to mixed land use to fully non residential was associated with 16.9% more complaints resulting in informal police action. Finally, each additional major building permit issued in a tract in 2019 is associated with 0.2% more complaints resulting in informal NYPD action in 2019, all else equal.

Figure 3.11 shows the predicted number of complaints resulting in informal NYPD action in 2019 by tract type, holding covariates at their means. Figure 3.12 shows the predicted net differences for two reference groups. The panel on the left shows predicted net differences in per capita counts compared to poor tracts that did not

Figure 3.12: Predicted difference in number of complaints resulting in action by the NYPD in 2019 compared to poor and not whitening tracts and gentrifying and not whitening tracts

*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all other covariates at their means.*




whiten. There were more complaints per capita resulting in NYPD action in poor tracts that whitened compared to their non whitening counterparts – about 4 more complaints (p = 0.085), all else equal. The panel on the right shows predicted net differences in per capita counts compared to gentrifying tracts that did not whiten. Gentrifying tracts that did whiten had about 8 more complaints per capita resulting in NYPD action than their non whitening counterparts (p = 0.77). In 2019, whitening predicted 6% more complaints per capita resulting in informal police action in poor tracts and 14% more complaints per capita resulting in informal police action in gentrifying tracts.

Summons and arrests represent formal action the NYPD can take in response to a complaint. These actions require the conditions at the scene to meet some

Table 3.12: Modeling per capita complaints resulting in summons or arrest in 2011

*Note: This table shows the coefficients for the tract typology with three different reference categories: prosperous in the first column, poor but not whitening in the second column, gentrifying but not whitening in the third column.*

| | Complaints Resulting in Summons or Arrest | | |
|---|---|---|---|
| ***Tract Type*** | | | |
| Prosperous | | 1.115 | 0.896 |
| | | (0.08) | (0.07) |
| Poor and not Whitening | 0.897 | | 0.801** |
| | (0.07) | | (0.06) |
| Poor and Whitening | 0.734** | 0.818** | 0.655*** |
| | (0.07) | (0.06) | (0.07) |
| Gentrifying but not Whitening | 1.119 | 1.249** | |
| | (0.09) | (0.10) | |
| Gentrifying and Whitening | 0.804* | 0.897 | 0.719** |
| | (0.08) | (0.09) | (0.07) |
| ***Controls*** | | | |
| Not White Pop % 2010 | 0.997* | | |
| | (0.00) | | |
| Log of Violent Crime Rate | 0.984 | | |
| | (0.02) | | |
| Log of Property Crime Rate | 1.044 | | |
| | (0.06) | | |
| # of Public Housing Buildings | 0.997* | | |
| | (0.00) | | |
| Average Land Use | 0.670*** | | |
| | (0.08) | | |
| # Major Building Permits | 1.002* | | |
| | (0.00) | | |
| ***Borough*** | | | |
| Manhattan (reference) | | | |
| The Bronx | 2.328*** | | |
| | (0.38) | | |
| Brooklyn | 3.372*** | | |
| | (0.49) | | |
| Queens | 4.509*** | | |
| | (0.66) | | |
| Staten Island | 2.216*** | | |
| | (0.41) | | |
| Logged Pop at Risk | 0.849*** | | |
| (Total Complaints Responded to by NYPD) | (0.03) | | |
| lnalpha | 0.294*** | | |
| | (0.03) | | |
| BIC | 11722.585 | | |

Note: Coefficients are exponentiated

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

legal threshold and they have consequences for the person on the receiving end of those formal actions. Table 3.12 shows the results from the model of complaints that resulted in a summons or arrest following an NYPD response. The table provides the coefficients for the tract typology based on three reference categories: prosperous, poor but not whitening, and gentrifying but not whitening. Figure 3.13 shows the predicted probability distribution of counts from the model plotted over the observed probability distribution. The relationship between summons and arrests in response

Figure 3.13: Predicted versus observed complaints resulting in summons or arrest in 2011

*Note: Figure shows the probability distribution of counts predicted by the model plotted against the observed probability distribution from one complaint through 99 complaints, which is a maximum count limit imposed by the user-generated -prcounts- Stata command that predicts count probabilities.*

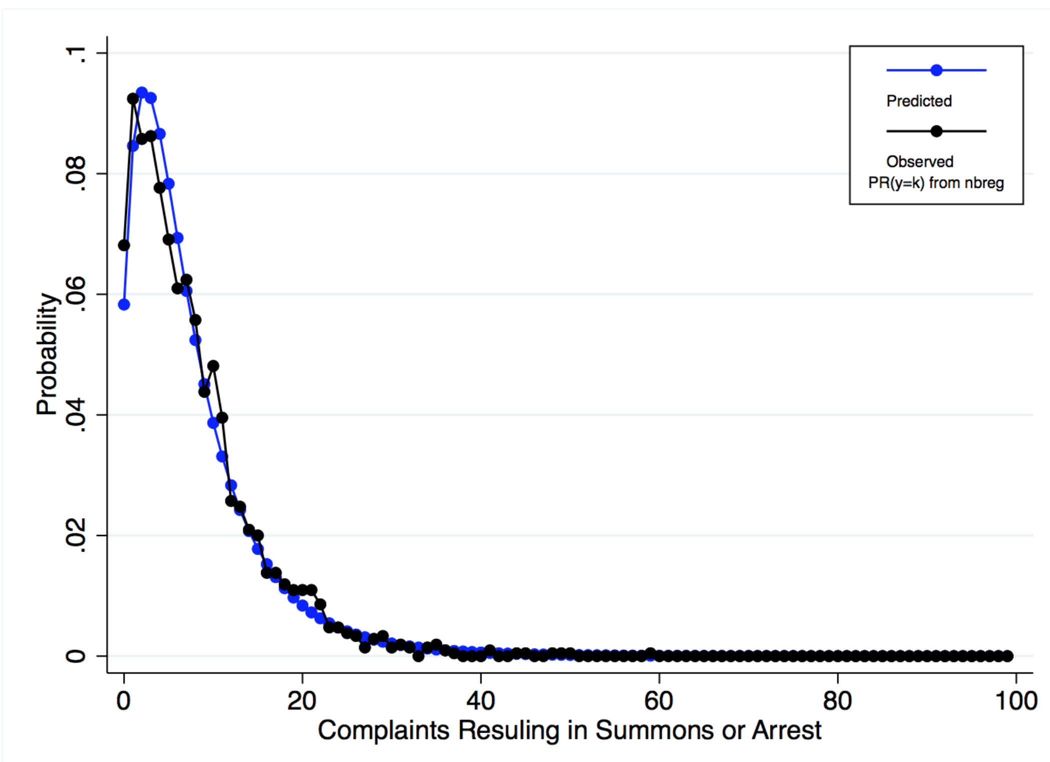
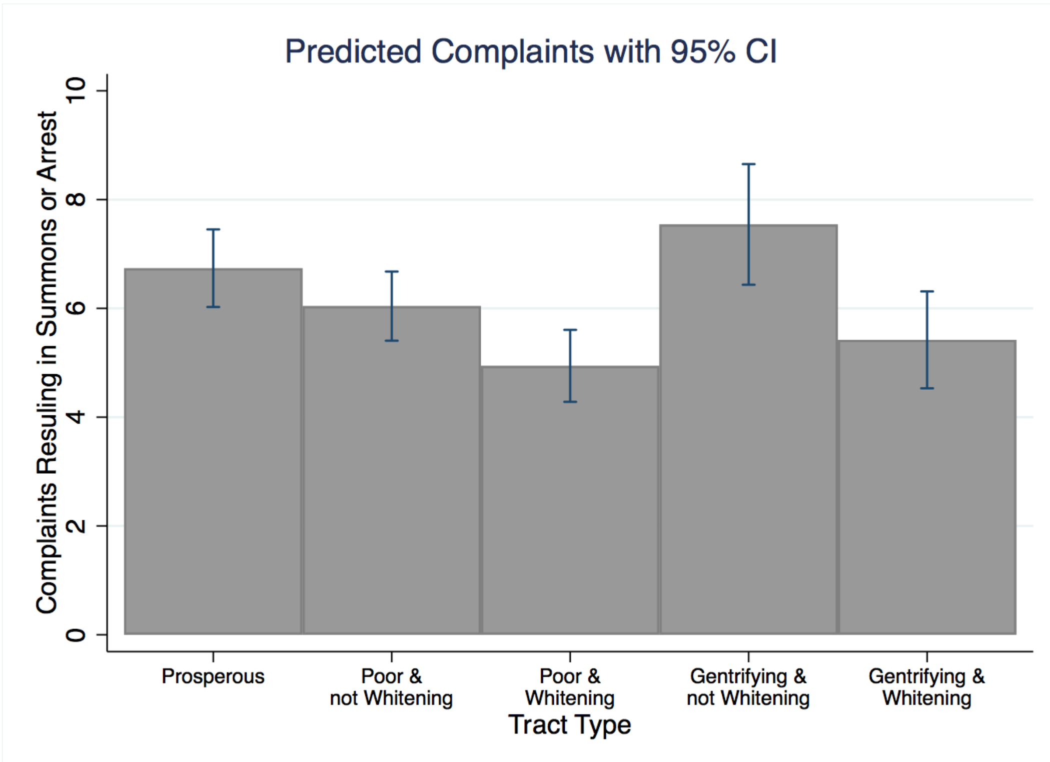


Figure 3.14: Predicted number of complaints resulting in summons or arrest in 2011

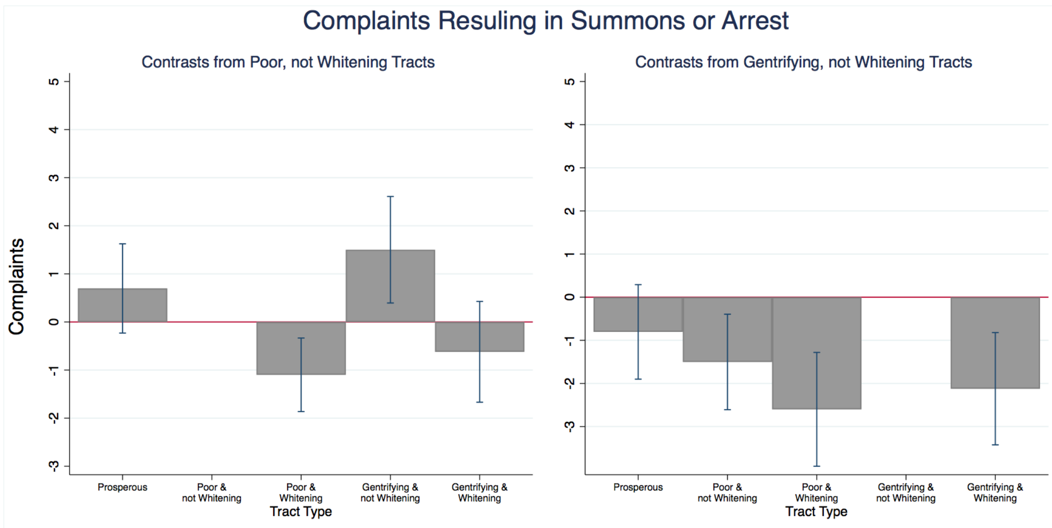
*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*




to 311 complaints and the tracts types follows a completely different pattern than what we might expect from the previous models in this dissertation. Furthermore, the pattern is completely opposite what I expected based on my hypothesis and based on the pattern for informal actions by the NYPD in response to 311 complaints. In the case of formal actions taken by the NYPD in response to 311 complaints, there are many fewer in Manhattan than the other boroughs despite there being many more complaints made in Manhattan. There are also fewer the more public housing buildings there are in a tract. Additionally, there are fewer formal actions in response

Figure 3.15: Predicted difference in number of complaints resulting in summons or arrest in 2011 compared to poor and not whitening tracts and gentrifying and not whitening tracts

*Note: Figure shows net predicted differences for each tract type from a reference category holding all covariates at their means.*




to 311 complaints the more commercial the land use of the tract.

Figure 3.14 shows the predicted counts of formal actions taken by the NYPD in response to 311 complaints by tract type, holding all other covariates at their means. Figure 3.15 shows the predicted net differences in counts of formal action taken in response to complaints compared to two reference categories: poor tracts that did not whiten are the reference in the figure shown in the left panel and gentrifying tracts that did not whiten are the reference shown in the right panel. In the case of complaints resulting in summons or arrest following an NYPD response, there were fewer in both poor tracts that whitened and gentrifying tracts that whitened compared to their non-whitening counterparts. The differences were small but significant – on average, there was one fewer complaint resulting in a summons or arrest following an NYPD response in poor tracts that whitening compared to those that did not and two fewer complaints of this type in gentrifying tracts that whitened compared to those that did not.

Figure 3.16: Predicted versus observed complaints resulting in summons or arrest in 2019

*Note: Figure shows the probability distribution of counts predicted by the model plotted against the observed probability distribution from one complaint through 99 complaints, which is a maximum count limit imposed by the user-generated -prcounts- Stata command that predicts count probabilities.*

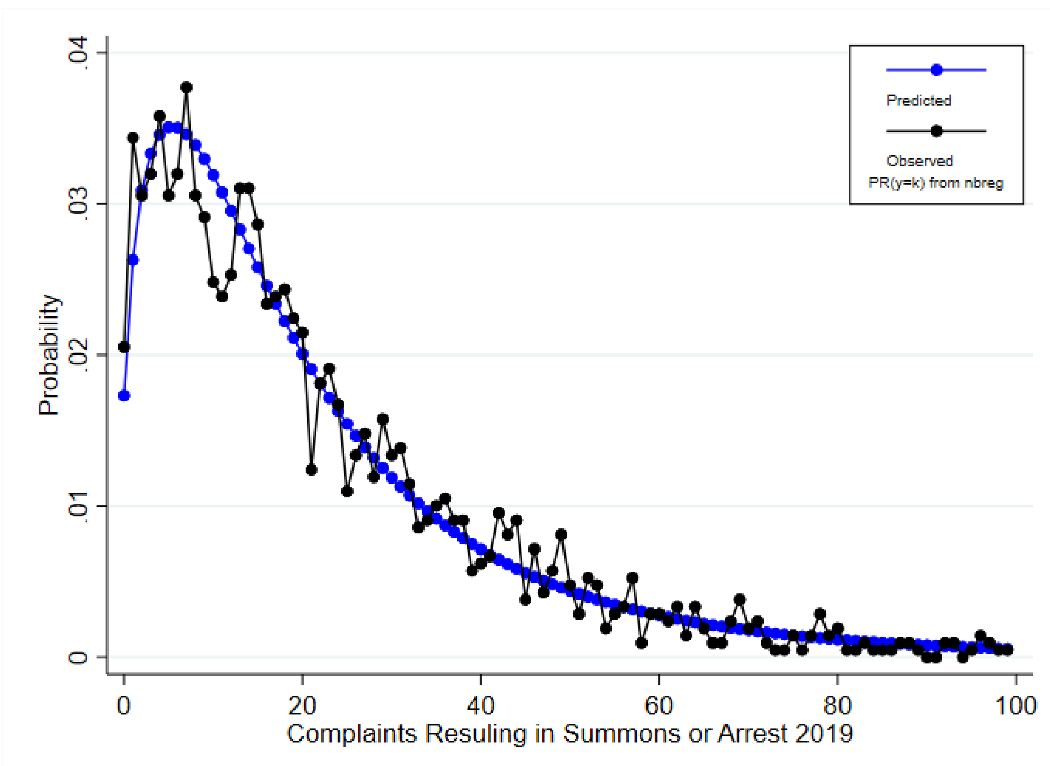



Table 3.13 shows the results from the models of formal action following an NYPD response to a 311 complaint for 2019. Figure 3.16 shows the predicted probability distribution plotted over the observed probability distribution. In 2019, there were

Table 3.13: Modeling per capita complaints resulting in summons or arrest in 2019

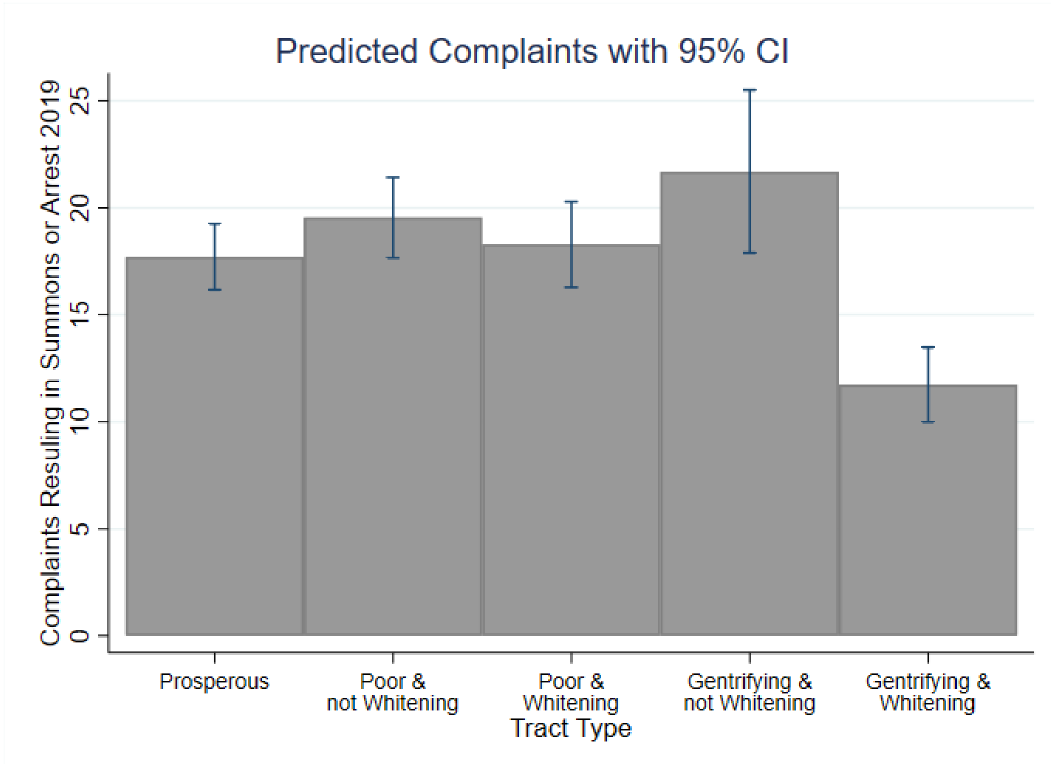
*Note: This table shows the coefficients for the tract typology with three different reference categories: prosperous in the first column, poor but not whitening in the second column, gentrifying but not whitening in the third column.*

| | **Complaints Resulting in Summons or Arrest'** | | |
|---|---|---|---|
| ***Tract Type*** | | | |
| Prosperous | | 0.907 | 0.816* |
| | | (0.05) | (0.07) |
| Poor and not Whitening | 1.103 | | 0.901 |
| | (0.06) | | (0.07) |
| Poor and Whitening | 1.032 | 0.936 | 0.843 |
| | (0.07) | (0.06) | (0.08) |
| Gentrifying but not Whitening | 1.225* | 1.110 | |
| | (0.11) | (0.08) | |
| Gentrifying and Whitening | 0.662*** | 0.600*** | 0.541*** |
| | (0.05) | (0.06) | (0.06) |
| ***Controls*** | | | |
| Not White Pop % 2010 | 0.998 | | |
| | (0.00) | | |
| Log of Violent Crime Rate | 0.977* | | |
| | (0.01) | | |
| Log of Property Crime Rate | 0.992 | | |
| | (0.01) | | |
| # of Public Housing Buildings | 0.997** | | |
| | (0.00) | | |
| Average Land Use | 0.526*** | | |
| | (0.04) | | |
| # Major Building Permits | 1.000 | | |
| | (0.00) | | |
| ***Borough*** | | | |
| Manhattan (reference) | | | |
| The Bronx | 1.985*** | | |
| | (0.26) | | |
| Brooklyn | 3.408*** | | |
| | (0.41) | | |
| Queens | 4.144*** | | |
| | (0.52) | | |
| Staten Island | 2.806*** | | |
| | (0.36) | | |
| Logged Pop at Risk | 0.893* | | |
| (Total Complaints Responded to by NYPD) | (0.04) | | |
| lnalpha | 0.376*** | | |
| | (0.02) | | |
| BIC | 15953.617 | | |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure 3.17: Predicted number of complaints resulting in summons or arrest in 2019

*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*

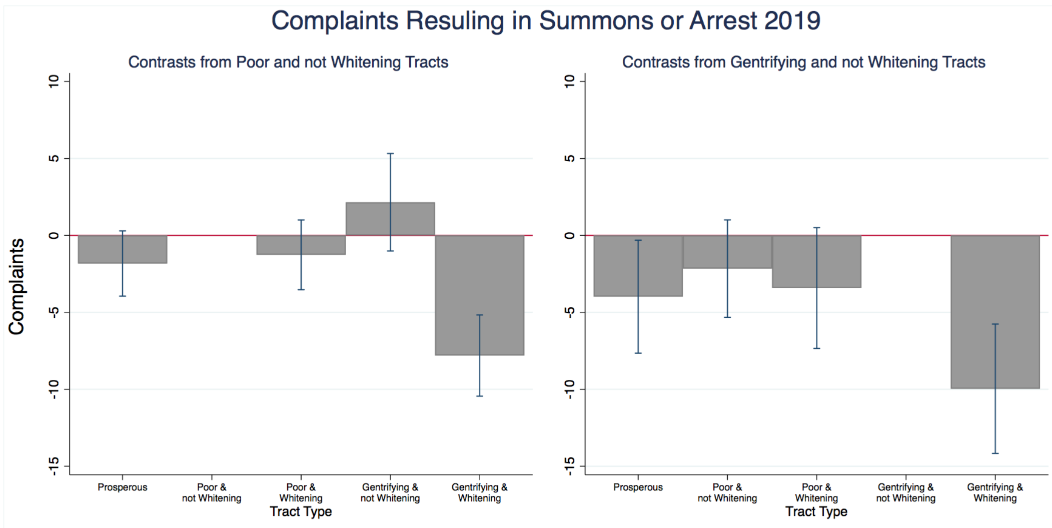



slightly fewer formal actions by the NYPD in response to 311 complaints in tracts with lower violent crime rates. There were fewer formal actions in tracts with fewer public housing buildings, and there were fewer formal actions in less residential tracts.

