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Race and Selective Enforcement in Public Housing

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Drugs, crime, and public housing are closely linked in policy and politics, and their nexus has animated several intensive drug enforcement programs targeted at public housing residents. In New York City, police systematically conduct "vertical patrols" in public housing buildings, making tens of thousands of *Terry* stops each year. During these patrols, both uniformed and undercover officers systematically move through the buildings, temporarily detaining and questioning residents and visitors, often at a low threshold of suspicion, and usually alleging trespass to justify the stop. We use a case-control design to identify the effects of living in one of New York City's 330 public housing developments on the probability of stop, frisk, and arrest from 2004–2011. We find that the incidence rate ratio for trespass stops and arrests is more than two times greater in public housing than in the immediate surrounding neighborhoods. We decompose these effects using first differences models and find that the difference in percent black and Hispanic populations in public housing compared to the surrounding area predicts the disparity in trespass enforcement and enforcement of other criminal law violations. The pattern of racially selective enforcement suggests the potential for systemic violations of the Fourteenth Amendment's prohibition on racial discrimination.

I. Introduction

Crime and public housing are closely linked in the popular and political imagination, and have been so for nearly 50 years (Dunworth & Saiger 1994; Holzman 1996; Popkin 2000; Fagan et al. 2006). This linkage has been tied to public housing's racial and socioeconomic composition (Schill 1993; Marcuse 1995), as well as to its association with drugs (Kotlowitz 1992). The resulting labeling of public housing has led to a set of law enforcement tactics that place residents under a very close police gaze, justifies efforts to "contain" residents within the boundaries of public housing sites, and legitimizes the close surveillance of visitors and neighbors from the surrounding communities who venture into public housing's perimeter.

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Relying on theories of order maintenance and on "hot spots" policing of "high crime areas" (Skogan & Frydl 2004; Weisburd & Braga 2006), police have adopted tactics that expose public housing residents to warrantless searches of their homes (Venkatesh 2000; *Pratt v. Chicago Housing Authority* 1994), banishment statutes (*Virginia v. Hicks* 2003; Beckett & Herbert 2010), and unilateral evictions (*Escalera v. New York City Housing Authority* 1970; White 1995). Public housing enforcement strategies in New York, home of the nation's largest public housing system, have been based on "stop and frisk" tactics that became the staple of policing in the early 1990s (Spitzer 1999; Fagan & Davies 2000; Geller & Fagan 2010). In New York, with the nation's largest public housing network, police have made hundreds of thousands of *Terry* stops in and around public housing, resulting in more than 35,000 trespass arrests each year since 2006.

This article looks at one particular crime, trespass, and one particular police tactic, the vertical patrol, to determine the role race and location play in enforcement. The article proceeds in three sections. First, we review the history of efforts to control crime in public housing, including the legal background and tactical details of the trespass enforcement regime as practiced in New York. Next, we discuss the details and results of our empirical test for disparate treatment of public housing residents and the racial components of the trespass enforcement strategy. The evidence shows that the level of trespass enforcement in public housing cannot be explained by its crime predicates or other social or economic conditions. We find racial disparities in trespass enforcement that result in disparate treatment of persons living in public housing based on the racial composition of the site, particularly the black population in public housing, even after accounting for counterfactuals of crime, socioeconomic conditions, and the amount and intensity of policing. The results contradict aspects of the political narrative and the core policing theories that are offered as justifications for intensive trespass enforcement. We conclude with thoughts on the social and emotional burdens of trespass enforcement that are borne by the residents who are the intended beneficiaries of the project.

II. Background

A. *Crime in Public Housing*

Modern public housing in the United States began in the 1930s as a benevolent social experiment to alleviate slum conditions and benefit the mostly (white) working-class populations in U.S. cities (Cavanaugh 2005). Public housing expanded after World War II and most of the new public housing construction consisted of clusters of high-rise towers sited in neighborhoods already in the midst of significant social and structural change (Schill 1993). Beginning in the 1950s, public housing became a source of social and political conflict as white working-class families—many of whom benefited from the GI Bill and access to the burgeoning (and effectively white-only) suburbs—were replaced by poor nonwhites (Marcuse 1995). This coerced racial heterogeneity led to conflicts in a wide range of social policy domains such as housing, education (school busing), and welfare policy (Katz 1989; Massey & Denton 1993; Perlstein 2008).

As the white population in public housing continued to decline, the aging buildings began to look more and more like reservations for the city's poorest residents of color. The racial threat of concentrated minority populations in public housing signaled "danger" for older, declining white populations in public housing and in the surrounding neighborhoods. By 1970, public housing had become known, somewhat ominously and unfairly, as "government ghettos" (Smith 1970).

The popular and political image of public housing hardened further as crime rates rose in lockstep with cascading drug epidemics. A heroin epidemic began in New York and other large metropolitan areas in the mid-1960s and continued into the early 1970s (Des Jarlais & Uppal 1980). Crime rose concurrently as homicides tripled from 1967–1973, stabilized, and then rose again from 1977–1981 (Roth 2009). Public housing was identified in these eras as a central location in the distribution of drugs to persons living in the surrounding communities (Curtis 2003).

Riots in minority neighborhoods in 47 U.S. cities in 1967–1968 reinforced both the threat of crime and racialized (however inaccurately) its narrative (Kerner Commission 1968). In the 1970s, that perception was fortified by rare but widely publicized episodes of youth violence (Time Magazine 1977), sequential drug epidemics, and elevated rates of drug-related violence (Chaiken & Chaiken 1990). With the onset of the crack epidemic in the mid-1980s, the high-rise towers of large, mostly black-occupied, public housing projects again came to symbolize drug and crime problems (Austen 2012).