Figure 3.17 shows the predicted number of formal actions taken by the NYPD in response to 311 complaints by tract type, holding all other covariates at their means. Figure 3.18 shows the predicted differences in counts by tract type holding covariates at their means for two reference groups: the panel on the left shows the predicted differences from poor tracts that did not whiten and the panel on the right

Figure 3.18: Predicted difference in number of complaints resulting in summons or arrest in 2019 compared to poor and not whitening tracts and gentrifying and not whitening tracts

*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all other covariates at their means.*




shows the predicted differences from gentrifying tracts that did not whiten. Unlike in 2011, there was not a meaningful difference between poor tracts that whitened and those that did not. There was, however, a difference between gentrifying tracts that whitened and those that did not. Gentrifying tracts that whitened had, on average, 10 fewer formal actions by the NYPD in response to 311 complaints, all else held equal. This is contrary to my hypothesis that NYPD action in response to 311 complaints would follow a pattern similar to NYPD stops as demonstrated in Chapter 2.

## 3.5 Supplementary Analyses

### 3.5.1 Prosperous Tracts

As in the previous chapter, I consider the possibility that prosperous tracts did not remain prosperous over the period of study. If tracts that met the criteria for being considered prosperous in the first year of the study period declined in socioeconomic status over the time between the first year and the last year, then we may expect that the processes related to social control are different than in those prosperous tracts that remained prosperous. I run the analysis for each outcome again, using the tract typology described in Chapter 2, Section 5.4, which divides prosperous tracts into those that remained prosperous and those that were prosperous but did not remain so. I considered tracts to no longer be prosperous if they had a median household income below the city average for the final year of the period of study – 2010 for the analysis of 2011 complaints and 2018 for the analysis of 2019 complaints. I then divide the formerly prosperous tracts into those that had increases in white population over the course of the study period and those that did not. Table 3.14 shows the expanded typology for tracts in the 2000-2010 and the 2011-2018 time frames.

Table 3.14: Summary of tracts by type 2000-2010 and 2011-2018, including disaggregation of prosperous tracts

| | Frequency | Percent | Frequency | Percent |
|---|---|---|---|---|
| Persistently Prosperous | 818 | 38.97 | 740 | 35.32 |
| Was Prosperous and not Whitening | 202 | 9.62 | 102 | 4.87 |
| Was Prosperous and Whitening | 27 | 1.29 | 51 | 2.43 |
| Persistently poor and not Whitening | 479 | 22.82 | 564 | 26.92 |
| Persistently poor and Whitening | 303 | 14.44 | 440 | 21.00 |
| Gentrifying but not Whitening | 86 | 4.10 | 82 | 3.91 |
| Gentrifying and Whitening | 184 | 8.77 | 116 | 5.54 |

In the simpler tract typology, there were 1,047 tracts categorized as prosperous based on their median household income in 2000 and 893 tracts categorized as prosperous based on median household income in 2011. Of those 1,047 prosperous tracts in 2000, 229 of them would no longer be considered prosperous by the same standard in 2010. Of the 893 prosperous tracts in 2011, 153 would no longer be considered prosperous in 2018. In both years, the majority of the tracts that were prosperous but did not remain so did not have increases in white population over the time period in which they were falling in socioeconomic status. However, 27 tracts from 2000 to 2010 and 51 tracts from 2011 to 2018 fell in socioeconomic status and simultaneously gained white population.

I rerun the analysis for each outcome in both years with the new tract typology to account for the tracts that did not remain prosperous over the period of study. The overall pattern for poor and gentrifying tracts is similar to what we saw in the main analysis, with the highest number of per capita complaints going to the NYPD from gentrifying tracts that also whitened. Formerly prosperous tracts that did not whiten during the period they were dropping in socioeconomic status had more complaints sent to the police than prosperous tracts. Formerly prosperous tracts that did whiten also had more predicted complaints than prosperous tracts, but the low end of the confidence interval just crosses zero. There is also not a statistically significant difference between per capita complaints sent to the NYPD in formerly prosperous tracts that whitened compared to those that did not whiten. Dividing out the formerly prosperous tracts does not change the finding in the main analysis that there are significantly more complaints per capita sent to the NYPD in gentrifying tracts that whitened compared to gentrifying tracts that did not whiten.

In 2019, as with 2011, the overall pattern for poor and gentrifying tracts remains the same when the formerly prosperous tracts are separated out. There are more complaints per capita sent to the NYPD in gentrifying tracts that whitened compared to all other tract types, all else equal. Both types of formerly prosperous tracts had more predicted complaints than prosperous tracts, all things equal, however the differences are barely statistically significant. Breaking out the formerly prosperous tracts does not change the finding of the main analysis that gentrifying tracts that whitened had significantly more complaints per capita sent to the NYPD than gentrifying tracts that did not whiten. Finally, there is no statistically significant difference between the formerly prosperous tracts that whitened and those that did not, all else equal.

For informal and formal action taken by the NYPD in response to 311 complaints, the results follow the same patterns as the main analysis when the additional tract types are included. The formerly prosperous tracts pattern with the persistently prosperous tracts in both 2011 and 2019. Figures and tables are available for the supplementary analysis upon request.

## 3.6 Discussion

When individuals with both socioeconomic and racial/ethnic privilege move into proximity to relatively disadvantaged populations, there is the possibility of conflict due to culture clash and different social norms, contested ownership of the place, and different preferred strategies for conflict resolution. Studies have shown that white individuals are more likely to trust and use local government, including the police, than are Black individuals and that neighborhoods with higher percentages of Black and Hispanic residents and lower socioeconomic status are less likely to use the 311 system than whiter, richer neighborhoods (Kontokosta et al., 2017; Cavallo et al., 2014; Tyler, 2005). While the 311 data do not tell us the race of the people making the complaints or the people being complained about, tract level analysis can illustrate how neighborhood change is associated with different patterns of use of the city complaint system to bring the police into neighborhood problem resolution.

I hypothesized that, given the differences in trust and use of local government services including the police, there would be more complaints sent to the NYPD, all else equal, in tracts that both gentrified and whitened over the course of the study periods compared to all other tract types. Indeed, I found that this was the case in both 2011 and 2019. Even when the differences were not statistically significant at the p=0.05 level, the predicted numbers of complaints sent to the NYPD followed this pattern.

I additionally hypothesized that there would specifically be more complaints in gentrifying tracts that whitened compared to gentrifying tracts that did not whiten. The combination of socioeconomic privilege and racial/ethnic privilege in the newcomers may bring with it social norms around neighborhood behavior that are different from the norms that have existed in that neighborhood for some time and, which, due to the greater social capital of the newcomers, will likely overpower the norms of the longer term residents. I find that in both 2011 and 2019, there is a significantly higher per capita rate of complaints made to the police, all else equal, in tracts that both gentrified and whitening compared to their non-whitening, gentrifying counterparts. Community Service Society (2019) found that whitening was related to more 311 complaints sent to NYPD in lower income neighborhoods that gained white population in 2017. They also found that there were more complaints sent to the NYPD in gentrifying tracts. They did not, however, consider the combination of neighborhood whitening and socioeconomic gentrification. I found that in 2011, whitening did not separate poor tracts in terms of complaints sent to the NYPD, but it did separate poor tracts in 2019. It may be that there was a change over time that started after 2011, which was captured in the analysis in Community Service Society (2019) of 2017 complaints and in my analysis of 2019 complaints.

One possible explanation lies in a reinterpretation of Legewie and Schaeffer (2016). They find that there were more 311 complaints in contested geographic areas, that is those transitional tracts between two homogeneous neighborhoods where the boundaries are fuzzy. Perhaps this is also true of transitional times, such as the transition over time from poor to gentrifying and the transition of neighborhood whitening. Neighborhood change may usher in transition where the boundaries between what the neighborhood was and what the neighborhood will become are fuzzy, creating conflict through the negotiation of social norms and behavioral expectations. Walton (2018) describes "habits of whiteness" to explain how white norms and social expectations are linked to greater social control and an emphasis on normative behavior, rule following, and surveillance in "stably diverse" neighborhoods. Perhaps, in terms of using the 311 system to summon police for the purposes of social control, it takes time for "habits of whiteness" to assert themselves when whiteness is not accompanied by commensurate increases in socioeconomic status, which could explain why whitening did not predict more complaints sent to the NYPD in poor tracts in 2011, but did in 2019.

Finally, I hypothesized that there would be more actions taken by the NYPD when responding to 311 complaints in both poor tracts that whitened and in gentrifying tracts that whitened compared to their respective non-whitening counterparts. This outcome is specifically about what the NYPD chooses to do once they have responded to a complaint and, therefore, I hypothesized that, consistent with the findings in Chapter 2 related to police stops, that whitening would be related to more police action in both poor and gentrifying tracts. I found this to be the case for informal, but not formal, action. All else equal, there were higher rates of informal action by the NYPD in response to 311 complaints in poor tracts that whitened compared to poor tracts that did not whiten and in gentrifying tracts that whitened compared to gentrifying tracts that did not whiten in. This was the case in both 2011 and 2019.

The story was very different for formal action taken by the police in the form of summons and arrests in response to 311 complaints. For these formal actions, there were fewer in poor tracts that whitened and in gentrifying tracts that whitened compared to their non-whitening counterparts. Perhaps this should not be surprising. Evidence from other studies of NYC's stop and frisk program has shown racial disparities in so-called successful stops – that is, stops where there was some demonstrable suspicion that results in arrest, summons, or seizure of contraband (Goel et al., 2016; Fagan and Geller, 2015). In this case, it may be that there are fewer formal police actions in response to 311 calls in whitening tracts because the complaints made in those tracts are less likely to be about legitimately problematic behavior. This would fit with the narrative of white people moving into neighborhoods and frivolously complaining about what was previously considered acceptable behavior in those areas (Weaver, 2018; Vo, 2018).

A limitation of this analysis is that the data do not tell us the race/ethnicity and socioeconomic status of the person who made the complaint or the person about whom the complaint was made. This limits what we can say about the impact of neighborhood change on neighborhood dynamics. It is easy to assume that when tracts gentrify and whiten, the white newcomers are also the gentrifiers. Based on that assumption it is easy to further assume that higher rates of complaints are being made by the white, gentrifying newcomers against lower income residents of color. But this may not be the case. It could be that when tracts gentrify and whiten, the longer term residents complain to the city about their new neighbors. Given what is known about how groups tend to trust and interact with government services, this is not the most likely scenario, but it is not out of the question. Further research is necessary to parse individual behaviors from overall tract level patterns.

In this chapter, I have demonstrated several things. First, neighborhood change happens over multiple dimensions. It is no longer enough to look at socioeconomic factors alone when studying neighborhood change. Socioeconomic gentrification does not tell the whole story – racial change is an important factor that must be separated out to see the full picture. Second, the combination of gentrification and whitening is associated with higher per capita complaints through the 311 system that can bring the NYPD to the neighborhood compared to gentrification on its own. Neighborhood whitening adds an additional burden to the neighborhood where the police are more likely to be called to enact social control more often for non-emergency matters. Third, whitening is associated with more informal action taken by the NYPD in response to 311 complaints in both poor tracts and gentrifying tracts. This means that in poor and gentrifying tracts that whitened, individuals about whom complaints were made are more likely to have negative encounters with the police in regards to non-emergency issues than they are in poor tracts and gentrifying tracts that did not gain white population in the recent past. Finally, formal action by the NYPD in response to 311 complaints is less likely in tracts that whitened compared to those that didn't. More research is necessary to determine if this is because the complaints are more likely to be baseless in whitening tracts or if there is some other mechanism at play.

These findings imply that there are different processes linking neighborhood change and individual citizen decisions to ask for social control compared to decisions made by the direct agents of social control, the police. In Chapter 2, I demonstrated that whitening was important in rates of stops of Black individuals, particularly in poor tracts. Here, I have demonstrated that whitening is particularly important in gentrifying tracts in individual citizen decisions to call on the city to send the police for assistance. These two mechanisms of social control combine when the 311 complaints induce the police to come and then result in police action, up to and including summons and arrest, against individuals about whom the complaint was made. This has implications for conflict mitigation in gentrifying and whitening neighborhoods. Community planning and policies should take into account the different ways in which multiple mechanisms of social control can be influenced by changing demographics. Community groups aimed at building collective efficacy should consider ways to manage different cultural expectations and social norms to avoid conflicts over means of conflict resolution. I suspect that efforts to minimize social segregation in demographically diverse neighborhoods would allow for greater community building across cultures[6] and develop a collective efficacy that includes all members of the neighborhood working together towards shared goals rather than having neighbors in conflict with each other. In the next chapter, I examine the most common kind of complaint that brings out the NYPD, residential noise complaints, and the two types of residential noise complaints most likely related to differences in cultural norms, complaints about loud talking and about loud music and parties.

[6] I do not mean to equate race with culture. Neither are biologically real categories. They are, however, social categories that tend to be correlated, especially in so far as segregation tends to be along the lines of these socially constructed categories and culture develops within social groups.

# Chapter 4

# "Can you keep it down over there?": Neighbor enacted social control through complaints made to the city about residential noise

## 4.1 Introduction

In the previous chapter, I discussed social control initiated by individuals in the form of complaints that are sent to the NYPD and result in NYPD action. The most common type of complaint that ends up with the NYPD is the residential noise complaint. These complaints represent individual attempts to compel the city government to curb the behaviors of other individual residents in their own homes. Once the complaint has been made, police officers are dispatched to the location about which the complaint was made within 8 hours, and respond to the complaint by engaging with the people at the address provided by the complainant if the behavior described in the complaint is still happening when the officers arrive. If the behavior is no longer occurring, then the officers note that the behavior had ceased by the time they responded and that the complaint is closed.

Residential noise complaints can be made in four main categories: loud banging/-pounding, loud television, loud talking, and loud music and parties. Banging and pounding may be from individuals doing some sort of home improvement work or it may be from people banging on the walls to signal to their neighbors that they are making too much noise. While the latter may be social sanctioning behavior, or passive aggressive attempts at conflict resolution, it is impossible to fully disentangle those kinds of complaints from complaints about any other activity that produces a loud banging noise. Loud television likely reflects the hearing ability of the residents or other noise conditions inside the apartment, such as a loud air conditioner making it hard to hear the television. Complaints about loud talking and loud music and parties, on the other hand, are complaints about social behavior. Complaints can also be made about loud talking and loud parties/music that occur on the sidewalk or street outside residential buildings, which get categorized as street noise rather than residential noise but are also sent to the NYPD. In this chapter, I investigate residential noise complaints in the aggregate, and then I look separately at all complaints about loud talking and all complaints about loud music and parties including those about behavior happening on the street or sidewalk, to see how neighborhood change is associated with attempts by individuals to curb behaviors by their neighbors that audibly encroach on their private space.

## 4.2 Background and Literature

### 4.2.1 Culture Clash?

When newcomers move into a neighborhood, they bring with them cultural expectations about acceptable social behavior, both in public with neighbors, and inside residences where there is some expectation of privacy. Expectations of privacy within an urban setting can be shaped by many things including past experience, culture related to race/ethnic group, and socioeconomic status. Expectations may also be more or less reasonable depending on the type of neighborhood, with more possibility of privacy in neighborhoods where housing is more spread out, such as suburban areas, and less possibility of privacy in urban areas where housing is concentrated in apartment buildings with next door neighbors sharing walls and floors and ceilings. Middle and upper-middle class residents tend to have an expectation of greater privacy rather than intimacy with their communities, even in dense urban settings, as compared to poor and working class residents who are more likely to accept intimacy within their dense urban neighborhoods (Engle Merry, 1993; Gans, 1962).

For some people, noise heard in their dwelling from other peoples' dwellings represents transgressions of the "fragile private-public boundaries" separating one home from another, and neighbors should not intrude on private spaces (Gurney et al., 2000; Stokoe, 2006). However, in urban neighborhoods, it is often difficult to avoid hearing sounds from your neighbors, especially in areas with older building stock, which tend to have thinner walls due to landlords breaking originally larger apartments into a many smaller apartments with poor sound insulation between them.

A cross-cultural, multi-national study of noise showed that there are national cultural differences in individuals' ability to habituate to noise and that lack of habituation was associated with higher sensitivity to noise, which suggests that, depending on previous exposure, some people will be better able to deal with noisy neighbors than others (Namba et al., 1986). What constitutes noise and what constitutes appropriate volume are also socially constructed and contextually dependent (Stokoe and Hepburn, 2005). Too loud in one neighborhood may be normal in another.

In general, in the United States, white people are less likely to be exposed to noise pollution, and are exposed to lesser noise pollution when they are exposed, than Black people, so it may be that when white people move into predominantly Black and Hispanic neighborhoods they are not used to the overall level of noise (Casey et al., 2017). Higher levels of noise pollution may lead people to talk louder, play the television louder, and play music louder to compensate for the background noise. In a study of music volume in personal listening devices in NYC, researchers found that on average African Americans listened at the highest decibel levels compared to other study participants from different backgrounds (Fligor et al., 2014).[1] This is likely due to a habituation to higher volumes due to exposure to higher levels of noise pollution, which may be read by others as a cultural preference.

Given these differences in exposure to noise and social norms around privacy,

[1]This study involved researchers stopping people in Union Square Park to ask about volume and testing decibel levels. It is problematic in that it does not differentiate across subgroups and lumps all people coded by the researchers as African American together. But it does suggest a probabilistic likelihood to tolerate music at higher volumes.

when white, middle and upper-middle class residents move into poor and gentrifying areas, culture clash is likely to occur. The question is then, how do neighbors with different expectations about noise and privacy deal with each other?

### 4.2.2 Policing "Non-Normative" Behavior

Evidence on gentrification in London suggests that contemporary gentrifiers are living their lives completely separately from their lower SES neighbors and potentially contributing to increasing social polarization, rather than social cohesion, by inhabiting entirely separate social spaces from their neighbors despite being in the same geographic places (Butler, 2003). Communities that are more "racially fragmented" have lower overall levels of trust than those that are homogeneous (Alesina and La Ferrara, 2002). Additionally, residents in diverse neighborhoods tend to "hunker down" (Putnam, 2007, 149) and not participate in neighboring behaviors with each other across group lines (Alesina and La Ferrara, 2000, 2002; Costa and Kahn, 2003; Neal and Neal, 2014; Unger and Wandersman, 1982). When neighbors do not tend to interact, the social relationships necessary to deal with conflict over differing social norms are likely not present.

African Americans living in cities are more likely to be exposed to deviant behavior based on the social-ecological context of their neighborhoods (Sampson and Bartusch, 1998).[2] (Sampson and Bartusch, 1998) found that African Americans and Hispanics espoused greater intolerance for deviant behaviors in their neighborhoods than whites, but that these same behaviors were tolerated in practice in predominantly African

[2] In their study, Sampson and Bartusch (1998) measured tolerance for deviance by asking how wrong it was for teenagers to smoke cigarettes, use marijuana, drink alcohol, and get into fistfights

American and Hispanic neighborhoods due to greater levels of cynicism and distrust towards the police. Legal cynicism can lead to a lower likelihood of involving the state in conflict resolution (Sampson and Bartusch, 1998). On the other hand, white Americans report lower levels of trust in their neighbors when they live among out-group members, particularly if their neighbors are Black (Abascal and Baldassarri, 2015). Gentrification and whitening may lead to neighborhoods with existing residents who have, on average, lower levels of trust in the police gaining new residents who, on average, are more likely to trust the police and less likely to trust their new neighbors.

There is anecdotal evidence that when white people move into NYC neighborhoods that previously were predominantly inhabited by Black and Hispanic residents, they bring more police with them due to increases in quality-of-life complaints about things like noise, which threaten to change neighborhood traditions by attempting to police what were previously normative behaviors in those places (Vo, 2018; Evelyn, 2019; Levin, 2015). In community conversations around gentrification in Portland, Oregon, Black residents complained that their White neighbors could have loud parties without the threat of social control consequences, while the Black residents worried "we have to be real careful about our noise level because we know that the second it gets too loud, they'll call the police on us. It didn't even occur to them that the police would be called on their noise" (Drew, 2012). Sounds can be racialized and policed just like any other behavior, with race and class-based disparities in who does the sanctioning and who gets sanctioned (Stoever, 2016).

Based on race/ethnicity and class based differences in cultural expectations around noise, privacy, norm violations, and when to call upon the state for social sanction, I hypothesized that the combination of gentrification and neighborhood whitening would be associated with more complaints about residential noise overall, more so than economic gentrification on its own. Additionally, I hypothesize that the combination would be more important for predicting complaints about loud music and parties than about loud talking. Talking is something everyone does in their homes, and I anticipated that, even at loud volumes, it would be more tolerated than loud music and parties, which I assume are more likely to be seen as avoidable impositions on neighbors. Additionally, speech cannot reach the same decibel levels as music. According to the Centers for Disease Control and Prevention, normal conversation is usually about 60 decibels, while music from a loud stereo or radio can be 105 to 110 decibels in volume (CDC, 2019). Therefore, loud music can more easily become a nuisance to neighbors than loud speech just by virtue of its higher possible upper limit.

## 4.3 Data and Models

To investigate the relationship between neighborhood change and 311 calls from individual citizens to complain about residential noise, I look at complaints made in 2011 and in 2019 using the data sets described in Chapter 1. As in Chapters 2 and 3, the predictor of interest is my gentrification and whitening tract typology. I hypothesized that gentrification and whitening will predict higher rates of complaints against neighbors for at-home behaviors that produce residential noise. Residential noise complaints can be made about banging or pounding, loud talking, loud television, and loud music/parties. First, I analyze all complaints made about residential noise. Then I focus on all complaints about loud talking and all complaints about loud music and/or parties.[3] I use the same base model to investigate each outcome. Similar to the analysis of stops in the previous chapter, I have fixed the temporal order by predicting complaints made in 2011 with neighborhood change occurring between 2000 and 2010 and predicting complaints made in 2019 with neighborhood change occurring between 2011 and 2018.

Table 4.1: 311 complaints about loud talking, TV, and music in 2011 (n=2,099)

| | Mean | Std Dev | Min | Max |
|---|---|---|---|---|
| Residential Noise Complaints | 53.01 | 65.88 | 0 | 735 |
| Loud Talking Complaints | 8.04 | 16.89 | 0 | 378 |
| Loud Music Complaints | 46.78 | 51.79 | 0 | 562 |

Table 4.2: 311 complaints about loud talking, TV, and music in 2019 (n=2,095)

| | Mean | Std Dev | Min | Max |
|---|---|---|---|---|
| Residential Noise Complaints | 109.89 | 135.29 | 0 | 1,684 |
| Loud Talking Complaints | 18.57 | 40.81 | 0 | 1,162 |
| Loud Music Complaints | 121.12 | 160.78 | 0 | 1,725 |

Tables 4.1 and 4.2 show a summary of complaints made in these three categories in 2011 and 2019, respectively. There were overall many more of these complaints made in 2019 than in 2011. In both years, there were more complaints made about loud music and parties than loud talking.

[3] Here I specify all complaints of these types to indicate that I include those that are residential, as in they are complaints about behavior inside a residential building, and those that are from noise on the street or sidewalk outside the building. Whether these noise complaints are categorized as residential or street/sidewalk, they all are sent to the NYPD for response. I do not differentiate between complaints about loud talking and loud music and parties that happened inside the building versus outside because they all represent complaints about audible social behavior that the complainant seeks to sanction.

Tables 4.3 and 4.4 show descriptive statistics for the relevant covariates for the 2011 and 2019 analyses, respectively. Following the same methodological strategy as in Chapters 2 and 3, I start with a simple conceptual model and subsequently add theoretically motivated controls. Equation 4.1 represents the simplest form of the conceptual model, predicting the number of complaints in tract $i$ in year $t$, where $t$ is either 2011 or 2019, with the logged population at risk to make the outcome interpretable as a count per capita:

$$complaints_{it} = \beta_{i0} + \beta_{i1} TractType_{i(t-1)} + \beta_{i2} LoggedRiskPopulation_{i(t-1)} + u_{it} \quad (4.1)$$

It may be that differences in racially and ethnically correlated norms influence whether neighbors are more likely to reach out to the city for help dealing with unwanted residential noise. To account for this possibility in the context of neighborhood whitening, and given that white individuals are most likely to trust and seek help from local authorities, I control for the percentage of the population of the tract that was non-Hispanic white in 2010 for the analysis of complaints made in 2011 and in 2018 for the complaints made in 2019.

Residents may be more likely to complain to the city about residential noise in neighborhoods with higher crime rates. This may be because they do not wish to confront neighbors personally for fear of conflict. To account for this, I control for the violent and property crime rate in the tracts in the same year as the complaints. I include a control for the number of public housing buildings in the tract since NYCHA buildings tend to be in poor repair, which might lead to conditions where people are more likely to complain (Mays, 2014). Additionally, I include controls for

Table 4.3: Descriptive statistics by tract for analysis of 2011 complaints (n=2,099)

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| White Population % in 2000 | 35.75 | 32.51 | 0.11 | 99.00 |
| White Population % in 2010 | 33.51 | 30.95 | 0.07 | 99.60 |
| Crime Rate/1,000 pop | 19.16 | 99.06 | 1.17 | 3470.09 |
| Violent Crime Rate/1,000 pop | 5.99 | 19.01 | 0 | 619.05 |
| Property Crime Rate/1,000 pop | 13.17 | 82.95 | 0.57 | 2974.36 |
| Median Household Income 2000 in 2010$ | 40803.36 | 18919.07 | 6771 | 188697 |
| Median Household Income 2010 | 57068.22 | 27622.64 | 9675 | 250001 |
| # NYCHA Buildings | 4.92 | 17.32 | 0 | 193 |
| Average Building Age | 74.83 | 15.58 | 12.34 | 120.80 |
| % of Population over age 75 | 5.69 | 3.78 | 0 | 68.38 |
| Population | 3884.54 | 2105.34 | 73 | 26588 |

Table 4.4: Descriptive statistics by tract for analysis of 2019 complaints (n=2,095)

| | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|
| White Population % in 2011 | 33.89 | 31.33 | 0 | 100 |
| White Population % in 2018 | 32.32 | 29.34 | 0 | 99.59 |
| Crime Rate/1,000 pop | 0.70 | 3.62 | 0 | 118.18 |
| Violent Crime Rate/1,000 pop | 0.25 | 1.09 | 0 | 45.45 |
| Property Crime Rate/1,000 pop | 0.46 | 2.80 | 0 | 72.73 |
| Median Household Income 2011 in 2018$ | 54,577.76 | 26,283.17 | 9,212 | 239,614 |
| Median Household Income 2018 | 58,286.86 | 28,652.66 | 8,611 | 216,604 |
| # NYCHA Buildings | 4.93 | 17.33 | 0 | 193 |
| Average Building Age | 73.27 | 15.83 | 12.55 | 120.6 |
| % of Population over age 75 | 6.33 | 4.16 | 0 | 65.29 |
| Population | 4,014.52 | 2,178.53 | 60 | 28,272 |

the average age of the buildings in the tracts and the percentage of the population in each tract that is above the age of 75. Building age tells us something about construction and wall thickness, which might contribute to complaints about noise when everything that happens next door is audible. Elderly residents may be hard of hearing and, therefore, more likely to watch television loudly or talk loudly. On the other hand, elderly residents may be more likely to complain about loud music and parties coming from their neighbors apartments late at night. Finally, I include dummy variables for each borough (Manhattan is the omitted category) to capture possible borough-specific tendencies toward complaining.

To achieve linear bivariate relationships with the outcomes, I log both crime rates. As with the analysis of stops, I estimate robust standard errors clustered on Neighborhood Tabulation Area (NTA) to address the possibility of a violation of the assumption of independence of errors due to the spatial relationship of tracts within larger spatial boundaries. Equation 4.2 shows the full model:

$$\begin{aligned}complaints_{it} = \beta_{i0} + \beta_{i1}TractType_{i(t-1)} + \beta_{i2}PercentNotWhite_{i(t-11)} + \\ \beta_{i3}LoggedViolentCrimeRate_{it} + \beta_{i4}LoggedPropertyCrimeRate_{it} + \\ \beta_{i5}[\mathbf{Z}_{i(t-1)}] + LoggedRiskPopulation_{i(t-1)} + u_{it}\end{aligned} \tag{4.2}$$

where $\mathbf{Z}$ is a matrix of tract characteristics: total public housing buildings, average age of the buildings, percent of the population over age 75, and borough. Finally, the population at risk is the full population of the tract because that constitutes the known population who may be at risk of having a complaint made about their behavior and the known population who might make a complaint.[4]

[4]By specifying known population, I acknowledge that the daily population of a given tract may not be accurately reflected in the residential population. This means that the population at risk may be underestimated for some tracts and overestimated for others. This may be more of a problem for other kinds of complaints, but likely does not pose a problem for complaints made about residential noise since by their nature they imply complaints made by residents about residents.

## 4.4 Findings

### 4.4.1 Complaints about residential noise

To test my hypothesis that gentrification and whitening will be associated with higher rates of complaints about residential noise, I run the full and constrained models predicting total complaints about residential noise in 2011. Table 4.5 shows the output from the simplest model predicting complaints with just tract type and the logged population at risk, a model adding the not-white percentage of the tract population in 2010, and the full model with additional tract characteristics as controls. Figure 4.1 shows model fit with predicted counts plotted with observed counts. The model provides a good fit for the observed data despite the variance. The *lnalpha* parameter is significant for all three models, confirming the appropriateness of using the negative binomial model instead of the Poisson model. Finally, the smaller BIC on the full model provides additional evidence that the full model is preferable to the constrained models. For this reason, I will limit the discussion below to the results from Model 3.

Table 4.6 shows the effects for the main predictor – tract type – for three reference categories. There were more complaints about residential noise in all other tract types compared to prosperous tracts, although not that many more in gentrifying but not whitening tracts. Figure 4.2 shows the predicted counts for each tract type holding the covariates at their means. Prosperous tracts are predicted to have the fewest complaints per capita about residential noise compared to all other tract types, all else equal. Poor tracts that did not whiten are predicted to have 46.3% more

Table 4.5: Modeling per capita complaints about residential noise in 2011

| | Complaints about Residential Noise | | |
|---|---|---|---|
| | **(1)** | **(2)** | **(3)** |
| ***Tract Type*** | | | |
| Gentrifying but not Whitening (reference) | | | |
| Prosperous | 0.793** | 0.826* | 0.832* |
| | (0.07) | (0.07) | (0.07) |
| Poor and not Whitening | 1.764*** | 1.316** | 1.218* |
| | (0.16) | (0.12) | (0.11) |
| Poor and Whitening | 1.851*** | 1.250* | 1.166 |
| | (0.18) | (0.14) | (0.12) |
| Gentrifying and Whitening | 1.839*** | 1.351*** | 1.215* |
| | (0.18) | (0.12) | (0.11) |
| ***Controls*** | | | |
| Non-Hispanic White Pop % 2010 | | 0.992*** | 0.992*** |
| | | (0.00) | (0.00) |
| Log of Violent Crime Rate | | 1.156*** | 1.137*** |
| | | (0.04) | (0.04) |
| Log of Property Crime Rate | | 1.132** | 1.034 |
| | | (0.05) | (0.04) |
| # of Public Housing Buildings | | | 1.000 |
| | | | (0.00) |
| Average Building Age | | | 1.009*** |
| | | | (0.00) |
| % Pop above age 75 | | | 0.989 |
| | | | (0.01) |
| ***Borough*** | | | |
| Manhattan (reference) | | | |
| The Bronx | | | 1.047 |
| | | | (0.10) |
| Brooklyn | | | 0.805* |
| | | | (0.08) |
| Queens | | | 0.737** |
| | | | (0.07) |
| Staten Island | | | 0.814 |
| | | | (0.10) |
| Logged Pop at Risk (Total Pop) | 0.991 | 1.147** | 1.051 |
| | (0.05) | (0.06) | (0.05) |
| lnalpha | 0.589*** | 0.494*** | 0.460*** |
| | (0.04) | (0.03) | (0.03) |
| BIC | 19615.979 | 19251.122 | 19151.210 |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 4.6: Comparison of effects with different tract type reference groups for per capita complaints about residential noise in 2011

*Note: This table shows the coefficients for the tract typology with three different reference categories: prosperous in the first column, poor but not whitening in the second column, gentrifying but not whitening in the third column.*

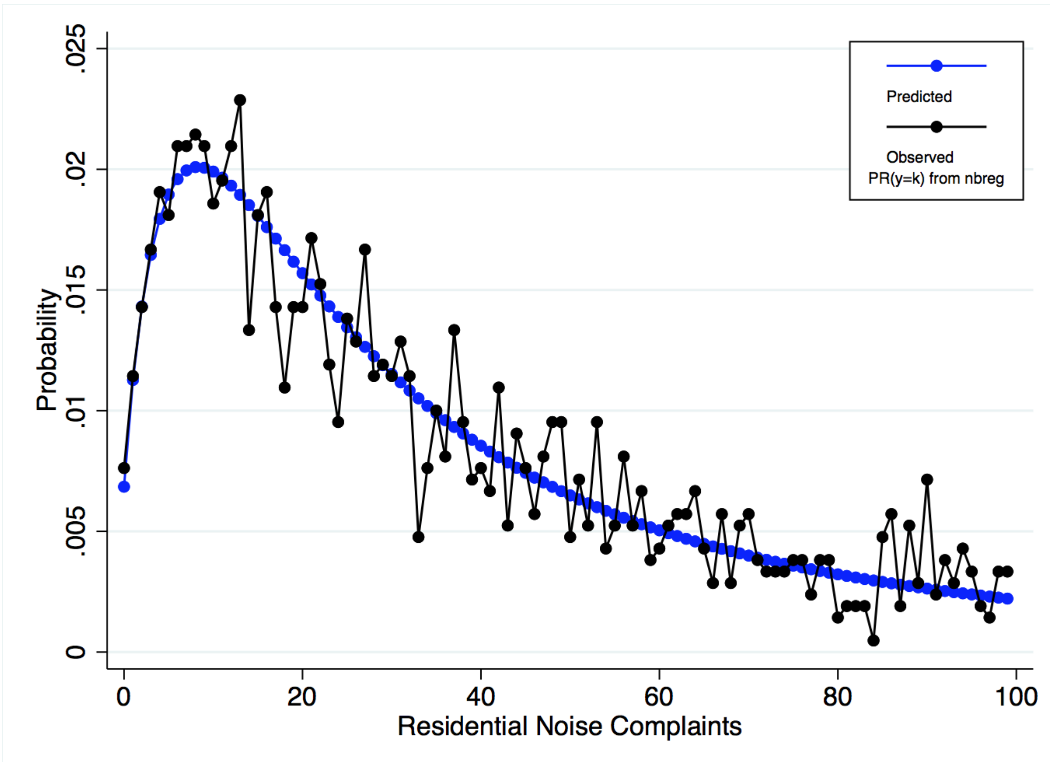
| | Complaints about Residential Noise | | |
|---|---|---|---|
| ***Tract Type*** | | | |
| Prosperous | | 0.683*** | 0.832** |
| | | (0.05) | (0.07) |
| Poor and not Whitening | 1.463*** | | 1.218** |
| | (0.10) | | (0.11) |
| Poor and Whitening | 1.401*** | 0.957 | 1.166 |
| | (0.13) | (0.07) | (0.12) |
| Gentrifying but not Whitening | 1.201* | 0.821* | |
| | (0.10) | (0.07) | |
| Gentrifying and Whitening | 1.460*** | 0.998 | 1.215* |
| | (0.11) | (0.01) | (0.11) |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

complaints per capita and poor tracts that did not whiten are predicted to have 40% more complaints per capita than prosperous tracts, all else equal. Gentrifying tracts that did not whiten are predicted to have 20% more complaints per capita and gentrifying tracts that did whiten are predicted to have 46% more complaints per capita than prosperous tracts. Per capita complaints about residential noise in poor tracts that whitened are not statistically distinguishable from complaints in poor tracts that did not whiten. On the other hand, gentrifying tracts that whitened are predicted to have 21.5% more complaints per capita about residential noise than their non whitening, gentrifying counterparts, all else equal. Figure 4.3 shows the net differences in predicted counts, holding all covariates at their means, compared to poor tracts that did not whiten in panel one and compared to gentrifying tracts that did not whiten in panel two. There were between eight and nine more complaints per

Figure 4.1: Predicted versus observed complaints about residential noise in 2011

*Note: Figure shows count probabilities predicted by the model plotted against observed probabilities for counts one to 99, which is a maximum imposed by the user generated State command -prcounts- used to predict count probabilities.*

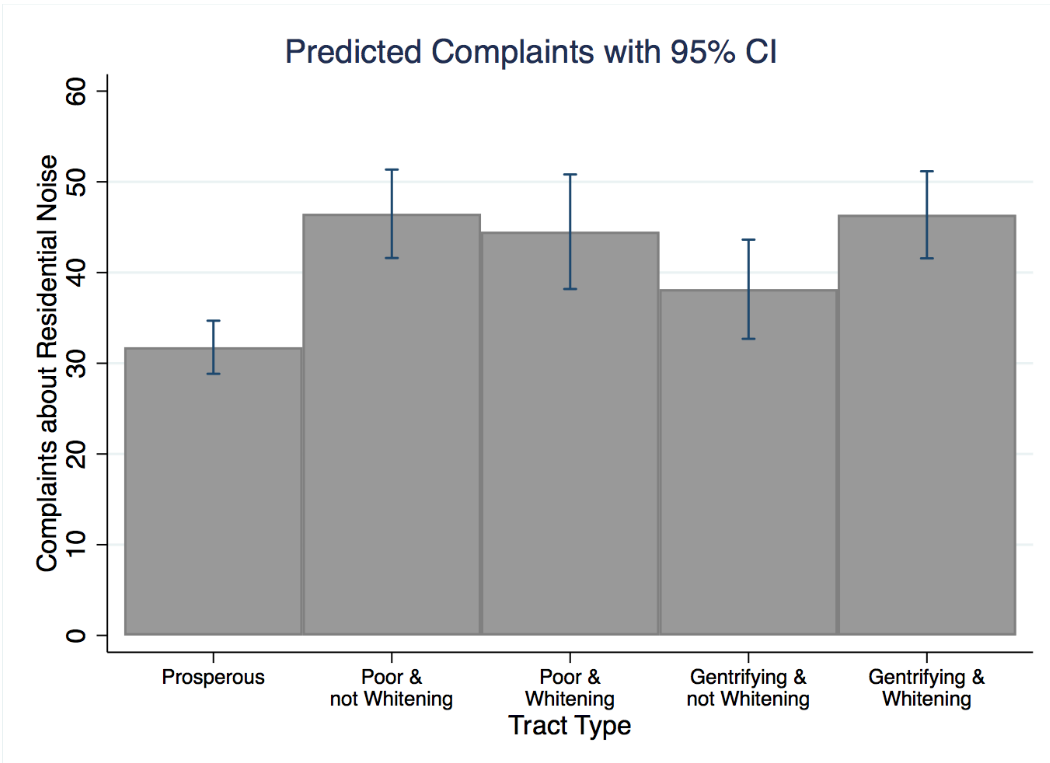



capita in gentrifying and whitening tracts compared to gentrifying tracts that did not whiten, all else equal.

There were 0.8% fewer complaints predicted for each one percentage point increase in non-Hispanic white population percent in 2010. Violent crime rate was associated with 13.7% more complaints for each one unit increase in the logged rate. Property crime, the number of public housing buildings, and the percentage of the population above age 75, on the other hand, were not associated with complaints about residential

Figure 4.2: Predicted number of complaints about residential noise in 2011 by tract type

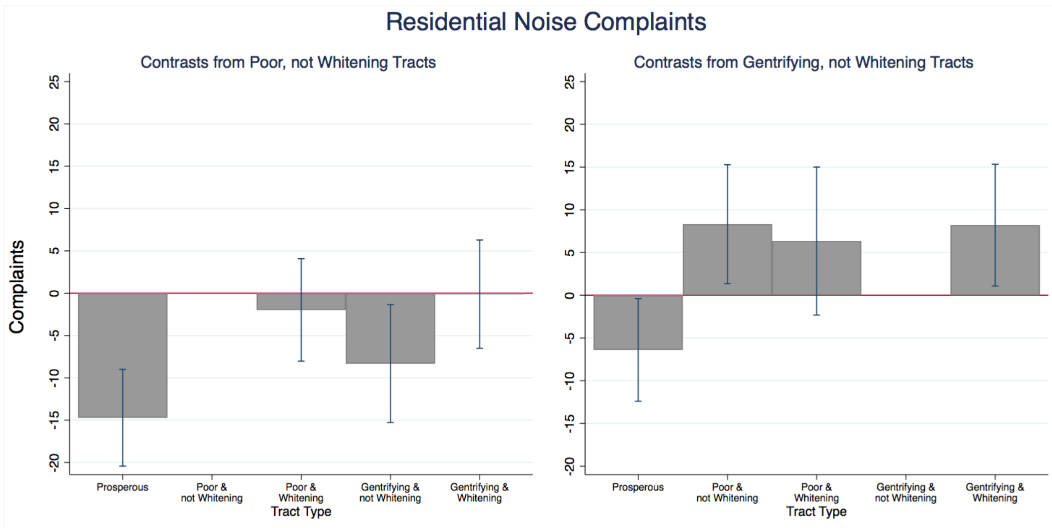
*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*




noise in 2011. It may be that in areas with higher violent crime rates, residents are reluctant to speak to their neighbors to resolve disputes for fear it may put them in danger. This may lead to the higher rates of complaints made about residential noise where residents ask the city to intervene in order to avoid a confrontation. If this is the case, it would make sense that property crime would not have the same effect as it is less likely to suggest possible danger in making personal complaints to neighbors. Average building age was associated with more residential noise complaints with 0.9% more complaints for each additional year in the average age. This may be because

Figure 4.3: Predicted net differences in per capita complaints about residential noise in 2011 compared to poor tracts that did not whiten and gentrifying tracts that did not whiten

*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all other covariates at their means.*




newer buildings have better construction or because apartments in older buildings tend to have been made by carving up larger apartments with dividing walls that are not part of the original construction and are less sound proof.

As in 2011, the most complaints about residential noise in 2019 were made in poor tracts, both whitening and not, and gentrifying tracts that whitened. Table 4.7 show the results from the model run on the 2019 data. Coefficients for the tract type variable are shown for three different reference categories: prosperous, poor and not whitening, and gentrifying but not whitening. The coefficients for the covariates are shown once because they remain the same regardless of the reference category for tract type. Figure 4.4 shows the model fit.