These connections are routinely revisited in the press, which has provided near constant reminders of the persistence of drug problems in public housing. As Schill (1993) explained: "Scarcely a day goes by without reports in the media about the . . . problems that plague some publicly-owned housing developments. Accounts of appalling apartment conditions, corrupt administrators, and innocent bystanders killed by gang warfare are commonplace. Negative images of public housing have even found their way into popular culture." This perception is reinforced by academic and media portrayals and leads to a situation where outsiders—those not intimately familiar with the neighborhoods—perceive public housing as more dangerous than the facts can substantiate (Quillian & Pager 2001; Sampson & Raudenbush 2004; Carlis 2009). The perception of public housing and its residents as the focal point of criminality in a neighborhood has justified, as Lazarus (2004) put it, "the use of every conceivable tool . . . to combat the ever-present criminal element in . . . housing projects."

B. Law and Social Control in Public Housing

Beginning with the heroin epidemic in the 1960s, drug law and policy began to specifically target public housing. Agar and Reisinger (2002) explain that while heroin initially received little mainstream attention, public scrutiny came toward the end of the decade "when, due to fear of urban crime and heroin use among American military personnel in Vietnam, it became defined as a threat." The conversation focused on public housing when dealers set up shop in "large apartment buildings . . . where landlords were not often present" (Curtis 2003). According to Curtis (2003) and other ethnographers of the crack epidemic (e.g., Hamid 1990; Johnson et al. 1990), drug dealers attempting to avoid street sweeps by New York Police Department (NYPD) officers during the crack epidemic of the 1980s and 1990s would later mimic this move to indoor drug sales. Evicting public housing tenants who participated in or supported drug dealing was a logical response (White 1995).

In New York, those evictions resulted in a protracted legal battle to determine what rights tenants had in their state-provided housing and under what conditions they could be evicted. The courts initially came to the tenants' defense and enforced a consent decree mandating that the housing authority adhere to certain procedural safeguards before terminating a tenant's lease, including detailed notice of charges and a full evidentiary hearing with a right to cross-examine hostile witnesses (White 1995). The housing authority and law enforcement institutions, viewing the decree as an unnecessary and inappropriate barrier that constrained police and protected wrongdoers from the consequences of their actions, sought to undermine it in the courts. They finally succeeded in 1996, when a New York district court concluded that the crack epidemic constituted "a quantum leap in the drug problem" that caused a "dramatic increase in the amount of crime and violence in the public housing developments throughout the city" and justified modifying the consent decree to facilitate the eviction of undesirable tenants (*Escalera v. NYCHA* 1996). Put another way, fighting the drug war justified tactics that just a few years earlier very well might have violated the Constitution.

That decision was mimicked nationwide when, in 1996, President Clinton announced the "One Strike" policy to encourage public housing authorities to speed the eviction of residents involved in criminal activity (Hellegers 1999). The Supreme Court sanctioned such evictions in *HUD v. Rucker* (2002), a case involving the eviction of a 63-year-old grandmother and her family based on the drug arrest of her mentally disabled granddaughter several blocks away from public housing grounds.

With both political and legal backing, policing followed suit. Enforcement strategies included order maintenance policing (OMP) (Livingston 1997; Spitzer 1999; Skogan & Frydl 2004) that relied on "high crime area" jurisprudence (Ferguson & Bernache 2008) to justify the targeting of public housing with special tactics such as vertical patrols. For its part, New York adopted a form of OMP based on Wilson and Kelling's (1982) "broken windows" theory. That theory argues that visible signs of disorder tell potential wrongdoers that the neighborhood tolerates misdeeds, thereby encouraging further transgressions. It suggests that law enforcement should "focus on quality of life crimes, eliminating visible signs of disorder before they spiral into something worse" (Levy 2008; Geller & Fagan 2010). The visible social disorder of crime and drugs in public housing was exactly the type of crime manifestation that served both the theory and justifying ideology of broken windows (Harcourt 1998; Kelling & Coles 1996). Adapting broken windows theory to indoor, apartment-based drug dealing suggested that the arrest of persons loitering in the hallways or stairwells could disrupt the indoor retail trade (Boland 1998). Using trespass law to eliminate those loiterers would (according to broken windows theory) eliminate visible lawlessness and therefore reduce the more serious crimes taking place in the building.

As with its strategic and policy predecessors, trespass enforcement in public housing was animated by the empirical and theoretical connection between drug selling and crime, but the modern version is a significant strategic departure from past public housing interventions to eliminate drug use and disrupt drug markets. Those efforts focused on evictions of tenants who were implicated in the drug business, as well as undercover drug buys in and around public housing to disrupt drug-selling enterprises. Trespass enforcement was something new: a larger-scale effort that was "wholesale" both in its scope and in the fact that it was implemented as a preemptive engagement with would-be offenders. Anyone in public housing, whether associated with the drug trade or not, is now subject to being stopped, frisked, and possibly arrested in the name of public order.

The trespass arrests resulting from this strategy take on additional normative and constitutional importance in light of the limited efficacy of OMP in preventing more serious crime (Harcourt & Ludwig 2006; Rosenfeld et al. 2007; Chauhan et al. 2011), the observed racial disparities in its implementation (Fagan & Davies 2000; Gelman et al. 2007; Fagan et al. 2010), and the constitutional concerns that have surrounded the policy (Carlis 2009).

That said, targeting trespass, rather than funneling resources toward direct enforcement of the drug laws, provides the police with a tactical benefit. Because probable cause is required to make an arrest, targeting street-level drug dealers usually involves undercover buy-and-bust operations, an expensive, dangerous, and time-consuming tactic. On the other hand, targeting trespassers eliminates the need for police officers to actually witness a drug crime. Instead, police officers can rely on the public-housing-specific trespass law, and the suspect's presence in the building, to make their initial approach. They are therefore able to question more people with less evidence. And, while overinclusive, these systematic stops do sometimes lead to the arrest of individuals for drug-related activity.