As in 2011, the least per capita complaints about residential noise came from

Table 4.7: Modeling per capita complaints about residential noise in 2019

*Note: This table shows the coefficients for the tract typology with three different reference categories: prosperous in the first column, poor but not whitening in the second column, gentrifying but not whitening in the third column.*

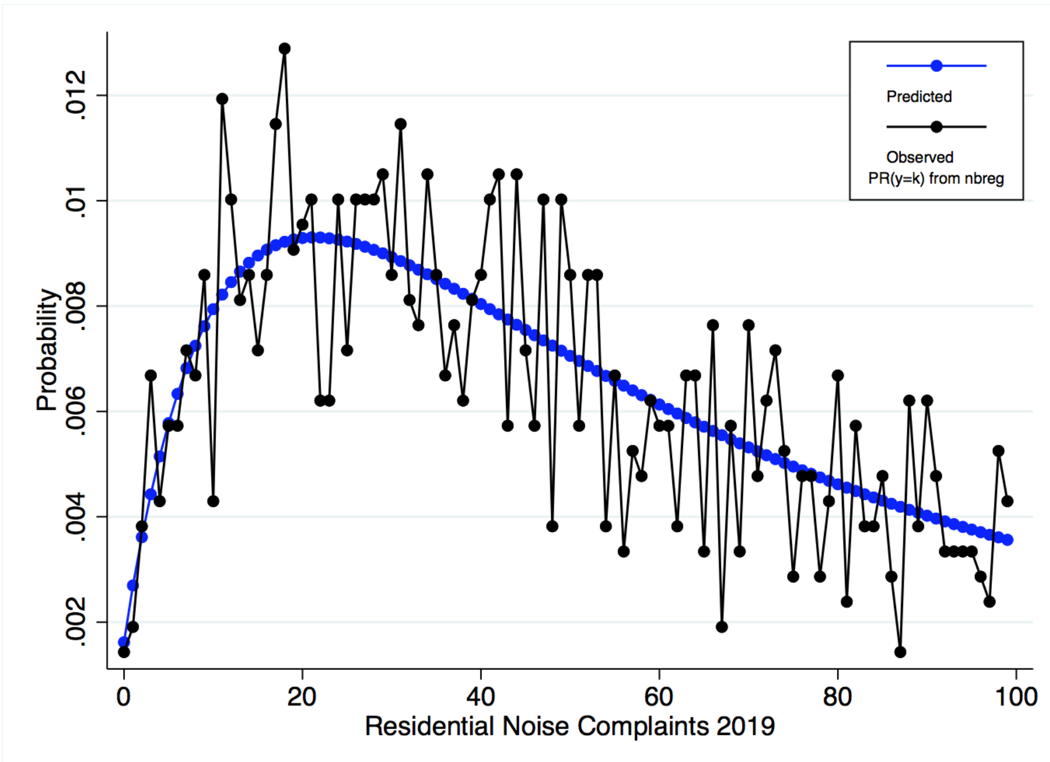
| | **Complaints about Residential Noise** | | |
|---|---|---|---|
| ***Tract Type*** | | | |
| Prosperous | | 0.739*** | 0.718*** |
| | | (0.05) | (0.07) |
| Poor and not Whitening | 1.353*** | | 0.972 |
| | (0.10) | | (0.10) |
| Poor and Whitening | 1.551*** | 1.146** | 1.114 |
| | (0.12) | (0.07) | (0.12) |
| Gentrifying but not Whitening | 1.392*** | 1.029 | |
| | (0.13) | (0.11) | |
| Gentrifying and Whitening | 1.975*** | 1.495*** | 1.419*** |
| | (0.17) | (0.13) | (0.17) |
| ***Controls*** | | | |
| Non-Hispanic White Pop % 2018 | 0.991*** | | |
| | (0.00) | | |
| Log of Violent Crime Rate | 1.030*** | | |
| | (0.01) | | |
| Log of Property Crime Rate | 1.012 | | |
| | (0.01) | | |
| # of Public Housing Buildings | 1.001 | | |
| | (0.00) | | |
| Average Building Age | 1.009*** | | |
| | (0.00) | | |
| % Pop above age 75 | 0.978*** | | |
| | (0.01) | | |
| ***Borough*** | | | |
| Manhattan (reference) | | | |
| The Bronx | 1.010 | | |
| | (0.11) | | |
| Brooklyn | 0.709*** | | |
| | (0.08) | | |
| Queens | 0.732* | | |
| | (0.08) | | |
| Staten Island | 0.954 | | |
| | (0.16) | | |
| Logged Pop at Risk (Total Pop) | 0.959 | | |
| | (0.04) | | |
| lnalpha | 0.454*** | | |
| | (0.03) | | |
| BIC | 22234.781 | | |

Note: Coefficients are exponentiated

$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure 4.4: Predicted versus observed complaints about residential noise in 2019

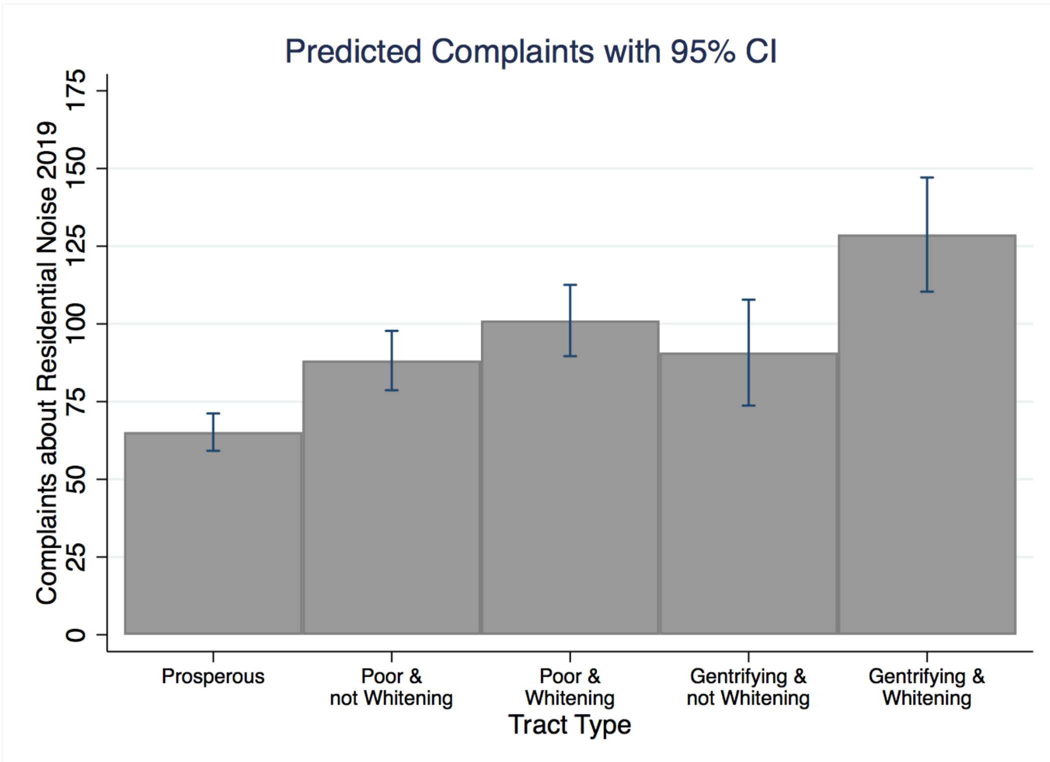
*Note: Figure shows count probabilities predicted by the model plotted against observed probabilities for counts one to 99, which is a maximum imposed by the user generated State command -prcounts- used to predict count probabilities.*




prosperous tracts. Figure 4.5 shows the predicted per capita counts of residential noise complaints by tract type, holding covariates at their means. The most complaints about residential noise came from gentrifying tracts that whitened. There were almost 42% more complaints per capita in gentrifying tracts that whitened compared to their gentrifying but not whitening counterparts. Unlike in 2011, in 2019 there was also a significant difference between poor tracts that whitened and those that did not. All else equal, there were 14.6% more complaints per capita in poor tracts that whitened

Figure 4.5: Predicted number of complaints about residential noise in 2019 by tract type

*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*

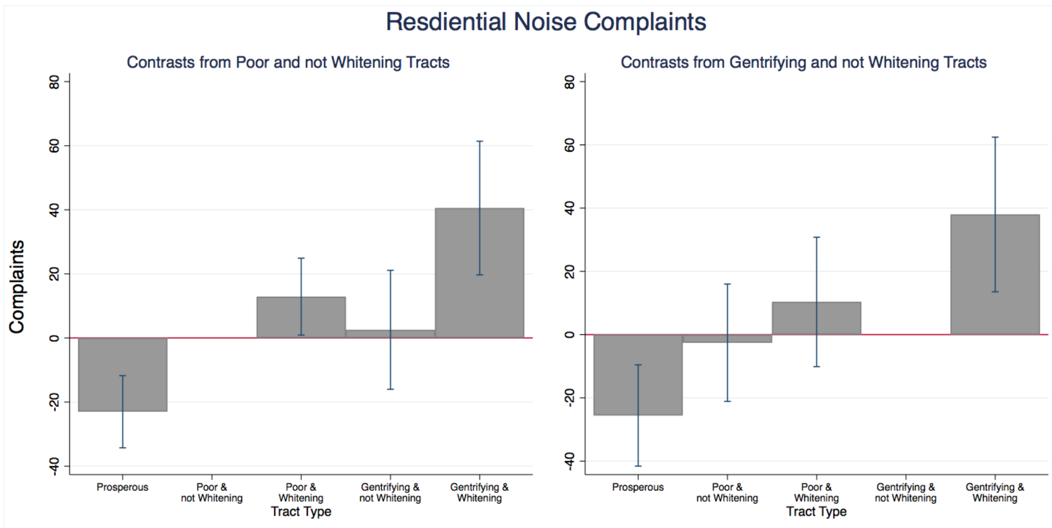



compared to poor tracts that did not whiten. Figure 4.6 shows the net differences in predicted per capita complaints compared to poor tracts that did not whiten in panel one and compared to gentrifying tracts that did not whiten in panel two. There were between 15 and 20 more per capita residential noise complaints in 2019 in poor tracts that whitened than in poor tracts that did not whiten. There were almost 40 more per capita residential noise complaints in 2019 in gentrifying tracts that whitened compared to gentrifying tracts that did not whiten.

Just as in 2011, in 2019 non-Hispanic white population percent was associated

Figure 4.6: Predicted net differences in per capita complaints about residential noise in 2019 compared to poor tracts that did not whiten and gentrifying tracts that did not whiten

*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all other covariates at their means.*




with 0.9% fewer complaints for each one percentage point increase. Violent crime rate was also associated with more complaints, as it was in 2011, although the magnitude of the association is quite a bit smaller in 2019 with 3% more complaints associated with a one unit higher logged violent crime rate as compared to 13.7% more complaints in 2011. As in 2011, in 2019 the average building age was associated with a higher number of per capita complaints about residential noise – about 0.9% more complaints for each additional year of average age. The population above age 75 was associated with complaints about residential noise in 2019 – one percentage point more elderly residents was associated with 2.2% fewer complaints. This may be because older residents are generally less likely to make loud noise in their apartments, or because they may be hard of hearing and therefore less likely to complain about

noise made by others. Although, it is unclear why this would be the case in 2019 but not in 2011.

In both 2011 and 2019, per capita complaints about residential noise appear to have been high in poor neighborhoods. There was little difference between those that experienced whitening and those that did not in 2011, but whitening made a difference in 2019. In gentrifying neighborhoods, however, all else equal, whitening was associated with much higher per capita rates of complaints about residential noise. In Chapter 2, I showed that stops of Black individuals were higher in both poor and gentrifying tracts that whitened compared to their non-whitening counterparts. In comparison, for complaints about residential noise, it appears that poverty matters, that gentrification on its own is associated with complaint levels similar to poor tracts and higher than prosperous tracts, and that whitening in gentrifying neighborhoods is associated with even more complaints about residential noise than poor neighborhoods, even when controlling for a host of tract characteristics. Next, I look at two categories of residential noise complaint, which constitute social behaviors: loud talking and loud music/parties

### 4.4.2 Complaints about loud talking

Table 4.8 shows the results from the full and constrained models predicting complaints about loud talking. Likelihood ratio testing indicates that the full model is preferable to the constrained models so I will limit my discussion to Model 3. This model passes the postestimation link test, indicating that it is properly specified. Figure 4.7 shows the model fit by plotting predicted counts versus observed counts.

Table 4.8: Modeling per capita complaints about loud talking in 2011

| | Complaints about Loud Talking | | |
|---|---|---|---|
| | **(1)** | **(2)** | **(3)** |
| ***Tract Type*** | | | |
| Gentrifying but not Whitening (reference) | | | |
| Prosperous | 0.791 | 0.642 | 0.606* |
| | (0.21) | (0.17) | (0.15) |
| Poor and not Whitening | 0.909 | 0.887 | 0.874 |
| | (0.26) | (0.27) | (0.22) |
| Poor and Whitening | 1.037 | 0.882 | 0.842 |
| | (0.30) | (0.26) | (0.22) |
| Gentrifying and Whitening | 1.976* | 1.462 | 1.277 |
| | (0.56) | (0.43) | (0.33) |
| ***Controls*** | | | |
| Non-Hispanic White Pop % 2010 | | 1.008*** | 1.008*** |
| | | (0.00) | (0.00) |
| Log of Violent Crime Rate | | 1.246*** | 1.222*** |
| | | (0.06) | (0.06) |
| Log of Property Crime Rate | | 1.610*** | 1.283*** |
| | | (0.14) | (0.09) |
| # of Public Housing Buildings | | | 0.998 |
| | | | (0.00) |
| Average Building Age | | | 1.011*** |
| | | | (0.00) |
| % Pop above age 75 | | | 0.977* |
| | | | (0.01) |
| ***Borough*** | | | |
| Manhattan (reference) | | | |
| The Bronx | | | 0.694* |
| | | | (0.11) |
| Brooklyn | | | 0.422*** |
| | | | (0.04) |
| Queens | | | 0.534*** |
| | | | (0.07) |
| Staten Island | | | 0.578*** |
| | | | (0.09) |
| Logged Pop at Risk (Total Pop) | 0.737 | 1.297** | 0.987 |
| | (0.22) | (0.11) | (0.08) |
| lnalpha | 1.148 | 0.901 | 0.795* |
| | (0.14) | (0.09) | (0.08) |
| BIC | 12650.732 | 12171.116 | 12010.666 |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure 4.7: Predicted versus observed counts of complaints about loud talking in 2011

*Note: Figure shows count probabilities predicted by the model plotted against observed probabilities for counts one to 99, which is a maximum imposed by the user generated State command -prcounts- used to predict count probabilities.*

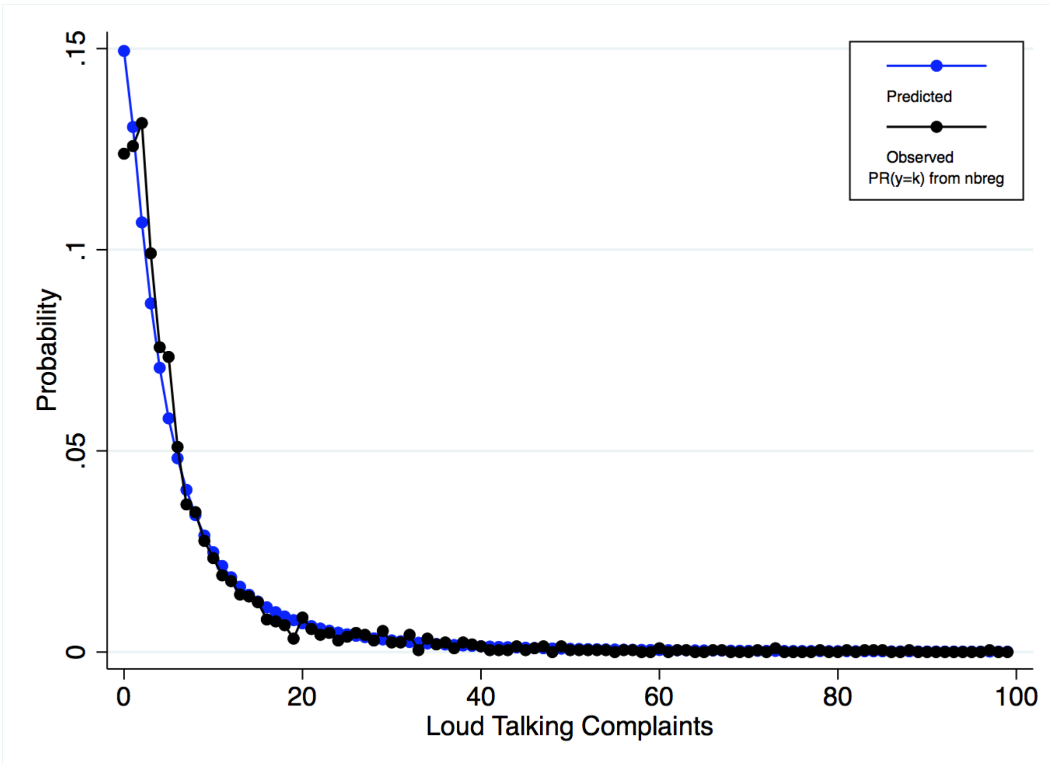
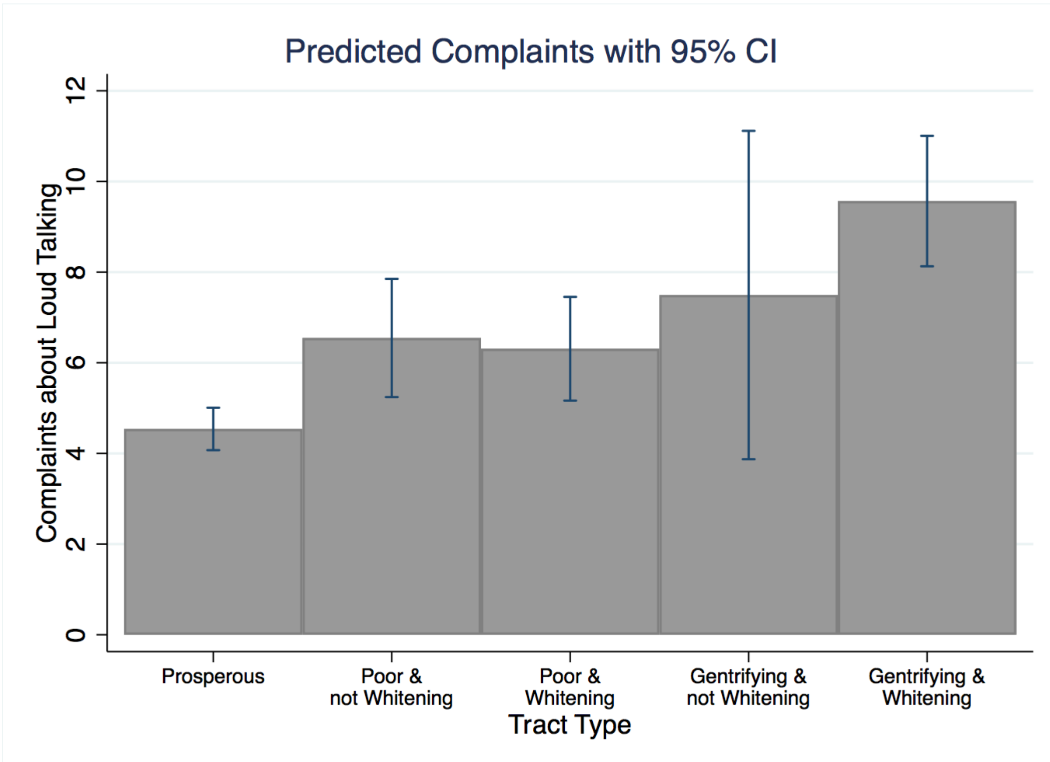



Figure 4.8 shows the predicted counts for each tract type holding all covariates at their means. Table 4.9 shows the effects for the different categories of tract type with different reference groups: prosperous tracts, poor and not whitening tracts, and gentrifying but not whitening tracts. There were 44.2% more complaints per capita in poor tracts that didn't whiten, 39% more complaints in poor tracts that did whiten, 65% more complaints in gentrifying tracts that didn't whiten, and 110% more complaints in gentrifying tracts that did whiten compared to prosperous tracts

Figure 4.8: Predicted number of complaints about loud talking in 2011 by tract type

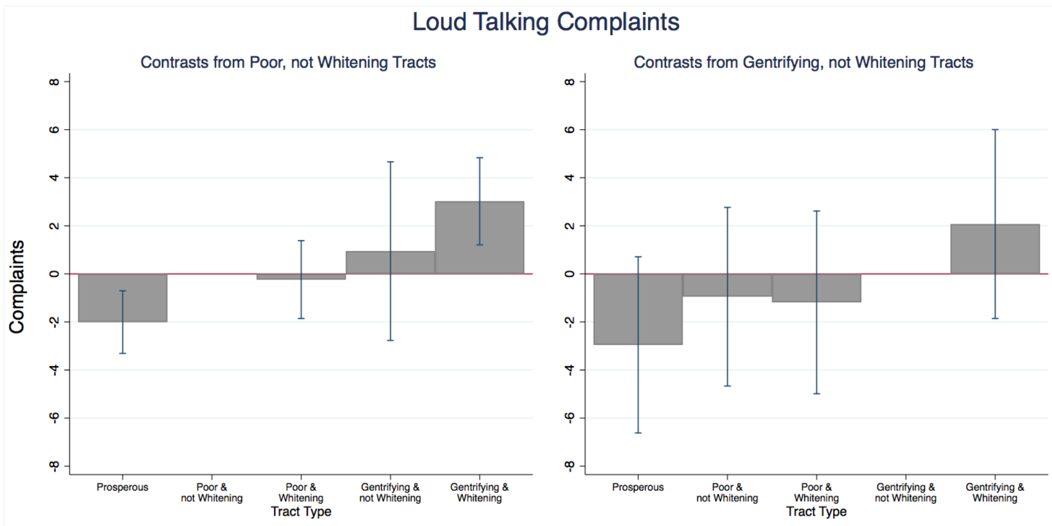
*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*




in 2011. Wald tests show that there was not a statistically significant difference in complaints in poor tracts whitening and not, nor in gentrifying tracts whitening and not, although the predicted margins in Figure 4.8 are suggestive of an effect of whitening on complaints made in gentrifying tracts. There we see that, all else equal, there were more complaints predicted in gentrifying tracts that whitened than in gentrifying tracts that did not whiten, but the confidence interval for gentrifying tracts that did not whiten is quite large and overlaps with the predicted complaints for gentrifying tracts that did whiten. Figure 4.9 shows the predicted net differences in

Figure 4.9: Predicted net differences in per capita complaints about loud talking in 2011 compared to poor tracts that did not whiten and gentrifying tracts that did not whiten

*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all other covariates at their means.*




per capita loud talking complaints, holding all covariates at their means, compared to poor tracts that did not whiten in panel one and compared to gentrifying tracts that did not whiten in panel two. Figure 4.9 shows there was not a significant difference in complaints about loud talking between poor tracts that did and did not whiten. It also shows that there were more complaints predicted in gentrifying tracts that whitened compared to gentrifying tracts that did not whiten, but the confidence interval overlaps with zero.

There were more per capita complaints about loud talking in tracts with more non-Hispanic white population in 2010. There were also more complaints per capita in tracts with higher violent and property crime rates. The older the average age of the buildings in a tract, the more complaints there were per capita – 1.1% more

Table 4.9: Comparison of effects with different tract type reference groups for per capita complaints about loud talking in 2011

*Note: This table shows the coefficients for the tract typology with three different reference categories: prosperous in the first column, poor but not whitening in the second column, gentrifying but not whitening in the third column.*

| | **Complaints about Loud Talking** | | |
|---|---|---|---|
| ***Tract Type*** | | | |
| Prosperous | | 0.693*** | 0.606* |
| | | (0.07) | (0.15) |
| Poor and not Whitening | 1.442*** | | 0.874 |
| | (0.15) | | (0.22) |
| Poor and Whitening | 1.390*** | 0.964 | 0.842 |
| | (0.14) | (0.12) | (0.22) |
| Gentrifying but not Whitening | 1.651* | 1.145 | |
| | (0.42) | (0.29) | |
| Gentrifying and Whitening | 2.107*** | 1.461** | 1.277 |
| | (0.19) | (0.17) | (0.33) |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

complaints for each additional year of average age. Surprisingly, higher percentage of residents over age 75 is associated with slightly lower rates of complaints about loud talking.

As I mentioned in the previous section, there were many more complaints in 2019 than in 2011. While there were about 8 complaints about loud talking in the average tract and the most complaints in any tract was 378 in 2011, there were between 18 and 19 complaints about loud talking in the average tract and the most complaints in any tract was 1,162 in 2019. Table 4.10 shows results from the analysis of complaints in 2019 using the same model. The table presents the effects for the main predictor across three different reference categories: prosperous tracts, poor tracts that did not whiten, and gentrifying tracts that did not whiten. The coefficients for the covariates are shown once because they remain the same regardless of the reference category for

Table 4.10: Modeling per capita complaints about loud talking in 2019

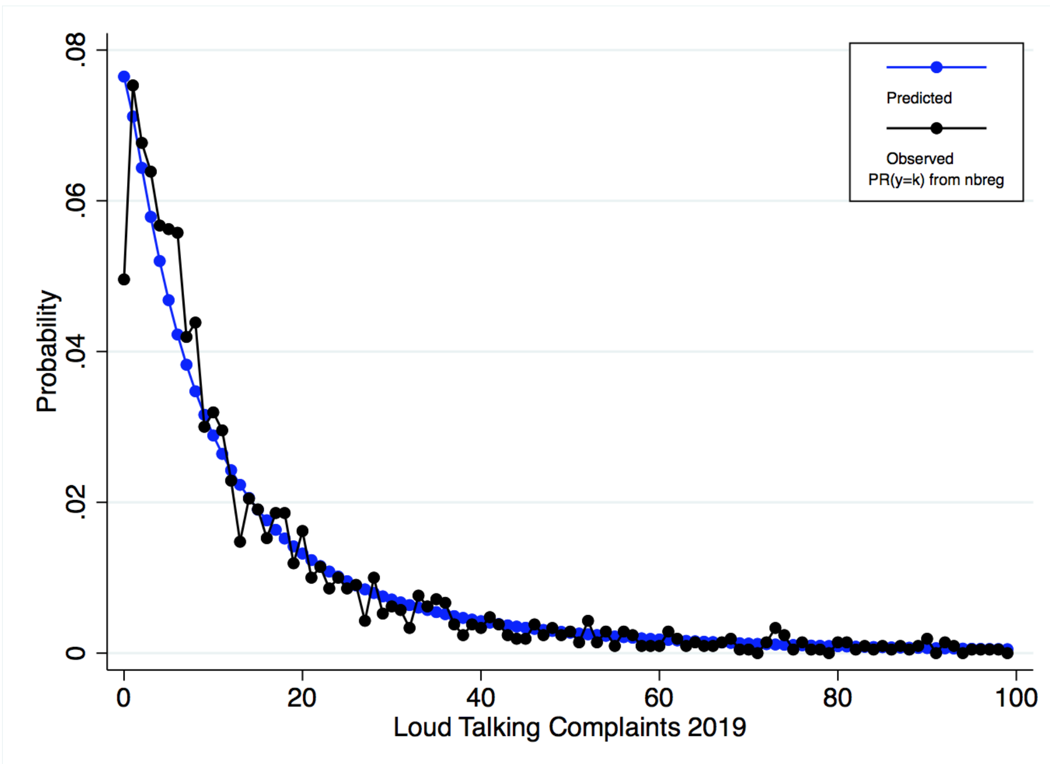
*Note: This table shows the coefficients for the tract typology with three different reference categories: prosperous in the first column, poor but not whitening in the second column, gentrifying but not whitening in the third column.*

| | Complaints about Loud Talking | | |
|---|---|---|---|
| ***Tract Type*** | | | |
| Prosperous | | 0.735** | 0.730* |
| | | (0.07) | (0.12) |
| Poor and not Whitening | 1.360*** | | 0.993 |
| | (0.14) | | (0.15) |
| Poor and Whitening | 2.014*** | 1.481*** | 1.470* |
| | (0.27) | (0.19) | (0.28) |
| Gentrifying but not Whitening | 1.369** | 1.007 | |
| | (0.22) | (0.16) | |
| Gentrifying and Whitening | 2.348*** | 1.726*** | 1.714** |
| | (0.27) | (0.19) | (0.30) |
| ***Controls*** | | | |
| Non-Hispanic White Pop % 2018 | 1.003 | | |
| | (0.00) | | |
| Log of Violent Crime Rate | 1.074** | | |
| | (0.02) | | |
| Log of Property Crime Rate | 1.043* | | |
| | (0.02) | | |
| # of Public Housing Buildings | 0.997 | | |
| | (0.00) | | |
| Average Building Age | 1.012*** | | |
| | (0.00) | | |
| % Pop above age 75 | 0.953*** | | |
| | (0.01) | | |
| ***Borough*** | | | |
| Manhattan (reference) | | | |
| The Bronx | 0.636* | | |
| | (0.12) | | |
| Brooklyn | 0.504*** | | |
| | (0.07) | | |
| Queens | 0.511*** | | |
| | (0.07) | | |
| Staten Island | 0.643 | | |
| | (0.15) | | |
| Logged Pop at Risk (Total Pop) | 0.844* | | |
| | (0.07) | | |
| lnalpha | 0.893 | | |
| | (0.06) | | |
| BIC | 15409.024 | | |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure 4.10: Predicted number of complaints about loud talking versus observed complaints in 2019

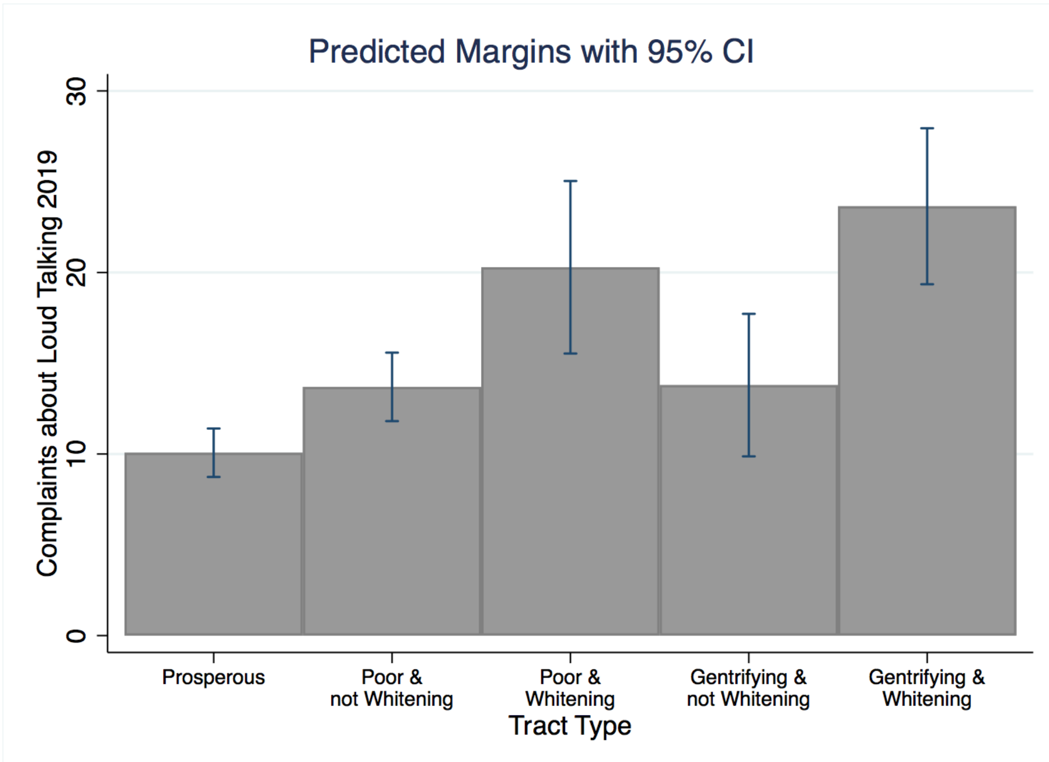
*Note: Figure shows count probabilities predicted by the model plotted against observed probabilities for counts one to 99, which is a maximum imposed by the user generated State command -prcounts- used to predict count probabilities.*




tract type. Figure 4.10 shows model fit with predicted and observed counts plotted against each other. The *lnalpha* parameter for the negative binomial model is not significant for this model. Generally this would suggest that the additional parameter is not necessary and the Poisson model is preferred. In this case, the loud talking complaint variable for 2019 is quite overdispersed, meaning the variance is much larger than the mean, counter suggesting that the negative binomial model is needed to account for the overdispersion. Using -countfit-, a user written Stata command,

Figure 4.11: Predicted number of complaints about loud talking by tract type in 2019

*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*




which compares the fit of different count models, I compare poisson and negative binomial regression. Countfit runs the analysis with the same covariates using both regression models and then compares fit via AIC and BIC, the mean observed and predicted count, the predicted and actual probabilities, and several other tests and fit statistics. The output from the -countfit- command ends with a summary table that indicates which model is preferred and the p-value associated with the strength of that preference. In the case of complaints about loud talking in 2019, -countfit- strongly prefers the negative binomial model over the poisson model.

Figure 4.12: Predicted net differences in per capita complaints about loud talking in 2019 compared to poor tracts that did not whiten and gentrifying tracts that did not whiten

*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all other covariates at their means.*

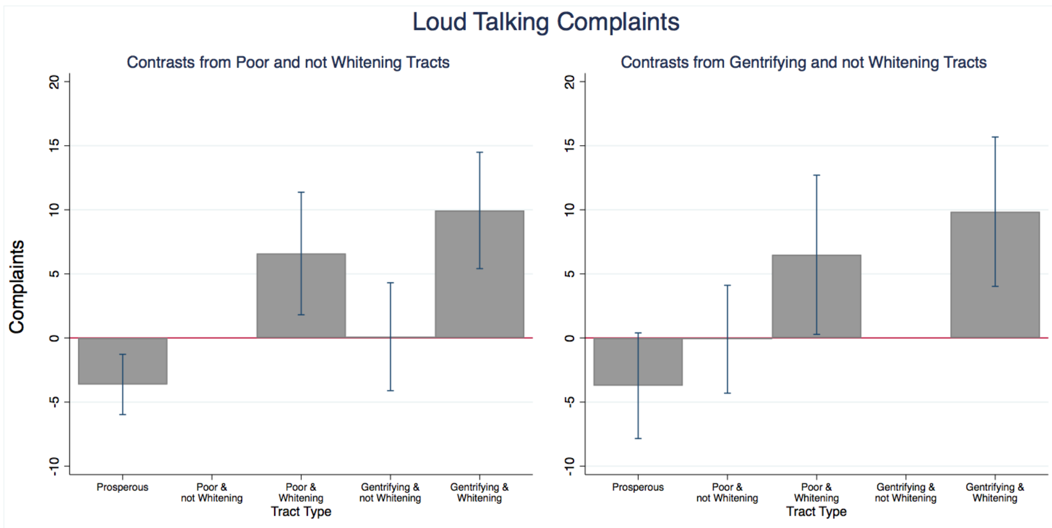



Figure 4.11 shows predicted counts holding covariates at their means. As in 2011, in 2019 there were more complaints about loud talking in all other tract types than in prosperous tracts, although only marginally more in gentrifying tracts that did not whiten. Poor tracts that whitened had 48% more complaints per capita than poor tracts that did not whiten. Similarly, gentrifying tracts that whitened had more complaints than poor tracts that did not whiten, 72.6% more. When compared to gentrifying tracts that did not whiten, poor tracts that whitened had 47% more complaints and gentrifying tracts that whitened had 71.4% more complaints. This demonstrates a pattern where whitening is associated with more complaints about loud talking regardless of whether a tract was poor or gentrifying. Figure 4.12 shows the predicted net differences in per capita complaints about loud talking, holding all

covariates at their means, compared to poor tracts that did not whiten in panel one and compared to gentrifying tracts that did not whiten in panel two. These contrast plots demonstrate that there were significantly more complaints about loud talking in poor tracts that whitened compared to their non whitening counterparts and in gentrifying tracts that whitened compared to their non whitening counterparts. More research, perhaps ethnographic research, is necessary to determine why whitening in both poor and gentrifying tracts is associated with significantly more complaints about loud talking in 2019, whereas it only suggested the possibility of more complaints in gentrifying tracts in 2011.

How white or not-white a tract was had no association with the number of complaints about loud talking per capita in 2019. Similarly to 2011, higher violent and property crime rates were associated with more complaints, and there were fewer complaints about loud talking in tracts with more population over the age of 75. Average building age was again associated with complaints – a one year higher average building age was associated with 1.2% more complaints per capita.

### 4.4.3 Complaints about loud music/parties

Social norms likely influence the volume at which someone thinks it is acceptable to play music in an apartment, the times when certain volumes are appropriate, and the extent to which noise generated by large gatherings should be tolerated by neighbors. Table 4.11 shows the results from the analysis of complaints about loud music and/or parties in 2011. As with the previous analyses, the full model passes the post estimation link test and is preferable to the constrained models according

Table 4.11: Modeling per capita complaints about loud music and parties in 2011

| | **Complaints about Loud Music** | | |
|---|---|---|---|
| | **(1)** | **(2)** | **(3)** |
| ***Tract Type*** | | | |
| Gentrifying but not Whitening (reference) | | | |
| Prosperous | 0.859 | 0.868 | 0.865 |
| | (0.12) | (0.10) | (0.09) |
| Poor and not Whitening | 1.346* | 1.027 | 1.005 |
| | (0.20) | (0.13) | (0.10) |
| Poor and Whitening | 1.685** | 1.103 | 1.056 |
| | (0.28) | (0.15) | (0.12) |
| Gentrifying and Whitening | 2.248*** | 1.556*** | 1.393** |
| | (0.32) | (0.17) | (0.14) |
| ***Controls*** | | | |
| Non-Hispanic White Pop % 2010 | | 0.995*** | 0.995*** |
| | | (0.00) | (0.00) |
| Log of Violent Crime Rate | | 1.274*** | 1.233*** |
| | | (0.04) | (0.04) |
| Log of Property Crime Rate | | 1.452*** | 1.263*** |
| | | (0.08) | (0.06) |
| # of Public Housing Buildings | | | 0.999 |
| | | | (0.00) |
| Average Building Age | | | 1.012*** |
| | | | (0.00) |
| % Pop above age 75 | | | 0.962*** |
| | | | (0.01) |
| ***Borough*** | | | |
| Manhattan (reference) | | | |
| The Bronx | | | 0.794** |
| | | | (0.07) |
| Brooklyn | | | 0.627*** |
| | | | (0.06) |
| Queens | | | 0.629*** |
| | | | (0.06) |
| Staten Island | | | 0.873 |
| | | | (0.09) |
| Logged Pop at Risk (Total Pop) | 0.683* | 1.060 | 0.899* |
| | (0.11) | (0.06) | (0.05) |
| lnalpha | 0.684*** | 0.470*** | 0.394*** |
| | (0.06) | (0.02) | (0.02) |
| BIC | 19632.989 | 18821.291 | 18515.162 |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

to likelihood ratio testing and a comparison of BICs, therefore, I will constrain my discussion to the results from Model 3. Figure 4.13 shows the model fit. The model underestimates in the range of five to ten complaints per capita, but provides a good fit across the rest of the probability distribution.

Figure 4.13: Predicted number of complaints about loud music/parties versus observed complaints in 2011

*Note: Figure shows count probabilities predicted by the model plotted against observed probabilities for counts one to 99, which is a maximum imposed by the user generated State command -prcounts- used to predict count probabilities.*

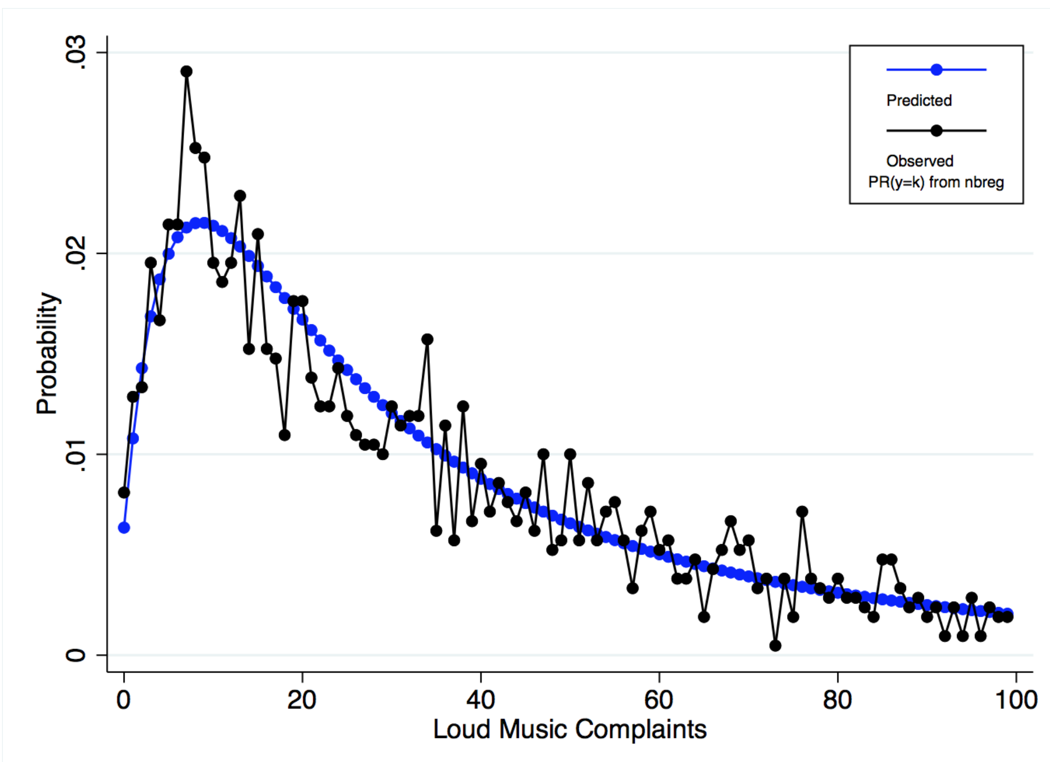



Table 4.12 provides the coefficients for the different tract types for three different reference categories and Figure 4.14 shows the predicted counts by tract type holding

Table 4.12: Comparison of effects with different tract type reference groups for per capita complaints about loud music/parties in 2011

*Note: This table shows the coefficients for the tract typology with three different reference categories: prosperous in the first column, poor but not whitening in the second column, gentrifying but not whitening in the third column.*

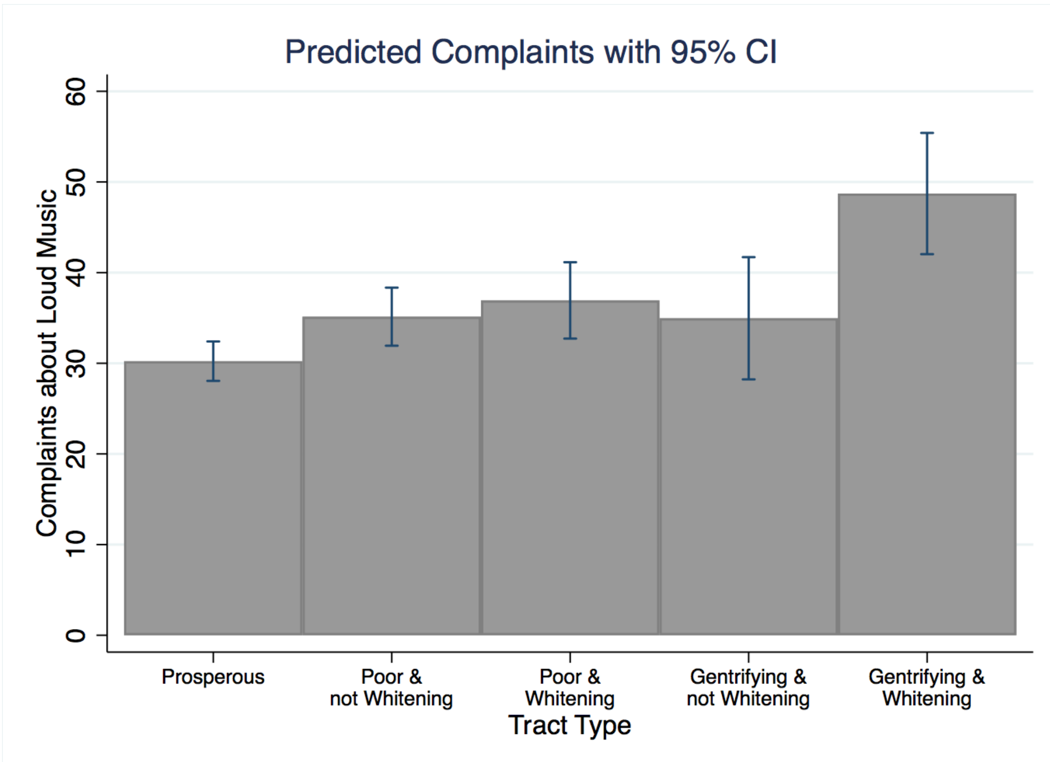
| | **Complaints about Loud Music** | | |
|---|---|---|---|
| ***Tract Type*** | | | |
| Prosperous | | 0.860* | 0.865 |
| | | (0.05) | (0.09) |
| Poor and not Whitening | 1.162* | | 1.005 |
| | (0.07) | | (0.10) |
| Poor and Whitening | 1.222** | 1.051 | 1.056 |
| | (0.09) | (0.06) | (0.12) |
| Gentrifying but not Whitening | 1.157 | 0.995 | |
| | (0.12) | (0.10) | |
| Gentrifying and Whitening | 1.612*** | 1.387*** | 1.393** |
| | (0.13) | (0.11) | (0.14) |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

all covariates at their means. All tract types are predicted to have more per capita complaints about loud music and parties compared to prosperous tracts, all else equal, except gentrifying tracts that did not whiten. On average, the number of per capita complaints about loud music and parties are indistinguishable in poor tracts that whitened and those that did not. Whitening does distinguish between complaints about loud music and parties in gentrifying tracts. Gentrifying tracts that whitened are associated with 39.3% more complaints per capita than gentrifying tracts that did not whiten, all else equal. Figure 4.15 shows predicted net differences in per capita complaints about loud music and parties, holding covariates at their means, compared to two reference groups: comparisons to poor tracts that did not whiten are shown in panel one and comparisons to gentrifying tracts that did not whiten are shown in panel two. While poor tracts were not substantially different based on their

Figure 4.14: Predicted number of complaints about loud music/parties by tract type in 2011

*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*

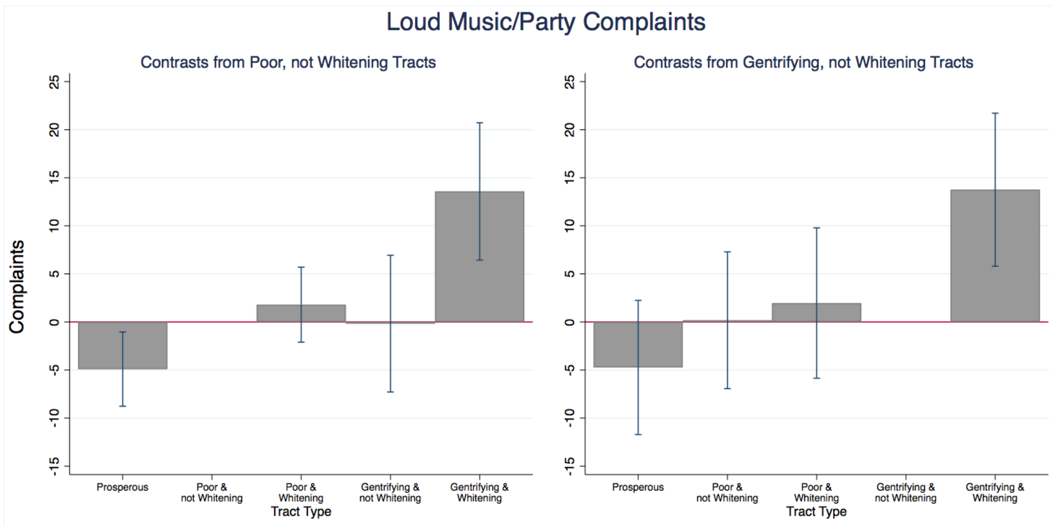



whitening status, gentrifying tracts that whitened had about 14 more complaints per capita on average compared to their non-whitening counterparts, all else equal.