C. *The Practice of Vertical Patrols*

In 1992, New York amended its trespass statute to criminalize entering or remaining in public housing without permission (Carlis 2009). The enforcement of that statute bears a striking resemblance to the vague and overbroad loitering, vagrancy, and disorderly conduct laws used to isolate and control the movement of nonwhites during the mid-1900s (Livingston 1997). Those statutes enabled "the police [to] seize just about anyone on the street" because they could be "applied to almost any public behavior" (Stuntz 1995). A dangerous confluence of unbridled police discretion and widespread racism developed, eventually leading to the invalidation of many of these statutes (Stuntz 1995). However, as Rosenthal (2000) points out, even some of the conventional, modern criminal statutes "allow . . . the police enormous freedom to undertake a variety of quite heavy-handed measures against the residents of inner-city minority communities." Some, like a Chicago anti-loitering ordinance, were struck down by the courts; others, like the public-housing-specific trespass law in New York, remain on the books.

The police tactic most frequently associated with trespass enforcement in urban high-rises in general, and in public housing in particular, is the vertical patrol, which the New York State Fraternal Order of Police (2010) describes "as a process by which a Police

Officer systematically and methodically checks each building one at a time, covering roof landings, stairwells and lobbies." Before the 1992 amendment to New York's trespass statute, nonresidents were permitted to occupy the public areas of these buildings. Now, even during the most routine vertical patrol stop, police officers can quickly develop probable cause for a trespass arrest. Under *People v. De Bour* (1976), the leading New York Court of Appeals case on state stop and frisk law, a police officer need only have "some articulable reason" to ask "basic, nonthreatening questions." This low bar for what has been termed a "Level 1 inquiry" prevents only those inquiries "undertaken with intent to harass or . . . based upon mere whim, caprice or idle curiosity." In *People v. Hollman* (1992), the New York Court of Appeals explained that inquiries "regarding . . . identity, address or destination" typically constitute Level 1 inquiries. As a result, current New York jurisprudence places almost no barriers between the police officer and a trespass arrest (Carlis 2009). Once the initial inquiry begins, a nonresident will quickly have to divulge his or her nonresidency and, absent some evidence that he or she is a lawfully present guest, that information alone justifies arrest. Many residents also face the same scrutiny, resulting in arrests of citizens entering or exiting their own homes (*Davis v. City of New York* 2012).

D. Race and Trespass Enforcement

Public housing in New York is dramatically segregated. In 2008, 91 percent of public housing residents were African American or Latino, and only 4.3 percent were white (New York City Housing Authority (NYCHA) 2009). When it comes to those residents most affected by vertical patrols and trespass stops, these numbers are even more dramatic. The white population contains a disproportionately high number of individuals over the age of 62 (NYCHA 2009). Senior citizens would seem both less likely to be targeted during a vertical patrol and less likely to be in the common areas of the building for an extended period of time. As the Second Circuit Court of Appeals noted in *Davis v. NYCHA* (2002), white residents are not uniformly distributed across all NYCHA buildings. Instead, they tend to be clustered in the more desirable buildings. Because vertical patrols are also not conducted uniformly across all NYCHA buildings, but targeted at those buildings where the police believe they will be most effective (New York City Police Department 2005), it is likely that many white residents escape the brunt of vertical patrol activity.

The demography of public housing makes racial disparity in the tactic's implementation inevitable, regardless of legal or policy justifications, but the tactic itself continues in part because of a racially charged perception of public housing. As Smith (1986) has found, "the likelihood of arrest and coercive action by police toward suspects appears to vary with certain dimensions of neighborhoods," namely, the "socioeconomic status of the community" and the "racial composition of neighborhoods." Public housing's concentration of poor people of color therefore makes it a prime target for intensive enforcement (Terrill & Reisig 2003; Kochel et al. 2011). Clarke (2009) has found an increase in incidents of police misconduct related to police stops and frisks, much as Smith (1986) would predict.

Moreover, Werthman and Piliavin (1967) concluded that "residence in a *neighborhood* is the most general indicator used by police to select a sample of potential law violators."

Kochel et al. (2011) show robust evidence of the effects of race and neighborhood context on police decisions to make arrests relative to any racial differences in offending rates. Smith (1986) explained that these selection processes will often result in a "process of ecological contamination in which all persons encountered in bad neighborhoods are viewed by police as possessing the moral liability of the area itself." Because of this "ecological contamination," adherents to broken windows theory are likely to view anyone in the common areas of public housing to be a visible sign of disorder, regardless of whether they are acting unlawfully. It is unsurprising, then, that systematic stops are the tactic of choice in public housing.

But just as the metrics for moving from perception of disorder to categorization of a place as disorderly are subjective and relativistic, sociologists and social psychologists have shown that perceptions of disorder are influenced by both the racial makeup of the community being observed and by the characteristics of the observer (Sampson & Raudenbush 2004). Indeed, Sampson and Raudenbush (2004) explained that "Americans hold persistent beliefs linking blacks and disadvantaged minority groups to many social images, including but not limited to crime, violence, disorder, welfare, and undesirability as neighbors." As a result, when viewing public housing, police and politicians may be prone to attributions of a higher level of disorder simply because the majority of residents are people of color (Quillian & Pager 2001; Sampson & Raudenbush 2004; Carlis 2009).

Of course, a legal challenge to vertical patrols under the equal protection clause would require direct proof that trespass enforcement in public housing was race dependent and purposeful. The police could argue, perhaps persuasively, that the higher crime rates in public housing, and other nonracial factors that are correlates of crime and disorder, motivated the higher rate of sweeps. Even if the inferences by police about race and crime rates of public housing residents were made plain, the state's interest in crime control may void a claim of intentional discrimination based on race. An equal protection claim would therefore have to squarely face the questions of crime and disorder that are the rationale for the allocation of vertical patrols. If trespass enforcement is indexed to crime, we should observe variation from one place to the next that is predicted by its crime rate, net of other nonracial factors that are correlated with crime.

In this case, the search for drugs and weapons are the two compelling policy justifications articulated by the NYPD (Bratton & Knobler 1998; Spitzer 1999; Maple & Mitchell 2000; Fagan et al. 2010), and indexing trespass enforcement to rates of drugs or other crime in public housing would provide a relevant benchmark against which to assess the distribution of police enforcement and the attendant burdens of police suspicion and interdiction. This is the test we conduct to determine if, in fact, the targeting of public housing in New York for trespass enforcement masks an underlying racial targeting, or excess of enforcement, that cannot be explained by crime rates alone. We consider two faces of trespass enforcement: trespass stops, pursuant to the ongoing tactics of stop, question, and frisk, and trespass arrests. We enhance the test by simulating public housing conditions through controls for one-off similarities to compare public housing with its immediate environs, and testing to see if the excess in enforcement above and beyond a "signal" of race-crime patterns can be identified.