There were fewer complaints per capita about loud music and/or parties the higher the non-Hispanic white population percentage in the tract, but only by a small amount – 0.5% fewer complaints per capita for each one percentage point increase in non-Hispanic white population in 2010. There were more complaints per capita the higher the violent and property crime rates. Violent crime rate consistently

Figure 4.15: Predicted net differences in per capita complaints about loud music and parties in 2011 compared to poor tracts that did not whiten and gentrifying tracts that did not whiten

*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all other covariates at their means.*




predicts higher numbers of complaints about residential noise, however, property crime rates have an inconsistent pattern. They are not associated with complaints about residential noise overall, but they are associated with complaints about loud talking and loud music. Further investigation reveals that property crime rate is either not associated with, or associated with fewer, complaints about the other two kinds of residential noise: loud television and banging or pounding.[5]

The total number of public housing buildings is not associated with complaints

[5]I suspect that some number of complaints about banging or pounding may be in response to a resident trying to signal to another resident that they should 'keep it down.' If this is true, then the complaint could possibly be made by the resident who created the noise in the first place and then complains through official channels about a neighbor who tried to make their own complaint through unofficial channels. I suspect that residents who fear confrontation with their neighbors are less likely to bang on their neighbors' walls in this way.

about loud music and/or parties. This may be due to a lower likelihood in the most disadvantaged communities to call the authorities on neighbors to settle disputes (Warner, 2007). There are more complaints per capita associated with older buildings. The model predicts 1.2% more complaints per capita for each additional year of average building age. As with loud talking, this is likely due to differences in construction and insulation in old buildings versus new buildings, with old buildings providing less sound proofing between apartments. Finally, there are fewer complaints about loud music and/or parties in tracts with more elderly people – the model predicts 3.8% fewer complaints for each additional percentage point of population over age 75. This may be because older residents are less likely to complain or because older residents are less likely to have loud parties or play loud music that annoys their neighbors.

Table 4.13 shows the results from the analysis of complaints about loud music and parties in 2019. Coefficients for the tract types are shown for three different reference categories. The coefficients for covariates are shown once because they remain the same regardless of the reference category for tract type. Figure 4.16 shows the model fit. There was a great deal more variation in observed counts in 2019 than in 2011, and the number of complaints in 2019 was much greater than in 2011. Figure 4.17 shows the predicted counts for each tract type, holding all covariates at their means.

Gentrifying tracts that also experienced whitening had, by far, the most complaints about loud music and parties compared to the other tract types. These gentrifying and whitening tracts are associated with 127% more complaints per capita about loud music and parties than prosperous tracts, 98% more complaints per capita than poor tracts that did not whiten, and 80.7% more complaints than gentrifying tracts

Table 4.13: Modeling per capita complaints about loud music & parties in 2019

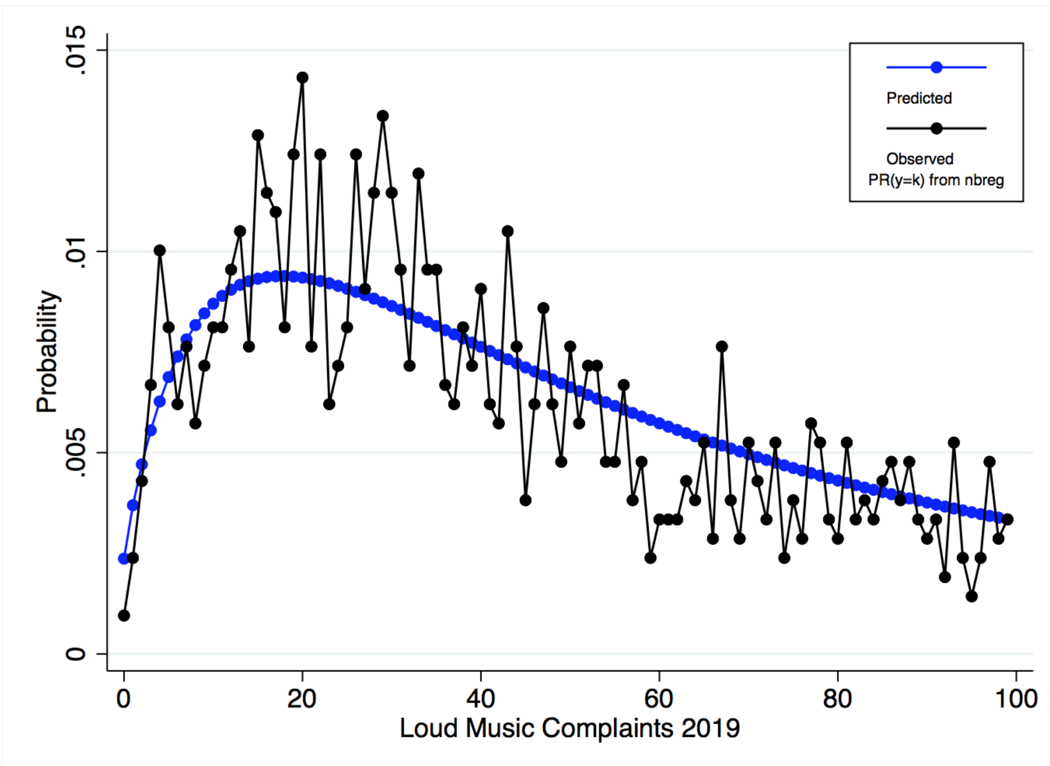
*Note: This table shows the coefficients for the tract typology with three different reference categories: prosperous in the first column, poor but not whitening in the second column, gentrifying but not whitening in the third column.*

| | Complaints about Loud Music | | |
|---|---|---|---|
| ***Tract Type*** | | | |
| Prosperous | | 0.872 | 0.795* |
| | | (0.07) | (0.09) |
| Poor and not Whitening | 1.147 | | 0.912 |
| | (0.09) | | (0.11) |
| Poor and Whitening | 1.496*** | 1.304*** | 1.189 |
| | (0.13) | (0.09) | (0.16) |
| Gentrifying but not Whitening | 1.258** | 1.096 | |
| | (0.14) | (0.14) | |
| Gentrifying and Whitening | 2.273*** | 1.981*** | 1.807*** |
| | (0.22) | (0.19) | (0.26) |
| ***Controls*** | | | |
| Non-Hispanic White Pop % 2018 | 0.991*** | | |
| | (0.00) | | |
| Log of Violent Crime Rate | 1.058*** | | |
| | (0.01) | | |
| Log of Property Crime Rate | 1.062*** | | |
| | (0.01) | | |
| # of Public Housing Buildings | 0.999 | | |
| | (0.00) | | |
| Average Building Age | 1.013*** | | |
| | (0.00) | | |
| % Pop above age 75 | 0.959*** | | |
| | (0.01) | | |
| ***Borough*** | | | |
| Manhattan (reference) | | | |
| The Bronx | 0.824 | | |
| | (0.10) | | |
| Brooklyn | 0.573*** | | |
| | (0.07) | | |
| Queens | 0.565*** | | |
| | (0.07) | | |
| Staten Island | 0.716* | | |
| | (0.10) | | |
| Logged Pop at Risk (Total Pop) | 0.752*** | | |
| | (0.04) | | |
| lnalpha | 0.540*** | | |
| | (0.03) | | |
| BIC | 22654.620 | | |

Note: Coefficients are exponentiated
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Figure 4.16: Predicted number of complaints about loud music/parties versus observed complaints in 2019

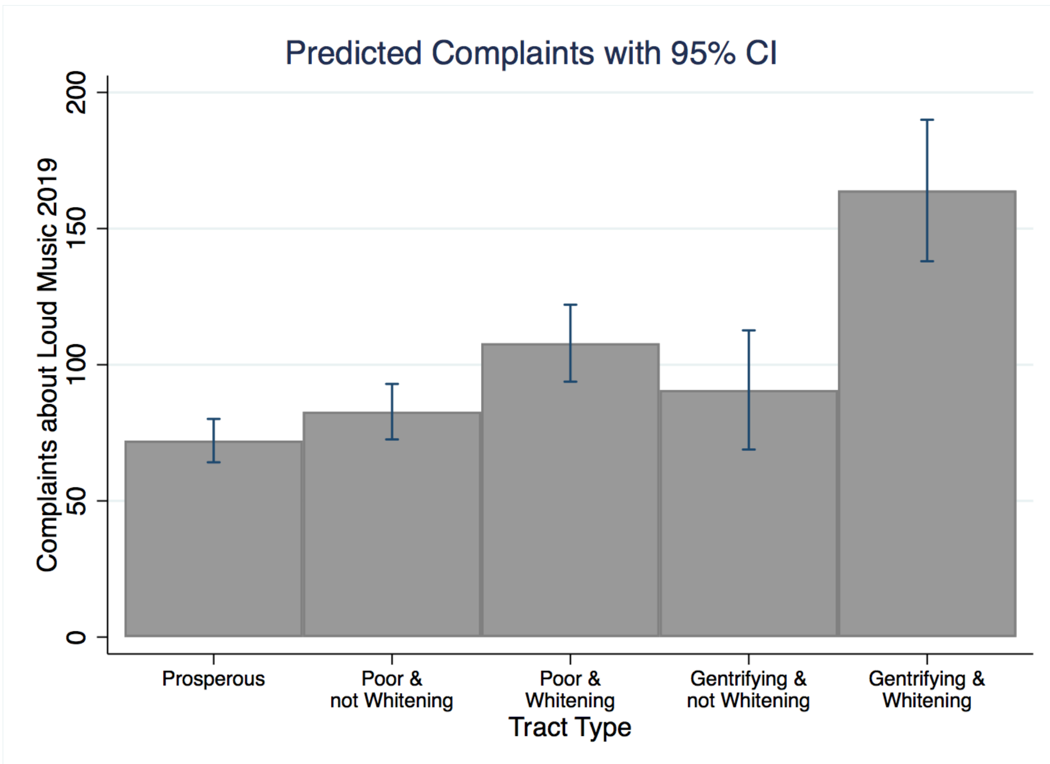
*Note: Figure shows count probabilities predicted by the model plotted against observed probabilities for counts one to 99, which is a maximum imposed by the user generated State command -prcounts- used to predict count probabilities.*




that did not whiten, all else equal. Whereas in 2011, there was not a significant difference, either statistically or in magnitude, between poor tracts that whitened and those that did not, in 2019 poor tracts that whitened were predicted to have 30% more complaints per capita than their non-whitening counterparts. Figure 4.18 shows net differences in per capita complaints about loud music and parties, holding covariates at their means, compared to poor tracts that did not whiten in panel one and compared to gentrifying tracts that did not whiten in panel two. On average, poor

Figure 4.17: Predicted number of complaints about loud music/parties by tract type in 2019

*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*

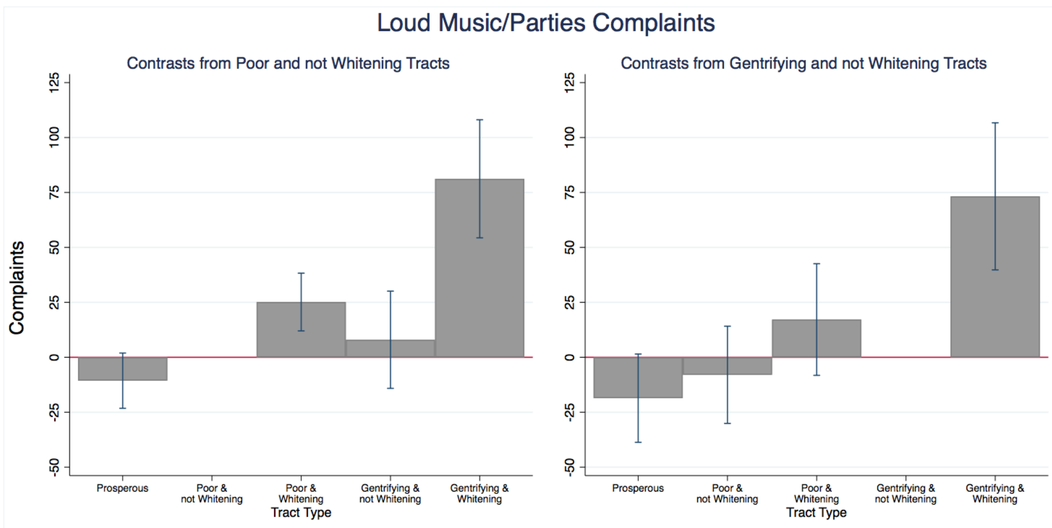



tracts that whitened are predicted to have about 25 more complaints per capita than poor tracts that did not whiten, all else equal. Gentrifying tracts that whitened are predicted to have about 75 more complaints per capita, on average, than gentrifying tracts that did not whiten, all else equal.

As in 2011, non-Hispanic white population is associated with fewer complaints per capita about loud music and parties, although the magnitude is consistently small with only 0.9% fewer complaints for each percentage point increase in non-Hispanic

Figure 4.18: Predicted net differences in per capita complaints about loud music and parties in 2019 compared to poor tracts that did not whiten and gentrifying tracts that did not whiten

*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all other covariates at their means.*




white population. Violent and property crime rates are both associated with more complaints. The population above age 75 is again associated with slightly fewer complaints per capita and the average building age is associated with slightly more complaints.

## 4.5 Supplementary Analyses

### 4.5.1 Prosperous Tracts

As in Chapters 2 and 3, we must consider what happened to the tracts that were prosperous at the beginning of the period of study but that did not remain so. These formerly prosperous tracts may follow a different pattern that would suggest they should not be lumped in with the persistently prosperous tracts in the analysis. I rerun the analyses in this chapter using the additional tract typology described in Chapters 2 and 3 to account for those tracts that were categorized as prosperous at the beginning of the study period but would not be categorized as prosperous if evaluated by their status at the end of the period. Table 4.14 shows the breakdown of city tracts into the new typology for 2000-2010 and 2011-2018. For the 2011 complaint analysis, 229 tracts were prosperous in 2000 but no longer met the criteria in 2010. For the 2019 complaint analysis, 154 tracts were prosperous in 2011 but no longer met the criteria in 2018.

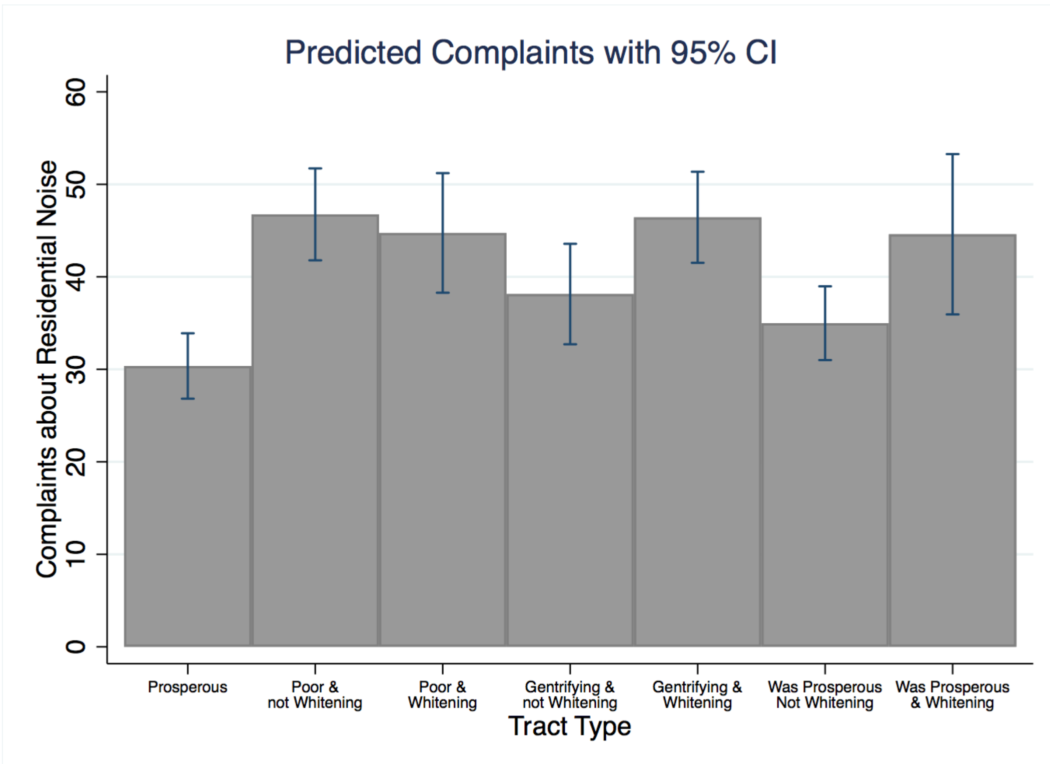
Table 4.14: Summary of tracts by type 2000-2010 and 2011-2018 including disaggregation of prosperous tracts

| | **2011** | | **2019** | |
|---|---|---|---|---|
| | Frequency | Percent | Frequency | Percent |
| Prosperous | 818 | 38.97 | 740 | 35.32 |
| Persistently poor and not Whitening | 479 | 22.82 | 564 | 26.92 |
| Persistently poor and Whitening | 303 | 14.44 | 440 | 21.00 |
| Gentrifying but not Whitening | 86 | 4.10 | 82 | 3.91 |
| Gentrifying and Whitening | 184 | 8.77 | 116 | 5.54 |
| Was Prosperous and not Whitening | 202 | 9.62 | 102 | 4.87 |
| Was Prosperous and Whitening | 27 | 1.29 | 51 | 2.43 |

Figure 4.19 shows the predicted number of per capita complaints about residential noise by tract type in 2011, holding all covariates at their means. Figure 4.20 shows predicted net differences in per capita complaints about residential noise compared to three reference groups: prosperous tracts, gentrifying tracts that did not whiten, and formerly prosperous tracts that did not whiten. Formerly prosperous tracts that did not whiten are not statistically significantly different than prosperous tracts.

Figure 4.19: Predicted number of complaints about residential noise in 2011 by tract type

*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*




Formerly prosperous tracts that whitened, on the other hand, have almost 15 more per capita complaints on average, all else equal, than prosperous tracts. Gentrifying tracts that whitened had more complaints per capita, all else equal, than their non whitening counterparts, consistent with the findings from the main analysis. Formerly prosperous tracts that whitened are predicted to have about 10 more per capita complaints about residential noise on average than their non-whitening counterparts, all else equal.