III. Data and Methods

A. Empirical Strategy

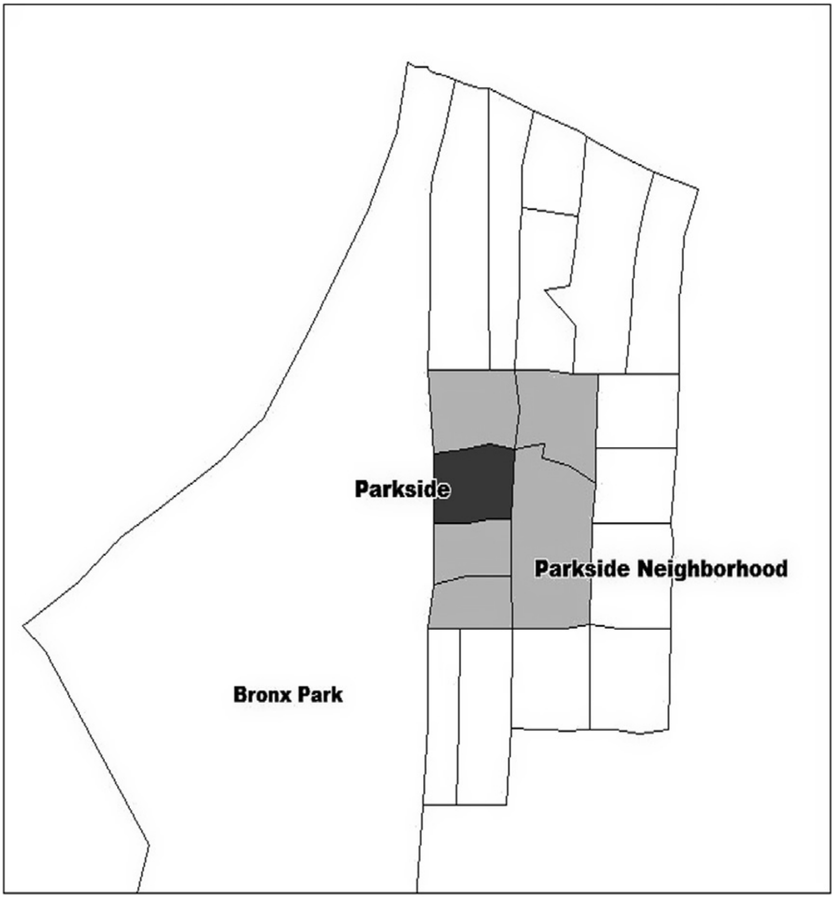
We conduct a disparate treatment analysis to determine, first, if public housing in New York is in fact targeted for trespass enforcement. Next, we assess whether the targeting of public housing for trespass enforcement masks an underlying racial targeting, or an excess of enforcement that cannot be explained by crime rates alone. We consider two faces of trespass enforcement: trespass stops in public housing, pursuant to the ongoing tactics of stop, question, and frisk (Fagan et al. 2010), and trespass arrests. The empirical strategy compares trespass and other enforcement activities in NYCHA's developments with the same parameters of enforcement in similarly situated areas that share many of the social, ecological, physical, and crime characteristics with the NYCHA developments but are not part of NYCHA housing services.

The comparison group is the area immediately surrounding each NYCHA site. This choice was motivated by two considerations. First, NYCHA sites are administratively drawn boundaries and NYPD enforcement is administered according to those boundaries. This means that an empirically derived "nearest-neighbor" model that estimates contiguity or shared spaces among (stop or crime) events (Levine 2006; Rogerson & Sun 2001; Paulsen & Robinson 2004) would most likely identify another building within the same public housing site comparisons. Accordingly, identifying a control group required a priori decisions about valid comparators within the framework of quasi-experimental design, rather than relying solely on statistically derived comparators.

Second, NYCHA sites are not randomly distributed across the city (Fagan et al. 2006; Marcusse 1995). Rather, they are more often concentrated in the city's poorer neighborhoods (Umbach 2011). The adjacent neighborhood strategy produced a set of comparators for NYCHA developments that were similar in most respects to NYCHA sites *other than* their NYCHA status and the unique enforcement strategies in those sites. The neighboring and contiguous (non-NYCHA) border areas allow us to do just that by taking into account the general crime and social conditions in the larger yet immediate neighborhood context. The contiguous area (nearest-neighbor) strategy thus allows us to better statistically identify the unique effects of NYCHA status on patterns of enforcement. The reliance on vertical patrol as a city-wide policing tactic also ensured that these places would be subject to the same policing regime as the NYCHA sites (Carlis 2009).

To identify the surrounding areas, a perimeter was drawn around each NYCHA site using geographical mapping software to identify the Census block groups that touched on the borders of each of the NYCHA developments. Block group boundaries from the 2000 Census were used, given the 2004–2011 timeframe for the analysis. Figure 1 illustrates one of these spatial clusters that surround a NYCHA site. Enforcement activity in the surrounding areas was compiled by summing all activity in the census block groups surrounding the NYCHA site and computing rates per crime and per capita. The socioeconomic and demographic characteristics for the surrounding areas were the weighted average of the component block groups. Public housing and surrounding areas were identified by a dichotomous variable coded 1 for a NYCHA site and 0 for a surrounding area.

Figure 1: Illustration of NYCHA site and surrounding neighborhood.



B. Data

1. Enforcement and Crime

We used two measures of enforcement: stops and arrests. In addition to total stops and total arrests, each of the measures was further divided into three subtypes: trespass, weapons, and drugs. We also combined stops and arrests to create *overall* enforcement measures. In sum, this produced 12 dependent variables. An index of all the variables used in this study, along with definitions and table references, is provided in the Appendix.

Counts and locations of stops and arrests were obtained from databases maintained by the NYPD. For stops, the NYPD records information on a form known as the UF-250 each time a citizen is stopped by the police, according to procedures set forth in the *NYPD Patrol*

Guide (2009). Geocoded records of stops from 2004–2011 are publicly available from the NYPD.[1] The stop records include information regarding the suspect's demographic and physical characteristics, the location and time of day of the stop, and a free-response section where officers indicate the suspected offense that generated the stop. Although officers may use any number of phrases to describe stops based on suspicion of trespass, we use a few key and recurring terms to identify these "trespass" stops.[2] We use similar procedures to identify stops for suspicion of carrying a concealed weapon (e.g., "CPW" for criminal possession of a weapon), and other suspected crimes, including drug offenses, violent crimes, and "quality-of-life" offenses. Using boundary maps provided by the New York City Department of City Planning, we located each stop either at a public housing site, in its immediately surrounding area, or elsewhere in the police precinct or borough.

Arrests were recorded in a similar fashion. Records of each arrest were obtained by one of the authors from the NYPD pursuant to litigation in *Floyd v. City of New York*.[3] These records identify the suspect's race and alleged offense, as well as the location of the arrest and the crime. Geocoding procedures identical to those used for stops were used to locate the arrests at a geographic space.

In this study, crime was measured by reported crime complaints. Similar to stops and arrest, crime was disaggregated into four categories: total, violent, weapons, and drugs. Data on reported crimes also were obtained from the NYPD as part of the *Floyd* litigation. Similar geocoding procedures were used to locate crimes in each of the spatial units. Crime complaints were aggregated for each month within each crime category for the NYCHA sites, the surrounding areas, or elsewhere in the surrounding police precinct. In the negative binominal models (see section entitled "Model Specification"), the natural logarithm of the crime variables is entered as an exposure variable (lagged by one month). We refer to these exposure variables as crime rates.

2. Policing

We used two measures of policing, vertical patrols and patrol strength, to estimate the extent to which variation in enforcement outcomes—stops and arrests—were a function of the differentials in police interventions between public housing and the surrounding areas. Each measure served as an estimate of the differential likelihood of encountering the police.

As noted above, vertical patrols involve systematic building checks by the police. The variable "vertical patrols" is a count of the number of these checks. Data on vertical patrols

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[1]Available at <http://www.nyc.gov/html/nypd/html/analysis_and_planning/stop_question_and_frisk_report.shtml>.

[2]Stops are identified as trespass stops from the "crimsusp" (i.e., "crime suspected") field. A 30-character string, crimsusp is entered by the officers at the time of a stop, and can take on virtually any value, including typographical errors. Variations on the spelling of the word trespass, or variations in the designation of the trespass statute under NYPL §§ 140.05, 140.10, 140.15, or 140.17, were recoded as trespass stops or abbreviations with the obvious connotation of trespass.

[3]Floyd v. City of N.Y., U.S. District Court, Southern District of New York, No. 08 Civ. 1034 (SDNY).

by month and location were obtained from the city. The data included the date, time, and location of the vertical patrol. Vertical patrols were then geocoded to x-y coordinates and assigned to census block groups and in turn to the relevant spatial units of analysis. This differential exposure of citizens to police may result in differential enforcement patterns across racial/ethnic groups, especially under conditions where there are differences in the racial makeup and concentrations of neighborhoods.

We also estimated the number of police officers who were on patrol in NYCHA sites and in the surrounding areas. The patrol strength for each spatial unit of analysis (based on block groups, as described above) was computed from the number of officers who made one or more stops each month in each spatial unit (i.e., NYCHA site or surrounding area). These data were computed by aggregating individual stops made by each officer, using the officer's unique identifier in the stop and frisk databases, to obtain a count of the number of officers making stops in that area in that time unit.

3. Social and Economic Conditions

Data on social and economic conditions were recorded separately for public housing sites and the areas adjacent neighborhoods.

The population characteristics of public housing sites were drawn from the NYCHA *Resident Data Handbooks* for 2004–20011. These records are based on annual tenant surveys that NYCHA conducts as part of its residency certification process. One limitation of these data is the incentive of NYCHA residents to underreport occupancy, and also to discount income totals and other economic indicators.

The critical measures for this analysis are population and age and race distributions. Nonreporting of unrelated adults in the household is far more likely than withholding information on unrelated children. Accordingly, population estimates and age distributions may have errors whose parameters are difficult to estimate. We doubt that there is distortion by race, given the very low rates of mixed-race households in the survey data. There is no ex ante reason to assume that nonreported adults or children would be from different racial or ethnic groups than the official residents. From the tenant survey data, we extracted measures of racial composition, percent minors (below 18), household size, per-capita income, and total population.

To reduce multicollinearity, we combined the measures of race, minors, income, and household size using principal components analysis (PCA). A one-factor solution was specified and obtained, with eigenvalues in excess of 2.5. Separate factor scores were constructed for each NYCHA site and surrounding area. The resulting factor scores, referred to as the SES FACTOR, were included as a covariate in the estimates, together with population (logged) and crime conditions (lagged and logged).[4]

[4]We considered, even attempted, to construct propensity scores for these conditions to simulate experimental conditions for the comparison (Rubin 1997; Bang & Robins 2005; Freedman & Berk 2008; Indurkhya et al. 2010). But we observed the same problem of multicollinearity, and as a result there was no variation in the computed propensity score.

C. Model Specification

The analysis proceeds in two stages. First, we test for evidence of disparate treatment of public housing residents using a model that takes the form:

$$\text{Outcome} = \alpha + \beta 0^* + \beta 1^*\text{NYCHA} + \beta 2^*\text{Minority} + \beta 3^*\text{Policing} + \\ \Sigma i \beta i^*(\text{Plausible Nonrace Influences}) + \varepsilon,$$

where *Outcome* is the stop or arrest rates, *Minority* is an indicator for the racial composition or status of the unit observed (i.e., precinct or person, depending on the outcome), *Policing* are the two measures of police activity in each place, *Plausible Nonrace Influences* are a set of variables representing nonrace factors that also might influence the outcome, and ε is an error term that captures the variation in the outcome that cannot be explained by either minority status or the nonrace influences. These models may include nonrace influences that are correlated with race, so as to better identify the unique effects of race that are present once the influence of proxies for race are removed (Campbell 1984; Greiner 2008).