Figure 4.20: Predicted difference in number of complaints about residential noise in 2011 compared to three reference groups

*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all other covariates at their means.*

Figure 4.21: Predicted number of complaints about residential noise in 2019 by tract type

*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*

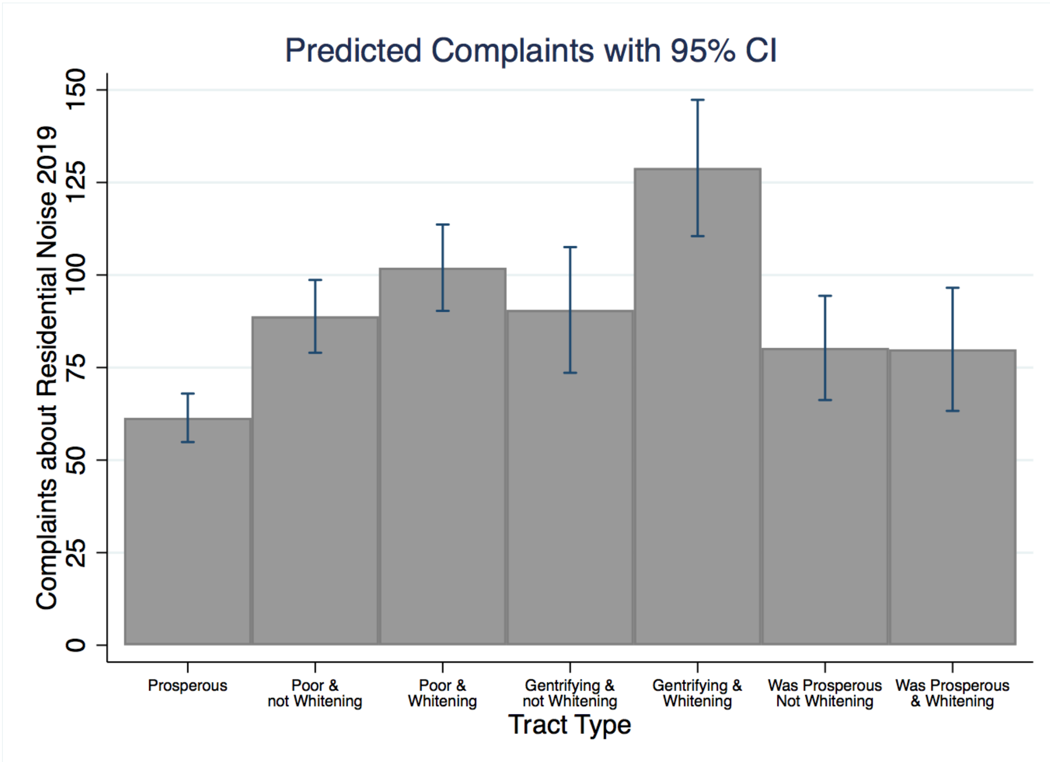
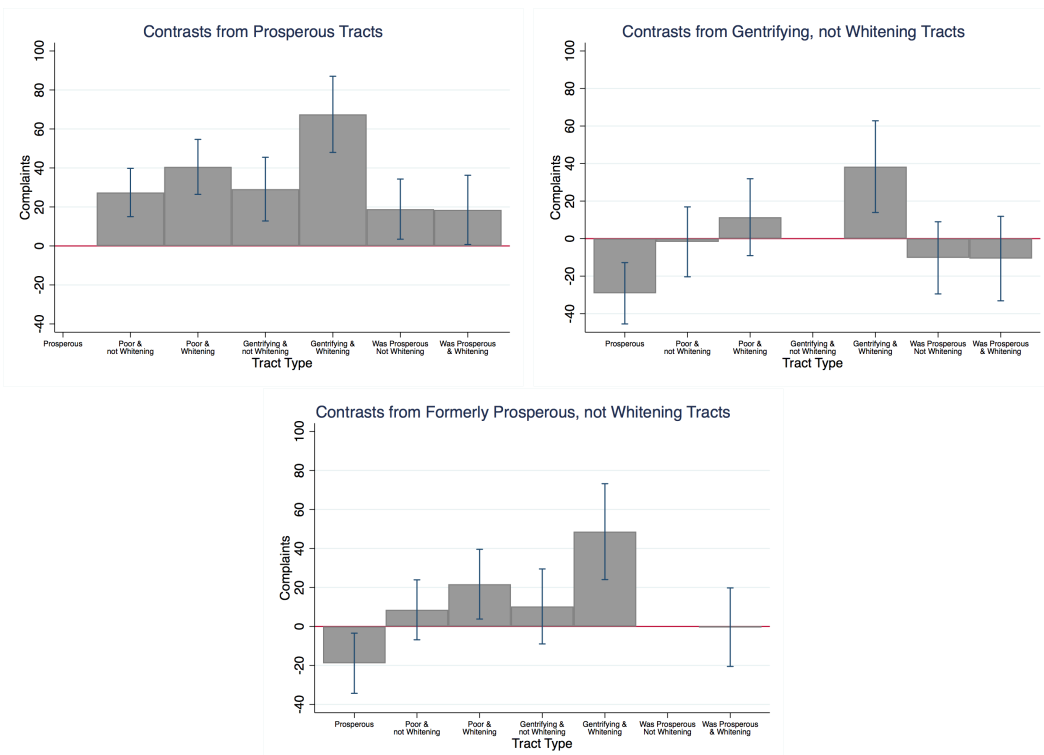



Figure 4.21 shows the predicted number of per capita complaints about residential noise in 2019 by tract type, holding all covariates at their means, and Figure 4.22 shows predicted net differences in complaints about residential noise in 2019, holding covariates at their means, with comparisons to three reference groups. Panel one shows the comparison to prosperous tracts. Both types of formerly prosperous tracts are predicted to have about 20 more complaints per capita about residential noise, all else equal, than their persistently prosperous counterparts. The bottom panel of Figure 4.22 shows that there is not a difference between formerly prosperous tracts,

Figure 4.22: Predicted difference in number of complaints about residential noise in 2019 compared to three reference groups

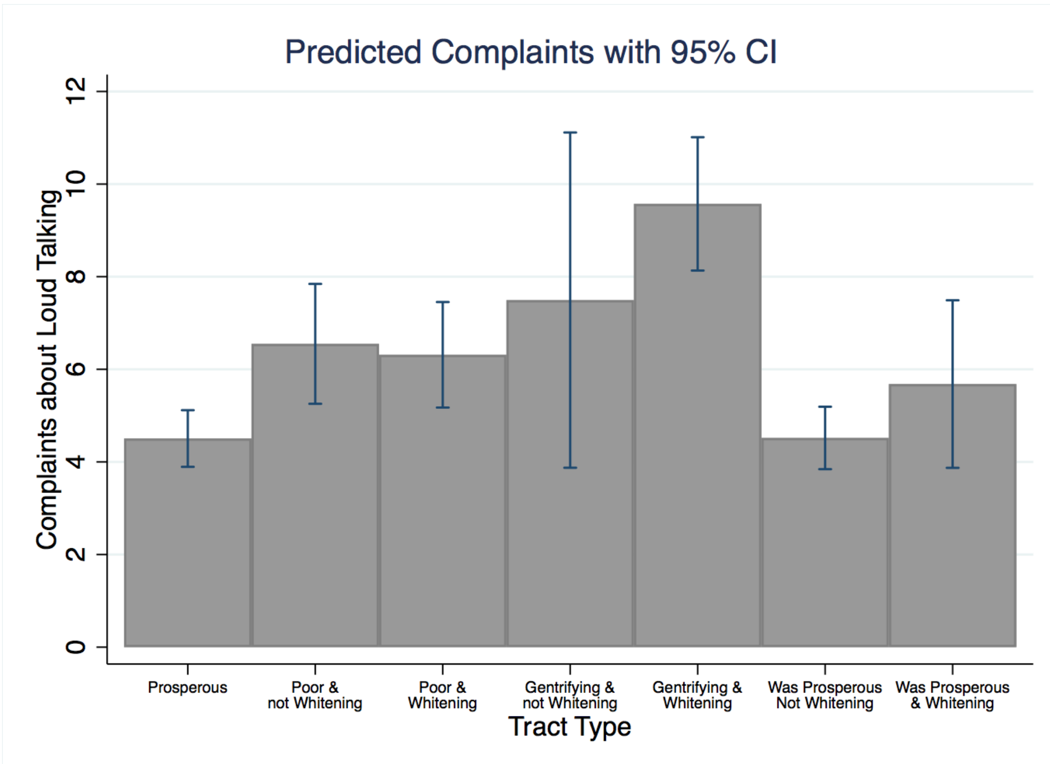
*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all other covariates at their means.*



whitening and not, in 2019, all else equal.

Figure 4.23: Predicted number of complaints about loud talking in 2011 by tract type

*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*




Figures 4.23 and 4.24 show the predicted number of complaints about loud talking, holding covariates at their means, and the net differences in complaints compared to three reference groups for 2011, respectively. The patterns remain when prosperous tracts are subdivided. In 2011, the average gentrifying tract that experienced whitening had the largest predicted number of complaints about loud talking. Both whitening and not whitening formerly prosperous tracts did not have statistically significantly different counts of complaints about loud talking compared

Figure 4.24: Predicted difference in number of complaints about loud talking in 2011 compared to three reference groups

*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all other covariates at their means.*

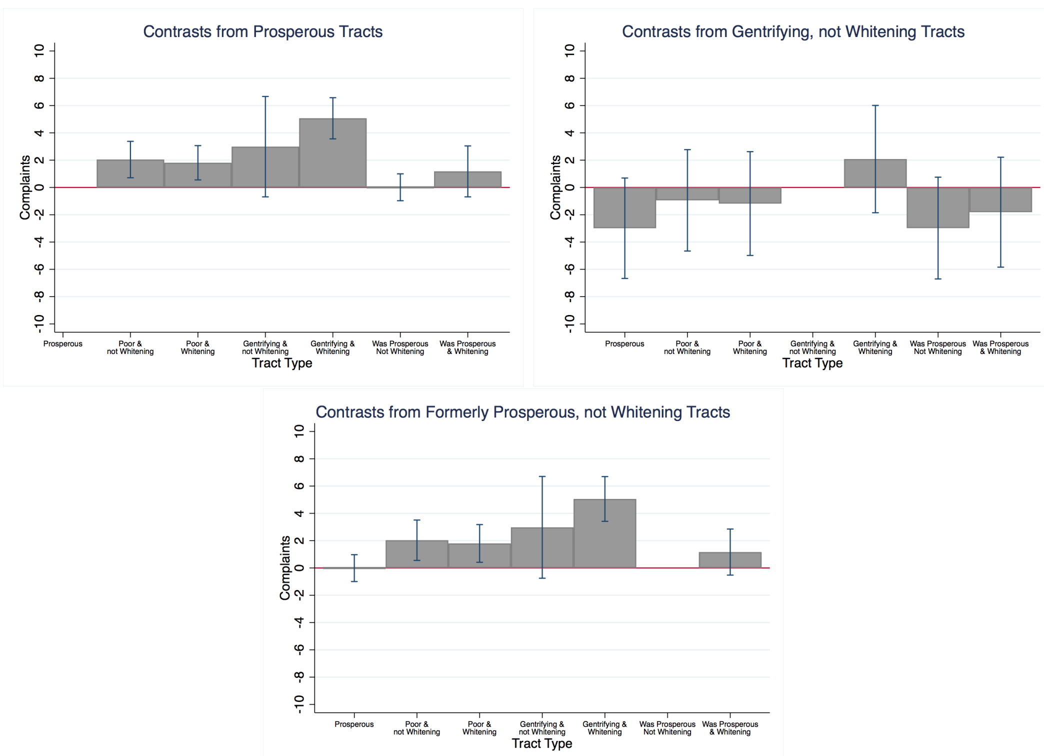
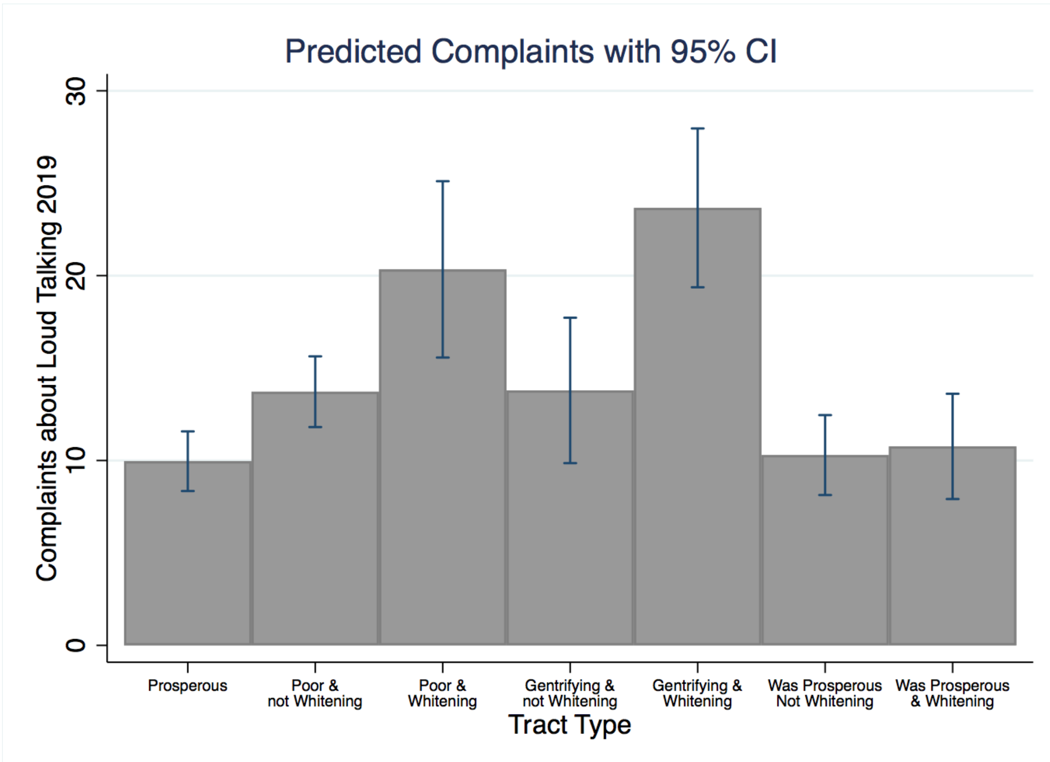


Figure 4.25: Predicted number of complaints about loud talking in 2019 by tract type

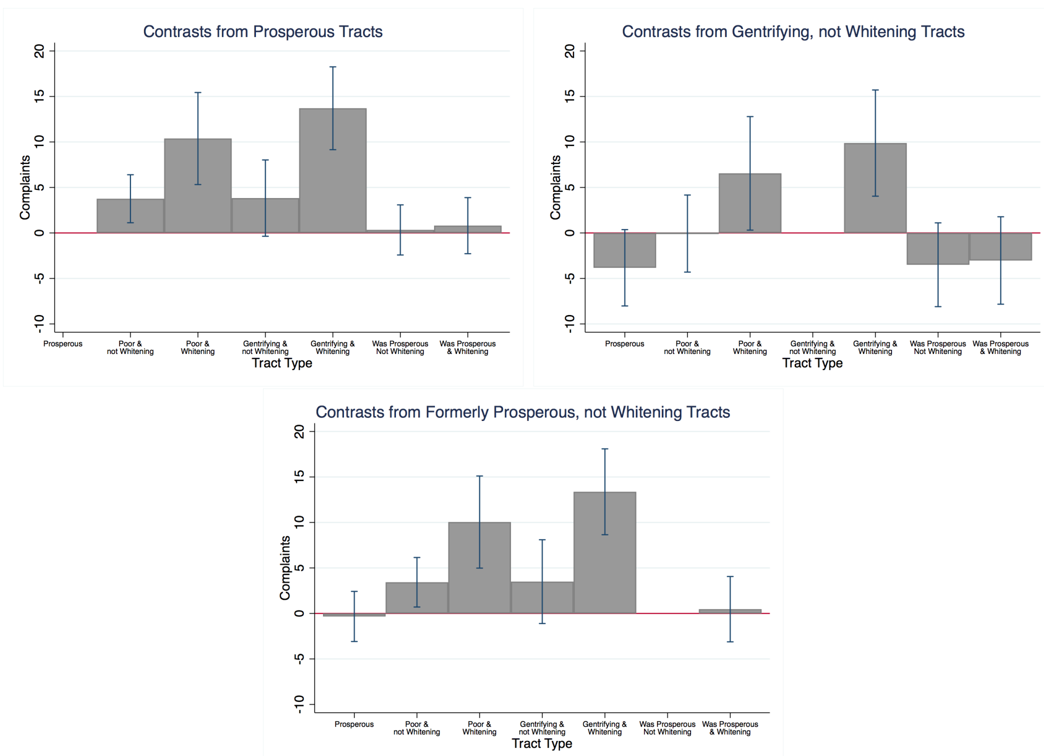
*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*




to prosperous tracts that remained prosperous. Formerly prosperous tracts both whitening and not were also not statistically different from each other in terms of complaints about loud talking, all else equal. Figures 4.25 and 4.26 show the predicted counts and predicted net differences in counts of loud talking complaints in 2019, holding covariates at their means. In 2019, as in 2011, the average gentrifying tract that experienced whitening had the most complaints about loud talking, significantly more than their average gentrifying but not whitening counterpart. Whitening in poor tracts appears to be more important in 2019 than in 2011, with significantly

Figure 4.26: Predicted difference in number of complaints about loud talking in 2019 compared to three reference groups

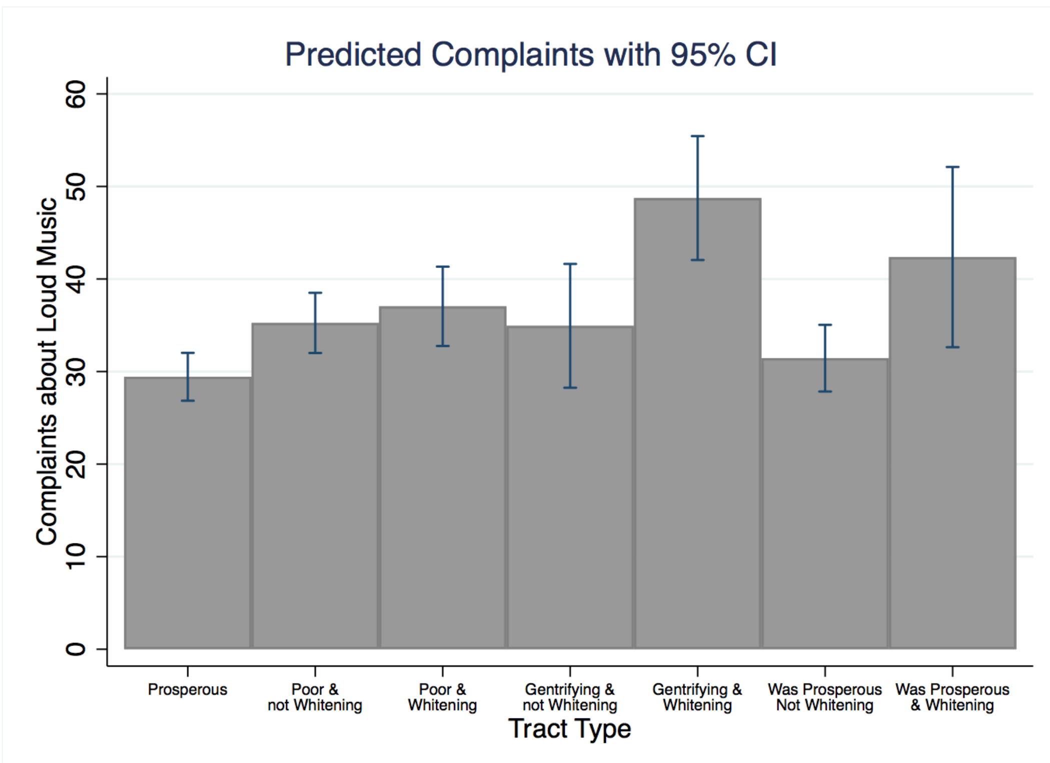
*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all other covariates at their means.*



more predicted complaints in the average poor and whitening tract compared to the average poor tract that did not whiten. The formerly prosperous tracts of both types have similar numbers of complaints to persistently prosperous tracts in 2019, and have similar numbers of complaints to each other, all else equal.

Figure 4.27: Predicted number of complaints about loud music/parties in 2011 by tract type

*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*



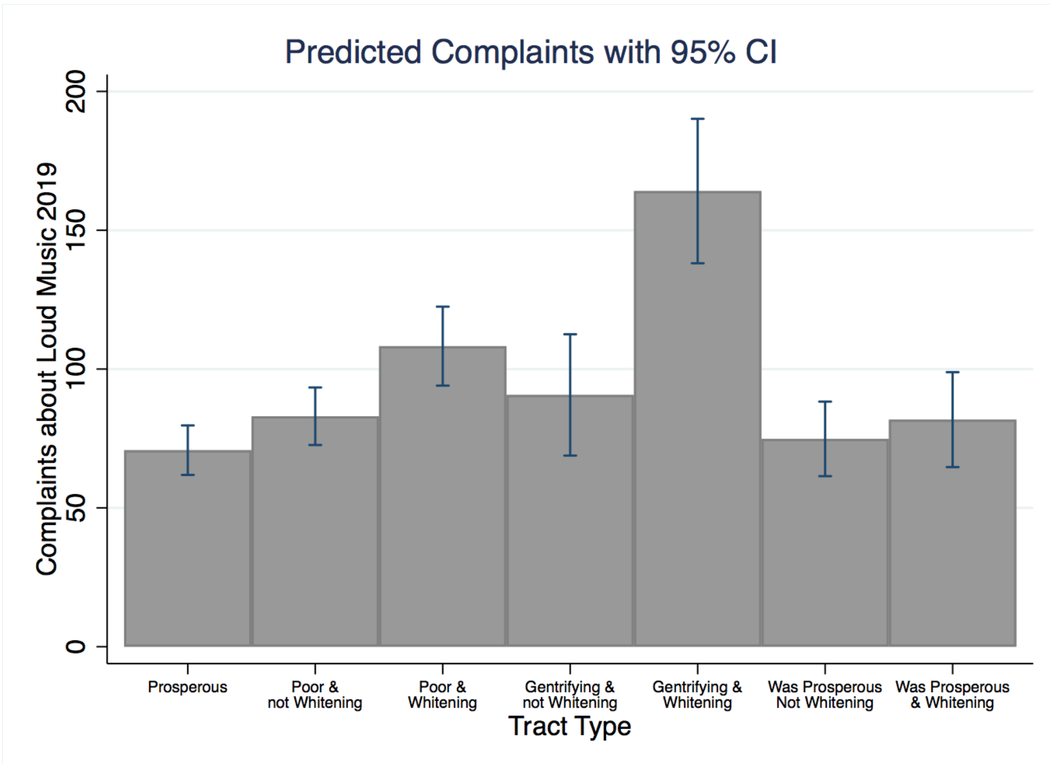

Figures 4.27 and 4.28 show the predicted number of complaints about loud music and parties holding covariates at their means and predicted net differences in complaints compared to three references groups for 2011, respectively. As with the

Figure 4.28: Predicted difference in number of complaints about loud music and parties in 2011 compared to three reference groups

*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all other covariates at their means.*

Figure 4.29: Predicted number of complaints about loud music/parties in 2019 by tract type

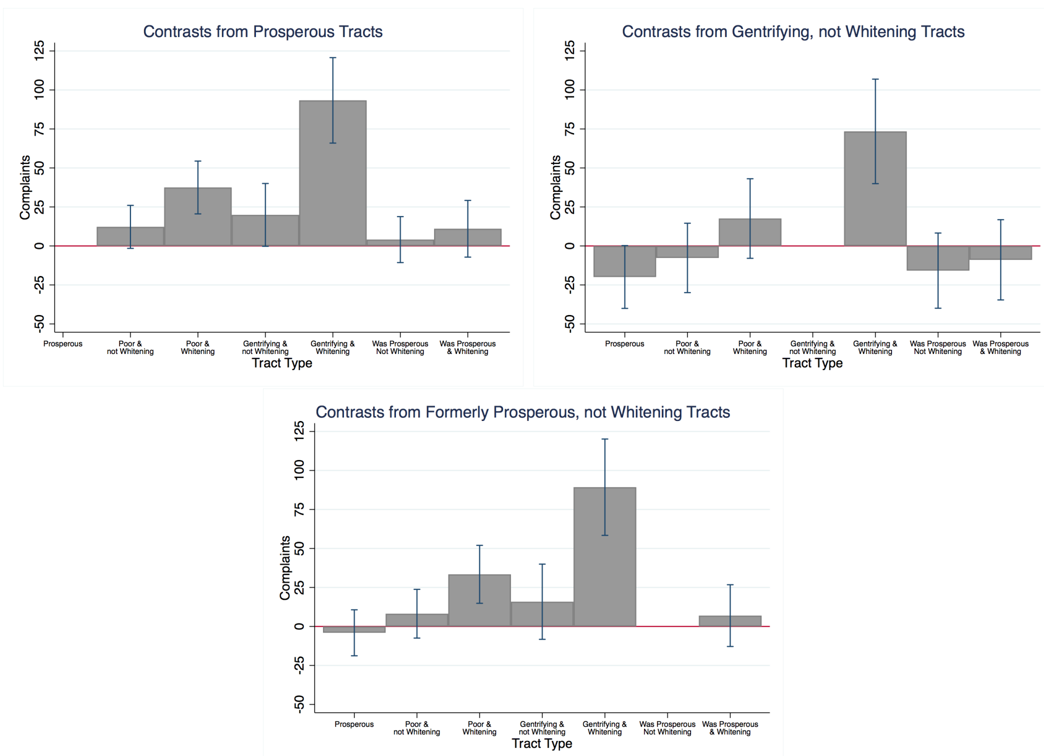
*Note: Figure shows counts predicted by the model by tract type holding all covariates at their means.*




other complaint outcomes, the pattern across tract types are consistent with both tract typologies and across both years. In 2011, the predicted number of complaints about loud music was biggest in the average gentrifying and whitening tract, significantly more than gentrifying tracts that did not whiten. As in the main analysis, whitening is more important to predicted loud music complaints than it was to predicted loud talking complaints. Per capita loud music complaints are predicted to be the same in persistently prosperous tracts and formerly prosperous tracts that did not whiten.