We begin with a basic regression model for counts of events:

$$\ln(\lambda) = \sum_{k=0}^{K} \beta_k x_k. \tag{1}$$

In this equation, the natural logarithm of the expected number of events, $\ln(\lambda)$, is related to a vector of explanatory variables, x_k, and their associated regression coefficients, β_k (β_0 is a constant multiplied by 1 for each case). With count data, the probability of the observed outcome, y, is often assumed to follow a Poisson distribution:

$$\Pr(Y = y \mid \lambda) = \frac{e^{-\lambda}\lambda^{y}}{y!}. \tag{2}$$

However, the Poisson distribution requires that the residual variance be equal to the fitted values, λ. This is unlikely to be true with events such stops or arrests, which cannot be assumed to meet the Poisson assumption of independence among individual events. Instead, the dependence of events will typically produce overdispersion, where residual variances are greater than λ. A common method of addressing potential overdispersion is to specify that the probability of the observed outcome, y, follows a negative binomial distribution:

$$\Pr(Y = y \mid \lambda, \alpha) = \frac{\Gamma(y+\alpha^{-1})}{y!\Gamma(\alpha^{-1})}\left[\frac{\alpha^{-1}}{\alpha^{-1}+\lambda}\right]^{\alpha^{-1}}\left[\frac{\lambda}{\alpha^{-1}+\lambda}\right]^{y}, \tag{3}$$

where Γ is the gamma function, λ is the mean or expected value of the distribution, and α is the overdispersion parameter.

We address the variability in the size of public housing developments by analyzing rates instead of counts. We do this through the use of an exposure variable. We modify Equation (1) by adding a denominator, n:

$$\ln\left(\frac{\lambda}{n}\right) = \sum_{k=1}^{K} \beta_k x_k. \tag{4}$$

Osgood (2000) notes that algebraic manipulation produces the following regression equation:

$$\ln(\lambda) = \ln(n) + \sum_{k=0}^{K} \beta_k x_k. \tag{5}$$

The *exposure* variable, $\ln(n)$, is assigned a fixed coefficient of 1, and the negative binomial regression is transformed into an analysis of rates (Osgood 2000). In many cases, the natural logarithm of the population is used as the exposure variable. However, general population is not an adequate denominator for this study (Brantingham & Brantingham 1998). The "risk" of being stopped or arrested in public housing (or its surrounding neighborhoods) is not confined only to residents; rather, people visiting or merely passing through these areas also are subject to police intervention. Instead of using population, we use crime rates (logged crime complaints) as our measure of exposure, since it is crime that informs the allocation of policing resources in various areas of the city (Fagan et al. 2010; Geller & Fagan 2010). Tables 2–5 each control for a different crime rate: weapons, drugs, violent, and total.

We use bootstrapped standard errors, which offer several advantages over either robust, clustered, or other forms of standard error computation under these conditions when distributions vary across observation units (Guan 2003; Efron & Tibshirani 1986; Nevitt & Hancock 2001). The traditional approach to statistical inference requires strong assumptions about the distributions of both of the predictors and the outcome variables, especially assumptions about the normality of the distributions. The bootstrap method calculates a distribution-free sampling distribution from just one sample through iterative resampling of the original sample. Accordingly, bootstrapping has several advantages over standard inferential techniques, especially its nonparametric assumptions and the capacity to rule out the undue influence or leverage of anomalous cases within a sample. The larger the number of bootstraps, the more accurate is the estimate of the standard error. In this design, 10 iterations are used to estimate the standard errors.

Finally, we include fixed effects for each month in the time series. Part of the policing regime in New York is the constant updating of crime information so that enforcement strength and tactics can be adjusted in "real time" to meet sudden changes and new patterns (Bratton & Knobler 1998; Maple & Mitchell 2000).

To estimate the racial component of trespass enforcement, we decompose the observed differences between public housing and the surrounding areas by estimating a series of difference-in-difference models, or DD, models (Abadie 2005; Athey & Imbens 2006; Cohen & Ludwig 2003; Card & Krueger, 1994). DD models are commonly used to organize data to mimic experimental designs under conditions when randomization is unavailable. Here, we estimate a linear mixed model regression to determine whether the differences in any of the trespass measures are predicted by differences between public housing sites and their surrounding areas in the crime or socioeconomic conditions. First, we assume:

$$Y_{it} = \beta_0 + \beta_1 S_{it} + \beta_2 \text{Policing} + \beta_3 \text{Race}_{it} + \beta_4 X_{it} + \varepsilon,$$

where:

Y_{it} = the difference in trespass arrests (or stops or totals) in site *i* and month *t* between public housing sites and the surrounding neighborhoods;
β_1 estimates the effects of the difference in crime conditions (drug crimes and weapon crimes) between public housing and the surrounding area lagged by one month;
β_2 estimates the effects of differences in policing measures (vertical patrols and patrol strength);
β_3 estimates the difference in racial composition of the two areas, including black, Hispanic, and other population groups; and
β_4 estimates the difference in a vector of demographic variables between public housing and the surrounding area (percent minors, household size, income per capita, and total population).

The estimates of differences by race use linear regressions on first differences using random effects models with robust standard errors and fixed effects for months.