Figure 4.30: Predicted difference in number of complaints about loud music and parties in 2019 compared to three reference groups

*Note: Figure shows predicted net differences in counts for each tract type compared to a reference category holding all other covariates at their means.*



On the other hand, formerly prosperous tracts that did whiten are predicted to have about 13 more complaints per capita than tracts that stayed prosperous and about 10 more complaints per capita than the formerly prosperous tracts that did not whiten. In 2019, formerly prosperous tracts were more similar to persistently prosperous tracts than they were in 2011. Figures 4.29 and 4.30 show the predicted counts and predicted net differences in counts for 2019. Formerly prosperous tracts are similar to their persistently prosperous counterparts and whitening does not distinguish between formerly prosperous tracts, all else equal. Gentrifying combined with whitening remains the most important combination in predicting complaints about loud music and parties, all else equal.

## 4.6 Discussion

People who live in urban neighborhoods generally have lower expectations of privacy in their homes than people who live in less populated areas. Apartments share walls with multiple other apartments. Walls may be thin. Windows do not provide as much sound insulation from the outside world as we would like, especially in older buildings. Unless you are on the top floor of a building, there will often be someone walking (or stomping)[6] around above your head. In addition to the physical and social constraints on privacy simply due to the realities of city life, people from different cultural and socioeconomic backgrounds may have differing expectations about what behaviors and impositions on neighbors are and are not acceptable.

[6] Or skateboarding, mariachi band practice, manufacturing, and nightly group salsa dancing lessons, all of which I have experienced while living in a variety of apartments in a variety of neighborhoods in NYC.

As neighborhood populations change, people with different expectations around social norms about things like noise are likely to come into contact and their differences in expectations may cause conflict. Previous research suggests that white, middle and upper-middle class residents are likely to have more stringent opinions on acceptable volumes for activities in neighboring apartments and outside their windows and are likely to be quicker to resort to external means of enforcing their social norms (Engle Merry, 1993; Gans, 1962; Gurney et al., 2000; Sampson and Bartusch, 1998). As I discussed in the previous chapter, the 311 data do not reveal the race of the complainant nor the race of the person complained about. However, patterns of complaints at the tract level can illustrate how different kinds of neighborhood change are associated with conflict over noise and the use of the city complaint system to bring formal social control to police the behaviors of individuals when those behaviors are perceived to intrude on the private spaces of their neighbors.

I hypothesized that gentrification combined with neighborhood whitening would be associated with the most complaints about residential noise, all else held equal, and specifically that gentrifying tracts that whitened would have more complaints of this type than gentrifying tracts that did not whiten. What I found was that in 2011 poor tracts that whitened and those that did not had approximately the same number of per capita complaints about residential noise as gentrifying tracts that whitened. Prosperous tracts and gentrifying tracts that did not whiten had the least complaints about residential noise. The first half of my hypothesis, that gentrifying and whitening tracts would have more per capita residential noise complaints than all other tracts types, was not supported by the 2011 data. The second half of my hypothesis, that whitening would differentiate gentrifying tracts, was supported by the data. Gentrifying tracts that whitened had about 8 more complaints per capita about residential noise than gentrifying tracts that did not whiten, all else equal. In 2019, however, both parts of my hypothesis were supported. Gentrifying tracts that whitened had the most per capita complaints about residential noise than all other tract types. In addition, in 2019 whitening served to differentiate between poor tracts and gentrifying tracts. On average, poor tracts that whitened had about 15 more complaints per capita about residential noise, all else equal, than poor tracts that did not whiten. Gentrifying tracts that whitened had, on average, about 40 more complaints per capita about residential noise than gentrifying tracts that did not whiten.

I additionally hypothesized that gentrifying combined with whitening would be associated with more complaints about loud talking and loud music, but with a greater effect for loud music due to the idea that talking may be seen as less of an imposition than music and due to the differences in how much louder music can get compared to talking. Whitening could also be associated with higher rates of complaints about music because of negative perceptions white people have of Black musical styles, like rap, which white people are more likely to perceive as harmful and threatening (Binder, 1993). Additionally, (Bryson, 1996) found that racism was associated with a dislike for musical genres disproportionately favored by Black and Hispanic people, such as rap, regae, gospel, and Latin music.

I found that in 2011, there were not differences between poor tracts and gentrifying tracts, whitening or not, when it came to complaints about loud talking. The least complaints were made in prosperous tracts, all else equal, but all other tract types were indistinguishable from each other when controlling for a host of other tract characteristics. In 2019, the pattern was different. Prosperous tracts still had the least per capita complaints about loud talking. Gentrifying tracts that also whitened had the most per capita complaints about loud talking. They also had about 10 more complaints per capita than their gentrifying but not whitening counterparts. Poor tracts were also differentiated based on whitening with poor tracts that whitening have about 6 more complaints per capita about loud talking compared to their non whitening counterparts, all else held equal.

Complaints about loud music most closely followed the patterns I predicted in my hypotheses. In 2011, the most complaints about loud music and parties were in gentrifying tracts that also whitened, all else held equal. While there was no substantive difference in complaints about loud music and parties between poor tracts that whitened and those that did not, there were about 14 more per capita complaints predicted on average for gentrifying tracts that whitened compared to their non-whitening counterparts, holding all covariates at their means. In 2019, the pattern was even more extreme. Gentrifying tracts that whitened had, on average, 75 more per capita complaints compared to their non whitening counterparts, all else equal. In addition, in 2019, poor tracts that whitened had 25 more per capita complaints about loud music and parties, on average, than their non-whitening counterparts, all else equal.

So why, just as in the analysis of complaints sent to the NYPD in the previous chapter, would whitening not differentiate poor tracts for any of the outcome variables in 2011 but would for all three in 2019? And why would it predict more complaints about loud talking in both poor and gentrifying tracts in 2019 when there was no difference predicted in either of those tract types based on whitening in 2011? It could be that the type of white residents who moved into poor and gentrifying neighborhoods qualitatively changed in the time between the two years of study. Hurricane Sandy hit NYC in 2012 and wreaked havoc on the city infrastructure and housing, especially in the hardest hit areas of the city. This may have impacted not only movement of people inside the city but also who moved to the city and how long they stayed. It may also be that when poor tracts whitened in 2019, the average increase in white population percent was larger than when they whitened in 2011. In 2011, on average, poor tracts that whitened increase the white percentage of their population by 3.7 percentage points. In 2019, that number was 4.26 percentage points. In 2011, on average, gentrifying tracts that whitened increase the white percentage of their population by 9.7 percentage points, while that number was 8.8 on average in 2019.

Additional research is necessary to determine if there were other qualitative differences between the type of white people moving into poor neighborhoods in 2011 compared to 2019. There is some evidence that neighborhood racial composition threshold effects exist, although they are complicated by other contextual and structural factors (Quercia and Galster, 2000). It could also be that there is a qualitative difference between the first wave of white residents who move into poor and gentrifying neighborhoods of color. Perhaps the first wave is more tolerant of the social norms of their new neighborhoods. But it may also be that the first wave provides the necessary threshold for less tolerant residents to feel comfortable moving in.

As with the previous chapter, the analysis presented above is limited by what the data do not tell us. If the data provided information on the characteristics of the complainants and the characteristics of those the complaints are about, we could say something more concrete about the extent to which increased conflict over noise is driven by racial differences in changing neighborhoods. We could assume based on prevalent narratives in the media about gentrification that white gentrifiers are the ones complaining to the city about the noise made by their neighbors, but without specific individual information, that is merely informed speculation. As is, what I can say is that gentrification in combination with neighborhood whitening is associated with more calls to the city to police the private, but noisy, behaviors of their neighbors, and that is particularly the case for complaints about loud music and parties.

Previous research on complaints and particularly complaints about noise found that class-based gentrification was associated with higher rates of complaints (Cheshire et al., 2019). These findings demonstrate the importance of considering both class-based gentrification and neighborhood racial change and the interaction between the two types of change. The study of neighborhood change must move beyond simplifying change to socioeconomic gentrification. Without also considering neighborhood whitening, we might miss patterns in both poor tracts and gentrifying tracts.

# Chapter 5

# Conclusion

Neighborhoods are changing across American cities. Whereas in the 20$^{\text{th}}$ century white residents fled city centers for the suburbs, leaving concentrated racial and socioeconomic poverty behind, more recently white and high-income residents are moving back to cities and, within cities, moving into disadvantaged neighborhoods made that way in part by the original flight. While there are strong arguments to be made for the potential benefits of increasing residential integration, there are also potential negative consequences that should be documented and understood, and the benefits cannot be fully realized if the negatives are not addressed. With neighborhood changes come questions of how rights to use public space are allocated and who gets to decide, and how social norms about behavior in public are negotiated and enforced.

In this dissertation, I examined patterns of social control in the form of police stops and 311 complaints in changing neighborhoods across New York City. My analysis explicitly considered two types of neighborhood change and their intersection: socioeconomic gentrification and neighborhood whitening. Both types of change represent increases of residents with two different, often overlapping, wells of social privilege. Previous research on gentrification has considered the socioeconomic aspects of change, but the racial component has been conspicuously absent from the literature. This may be because strong correlations between race and socioeconomic status in the US make it easy to assume that gentrifiers are white, or it may be due to an assumption that economic factors are more important.[1] But this dissertation demonstrates the importance of considering race and socioeconomics separately. Not all gentrifiers are white; not all white in-movers are gentrifiers. There are poor neighborhoods that whiten and gentrifying neighborhoods that do not. To understand the breadth of neighborhood change and its benefits and consequences, we must first start by accurately mapping the types and combinations of change that are occurring.

In Chapter 2, I presented an analysis of stops made by the NYPD as part of the Stop, Question, and Frisk program in NYC in 2011. Using a novel typology of neighborhood change, built on an existing gentrification typology used by Hwang (2019) following Hammel and Wyly (1996), Wyly and Hammel (1999), and Freeman (2009), I looked at the per capita rate of stops, in total and by race/ethnicity of those stopped, controlling for a host of tract characteristics. I argued that whitening is a particularly salient sign of neighborhood change, one that would be immediately visible to NYPD officers. I found that, all else equal, there were higher per capita

[1] This is despite the fact that literature on the consequences of urban disinvestment and concentrated disadvantage, opposite processes to gentrification and whitening, generally highlight the intersection of race and class (Wodtke et al., 2011; Sharkey, 2013; Sampson et al., 2008).

rates of stops of Black individuals in both poor and gentrifying tracts that whitened compared to their non-whitening counterparts. On the other hand, whitening was not associated with higher per capita stops of Hispanic individuals or white individuals. Separate from socioeconomic gentrification, increases in white population are linked to higher rates of stops of Black individuals.

In Chapter 3, I examined complaints made to 311 that were sent to the NYPD and complaints that resulted in the NYPD taking action to resolve the conditions described in the complaint. Rather than focusing on the content of the complaints, in this chapter I considered the intent – to summon the NYPD to exercise formal social control against neighbors for objectionable behavior – and the consequence – NYPD action against individuals as a result of complaints made by their neighbors. I hypothesized that the combination of gentrification and neighborhood whitening, with its accompanying increases in two types of social privilege, would be associated with more complaints sent to the NYPD because of a higher likelihood of socially privileged residents to call on city services to solve neighborhood problems. I found that, indeed, all else held equal, there were more complaints of the types sent to the NYPD in gentrifying tracts that also whitened compared to all other tract types. This was true in both 2011 and 2019. Whitening additionally differentiated poor tracts in 2019, with more complaints sent to the NYPD in poor tracts that whitened compared to poor tracts that did not whiten. Finally, I found that in both 2011 and 2019 the NYPD took informal action more when responding to complaints in both poor tracts that whitened and gentrifying tracts that whitened compared to their respective non-whitening socioeconomic counterparts, but took formal action less when responding to complaints in gentrifying tracts that whitened compared to those that did not. Given the findings from Chapter 2, it is easy to imagine who was most likely the victim of NYPD informal action, although additional research is necessary to test the assumption. Meanwhile, the pattern of formal actions taken by the NYPD in response to 311 complaint, which require a greater evidential threshold than informal action, suggests there may be more frivolous complaints made in gentrifying tracts that whitened compared to the other tract types. Additional investigation is necessary to determine whether or not this is the case.

In Chapter 4, I investigated the most common category of 311 complaint sent to the NYPD for response: residential noise complaints. I hypothesized that, due to differences in social norms about noise and the boundaries of private space, whitening, particularly in conjunction with gentrification, would be associated with the most complaints about residential noise. I further examined the two types of noise complaints most linked to social behavior: loud talking and loud music and parties. I found that in both 2011 and 2019 gentrifying tracts that whitened had more complaints per capita about residential noise than gentrifying tracts that did not whiten. In 2019, whitening also differentiated between poor tracts with more complaints per capita about residential noise in poor tracts that whitened compared to poor tracts that did not whiten. For loud talking, I found that there was not an association between whitening, socioeconomic gentrification, and loud talking complaints in 2011, but that in 2019 there were more complaints about loud talking in poor tracts that whitened and in gentrifying tracts that whitened compared to their respective non-whitening, socioeconomic counterparts. It may be that there was a qualitative difference between the white residents moving into poor and gentrifying tracts between 2000 and 2010 and those who moved in between 2011 and 2018. Finally, I found that the combination of gentrification and whitening was linked to the most per capita complaints about loud music and parties, all else held equal, compared to the other tract types. In both 2011 and 2019, there were more per capita complaints of this kind in gentrifying tracts that whitened compared to those that did not. In 2019, whitening also differentiated between poor tracts with more per capita complaints about loud music and parties made in poor tracts that whitened compared to those that did not. Comparing the distributions of socioeconomic and demographic tract characteristics between the two time periods, the white population got slightly smaller on average, the average median household income increased, and both violent and property crime declined dramatically. The directions of change for these variables lend credence to a cultural shift hypothesis to explain the increase in the importance of whitening between 2011 and 2019.

Taken together, the findings from these three chapters paint a layered picture of the relationship between social control and neighborhood change. They demonstrate the importance of parsing out socioeconomic gentrification from racial/ethnic change. They illustrate that gentrification and whitening operate in combination and together are implicated in higher levels of social control than gentrification on its own. They suggest that whitening plays a role in social control in poor neighborhoods as well, a dynamic that has been completely overlooked in the sociological literature up to this point.

The findings I have presented in this dissertation suggest one way in which socially distant groups moving into spatial proximity can negatively affect members of the less privileged group through increases in formal social control. Sociologists have not given sufficient attention to the potentially life-altering consequences of increased policing of Black and Hispanic individuals in response to increased white population in poor and gentrifying neighborhoods, nor to the consequences of individuals summoning the police via 311 to act as intermediaries in neighborhood disputes. Understanding these effects and the mechanisms behind them is necessary to develop both reactive and proactive public policy for housing and zoning, community organizing, community policing, police training, and the implementation of police practices related to suspicion and low-level offenses in order to mitigate and eventually eliminate the disparities and reap the full benefits that can come from increased integration.

## Future Research

Neighborhood change is an ongoing process whose impact on local communities has not been fully realized nor documented. In this dissertation, I have extended our understanding of how neighborhood change is linked to patterns of social control. I have demonstrated the importance of whitening and of considering racial change independently from socioeconomic change. However, there is much more to learn about the social dynamics in changing neighborhoods. Below I briefly describe several projects intended to further this line of research and to elicit the mechanisms linking neighborhood change to the increases in social control demonstrated in this dissertation.

## Individual stops and complaints

In this dissertation, I focused on stops and complaints aggregated to the census tract. The raw data, however, include individual observations for each stop and each complaint made. Data on individual stops include characteristics of the person stopped, including approximate age, gender, build, as well as details about the circumstances of the stop, the time and day of the week the stop was made, the reasons for suspicion, etc. Data on individual complaints include information about the subject of the complaint, the response to the complaint, and the resolution of the complaint. Using these data on individual stops and complaints, I will investigate the following questions: Are stops more likely to progress to a frisk, search, use of force, summons, or arrest in whitening neighborhoods that other neighborhood types? Are there particular kinds of complaints where the escalation from complaint to NYPD response to NYPD action is more likely, and is that escalation more likely to happen in certain types of neighborhoods?

## Neighborhood whitening and suburban values

Gene Demby of NPR's CodeSwitch has suggested an interesting theory to explain the noticeable culture clash and power struggle in gentrifying neighborhoods. He suggests that white people who gentrify city neighborhoods bring suburban values and understandings of public and private space to their new neighborhoods and try to impose them on their new neighbors.[2] I propose a study to test this hypothesis. I

[2] Quoted from Twitter: Lysol In E Flat @GeeDee215 Jun 29, 2018 "suburbs were a segregationist project – the explosion of amenities like private pools were a reaction to the notion of sharing public space w/ Black ppl. after generations of suburban living, gentrifiers bring with them those

will use a combination of interview and survey techniques to investigate "suburban values": what are they, how do they relate to expectations about neighborhood behavior, and how do they change with context? How do they differ from "urban values"? Where are white gentrifiers coming from when they gentrify? Are white people who move into gentrifying or poor urban neighborhoods more likely to hold suburban values than their neighbors? Are residents who hold suburban values more likely to call the city to request social control of their neighbors for perceived breaches of their social expectations?

## Neighborhood change and race out of place

How do different types of neighborhood change affect individuals' perceptions of neighborhoods and the people they may encounter in the context of those neighborhoods? Is there an out-of-place effect where individuals are perceived as more suspicious and a neighborhood is perceived as more dangerous, or more in need of social control, when individuals observed in a neighborhood do not match the neighborhood context based on commonly held social assumptions about who belongs where? How do perceptions of belonging change when the neighborhood context has recently changed? To investigate these questions, I will carry out a vignette study with factorial experimental design. Following Silva (2018), my survey will have a two-stage design with a waiting period between stages one and two using the Amazon

same foundational premises around city spaces ... it doesn't make sense that people move into CITIES and complain about the noise. That's what cities *are* — vital and shared and loud. But suburbanization was abt private everything – even the shared public spaces were...malls." https://twitter.com/geedee215/status/1012726552356933632

Mechanical Turk platform.[3] In the first stage, participants will be asked to fill out a screening survey to determine if they are eligible for the study. The screening will capture demographic characteristics of respondents, such as race/ethnicity, age, level of education, region of residence, and gender. Respondents will be considered eligible if they are over the age of 18 and living in the United States. If they are eligible, they will then be asked to take the black-white Implicit Association Test (IAT), which measures the strength of an individual's cognitive associations between the racial categories "African American" and "Caucasian" and the value categories "positive" and "negative."

In the second stage, following a 60-day waiting period, respondents who were selected to take the IAT in stage one will be sent an invitation to participate in the experimental survey. The invitation will not indicate that the study is connected to the IAT from stage one. They will again be asked to answer a series of demographic questions, similar to those in the screening survey, which will allow me to monitor for consistent answers among respondents across the two time points. Separating the IAT and the survey by a waiting period guards against the possibility that taking the IAT immediately before the survey will make respondents more aware of their biases and influence their survey answers due either to that increased awareness or to priming of their racial attitudes (Silva, 2018).

In the survey phase, I will randomly assign each respondent to one of 18 experimental conditions from a $3^2 2$ factorial design. The conditions will consist of

[3] Much research has been done on the validity of samples gathered via Amazon's Mechanical Turk, which has been shown to perform well for experimental studies. See Hauser and Schwarz (2016), Mullinix et al. (2015), and Weinberg et al. (2014) for more on the use of Mechanical Turk for survey research.

combinations across three factors: neighborhood socioeconomic status, neighborhood racial makeup, and the race of an individual who is singled out for attention in the context of the neighborhood. Neighborhood socioeconomic status (SES) will be divided into three possible categories: consistently high SES, recently gentrifying, and consistently low SES. Neighborhood racial makeup will also be divided into three categories: consistently majority white, majority Black but recently whitening, and consistently majority Black. Finally, the individual singled out for attention in the context of the neighborhood will be a young man described as either white or Black.[4] Each respondent will be asked to read a vignette for their assigned condition, which will describe the neighborhood characteristics and the focal individual in the context of the neighborhood, and include images to illustrate the experimental condition. Respondents will then be asked a series of questions about their perceptions of the neighborhood and of the focal individual, including questions about whether they found him to be suspicious in the context of the neighborhood, whether they think the police should pay particular attention to that neighborhood and/or particular individuals in that neighborhood, if they would feel safe walking around the neighborhood by themselves during the day and at night, and whether they would considering moving to that neighborhood.

This project will shed light on the ways in which individuals and neighborhoods are evaluated based on context – both the current context of the neighborhood

[4]I will constrain variation in the characteristics of the individual to race here in order to keep the number of treatments at 18 rather than 36. I choose to make the individual male in keeping with a wealth of literature on stereotypes about Black male criminality, although I suspect there are interesting patterns related to suspicion of Black women in different contexts, which I would like to investigate in later research.

and the context of the neighborhood as it is in relation to what it was – and how those evaluations vary by level of implicit bias/prejudice. As politicians, public officials, and advocates debate over policy interventions in racial residential and school segregation, it will be important to better understand the potential social consequences accompanying gentrification and neighborhood racial change. Policies intended to reduce racial segregation should attempt to account for these social consequences in order to achieve their goals and reap the attendant benefits.

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