IV. Results

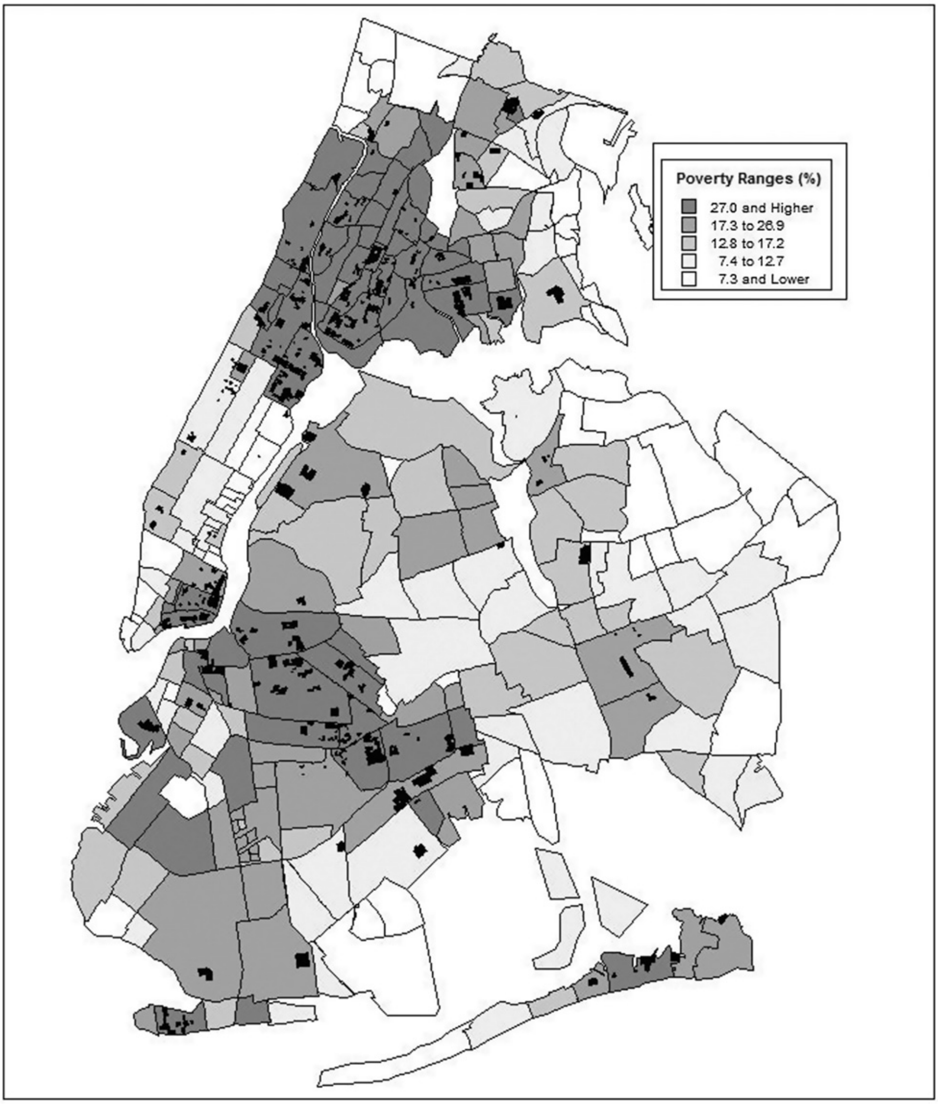
A. Public Housing in New York City

NYCHA is the nation's largest public housing authority, with an official population of over 600,000 residents in 179,000 units in 344 public housing developments (NYCHA 2011). Most public housing developments are large: one in three has more than 1,000 units, and less than one in 10 has fewer than 100 units. Most (65 percent) of the NYCHA developments were built before 1970, though most of the smaller ones were built after 1970 (Marcusse 1995).

Public housing is not randomly distributed across the five boroughs of New York City, nor is it randomly sited in the city's neighborhoods (Fagan & Davies 1999). Figure 2 shows that over 85 percent of all public housing is in three boroughs: Brooklyn, Manhattan, and the Bronx (Saegert et al. 1998), and most often in the city's poorest neighborhoods. This distribution reflects, in part, decades-old decisions on where to locate public housing, as well as the success of locally organized opposition in the wealthier neighborhoods.

For example, only a few public housing developments were constructed in Queens, a largely middle-class residential area. And there, the largest cluster of public housing is on the Rockaway peninsula, on the ocean side of Kennedy Airport, an area that is geographically much closer to eastern Brooklyn than to the center of Queens. Staten Island, with its network of predominantly working-class white residential neighborhoods, has only 10 public housing developments. These are concentrated in the borough's densely populated

Figure 2: Public housing sites by 2007 poverty rate in surrounding neighborhoods.



North Shore, near the ferry terminal that connects the island to Manhattan, and at some distance from the single-home residences in the hilly wooded neighborhoods on the island's interior.

In Manhattan, most developments are located above 110th Street or below midtown on the Lower East Side, well removed from the borough's wealthiest neighborhoods and commercial centers. Brooklyn has the most public housing in the city, with the largest

Table 1: Descriptive Statistics

	Public Housing		*Surrounding Areas*		*Rest of City*	
	Mean	SD	*Mean*	SD	*Mean*	SD
*Stop Rates**						
Total	150.0	178.1	131.2	160.9	82.7	445.4
Trespass	47.9	67.8	19.7	29.3	3.0	14.0
Violence	18.2	33.2	23.1	31.6	13.9	58.3
Weapons	44.4	57.1	43.8	67.3	14.0	110.8
Drugs	18.7	23.4	15.6	16.8	6.4	34.4
*Arrest Rates**						
Total	78.5	97.6	86.3	85.8	76.1	473.1
Trespass	12.2	21.4	5.8	5.8	2.1	13.3
Violence	10.1	13.7	13.2	16.9	10.9	55.5
Weapons	3.7	5.4	3.5	3.0	2.4	12.9
Drugs	29.8	43.0	27.9	27.2	14.0	58.3
*Enforcement Rates**						
Total	228.5	256.0	217.5	236.5	158.7	881.6
Trespass	60.1	80.5	25.4	32.8	5.1	23.8
Violence	28.2	39.4	36.3	40.6	24.8	101.0
Weapons	48.1	60.8	47.4	69.8	16.4	119.4
Drugs	48.6	61.1	43.5	41.9	20.4	87.0
*Crime Rates**						
Total	94.0	93.7	102.8	64.2	115.0	807.4
Trespass	4.3	10.5	2.0	2.6	0.7	3.3
Violence	20.7	19.9	22.6	15.4	17.7	80.6
Weapons	3.3	4.5	3.0	2.5	2.0	11.3
Drugs	14.3	22.3	10.9	10.3	5.0	28.8
Demographics						
White (%)	5.8	10.3	19.8	24.1	40.5	34.0
Black (%)	46.9	19.8	34.5	26.0	20.7	30.5
Hispanic (%)	42.4	17.4	36.3	22.6	24.1	24.9
Other (%)	5.0	8.4	9.7	14.0	14.7	17.5
Minors (%)	27.3	11.7	25.2	8.5	21.8	10.0
Household size	2.2	0.6	3.0	0.7	2.9	1.2
Per-capita income	20,654	4,098	20,776	17,948	31,884	27,327
Population	1,499	1,446	7,940	4,562	1,422	1,066

*Per 1,000 population.
SOURCE: 2007 ESRI and American Community Survey, Block Group Projection, 2007–2009.

concentrations in the heavily minority neighborhoods of Brownsville, Bushwick, and East New York. Particularly for the larger developments in the "outer boroughs," such as Queensbridge, Morrisania, or Brownsville, public housing tends to ecologically dominate the surrounding areas, suggesting that some areas are "public housing neighborhoods." These also are the neighborhoods with the most intensive police surveillance and highest rates of *Terry* stops per felony crime and per-capita population.

Table 1 shows the concentrated disadvantage of both public housing developments and their surrounding neighborhoods compared to the rest of the city. Public housing and the surrounding areas have comparable but lower per-capita incomes compared to the rest of the city. NYCHA's eligibility criteria for public housing narrow the range of incomes in public housing, but there is a large range in incomes in the surrounding areas. There are higher concentrations of nonwhites and higher concentrations of children and adolescents in public housing.

Despite their structural similarities, crime rates in public housing are slightly lower than in the surrounding neighborhoods, perhaps owing to the siting of public housing in the city's poorest places. However, drug crime rates, one of the rationales for intensive enforcement in public housing, are in fact higher there than in the surrounding areas. However, enforcement in public housing is consistently higher than in the surrounding areas or elsewhere in the city. Assuming that enforcement is distributed proportionately (though not necessarily monotonically) with crime, the enforcement differentials are far greater than would be predicted by the narrow crime rate differences with the surrounding areas. The large standard deviations in the crime rates in public housing suggest that there is quite a bit of variation in these rates across developments, far more variation than in the surrounding areas.

B. Trespass Enforcement in Public Housing

1. Relative Incidence of Trespass Enforcement

Figure 3 shows trends over time in the ratio of trespass stops to total crime complaints in public housing and the surrounding areas. At first glance, using crime as a benchmark, the lines show that relative to local crime conditions, the rate of *Terry* stops per crime is far greater in public housing than in similarly situated surrounding areas. One might expect that the policy mandate to link enforcement to crime (Maple & Mitchell 2000; Bratton & Knobler 1998) would lead to similar ratios but here the lines diverge, suggesting that there is additional attention to crime in public housing. It is this marginal enforcement that animates the analyses to identify the specific role of public housing relative to other social and crime conditions.

Tables 2–5 present results for three different types of trespass enforcement (stops, arrests, and overall enforcement) for four different crime exposures (weapons crimes, drug crimes, violent crimes, and total crimes). In each model, the extent of trespass enforcement—for all three measures—is significantly greater in public housing than in the surrounding areas, controlling for policing (vertical patrols and patrol strength), crime (lagged), and local social and economic conditions (SES factor and population). Moreover, the size of the coefficients for public housing is fairly large.

Other trends are noteworthy in these models. The SES factor is a significant predictor of enforcement in only five of the 12 models, and then only for total and drug crime exposures. This suggests that factors other than the social composition of these sites are driving enforcement rates, including perhaps race. The measures of policing strategy influence these outcomes. Patrol strength and vertical patrols both are significant predictors of each measure of enforcement and across crime types. Since both measures are

Figure 3: Ratio of trespass stops to total crime in public housing and surrounding areas, 2004–2011.

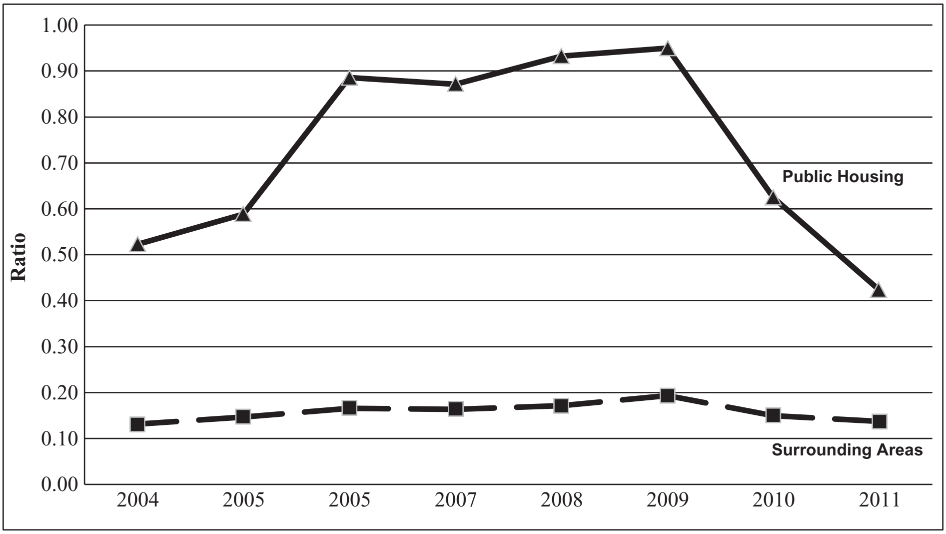


Table 2: Negative Binomial Regressions of Trespass Enforcement by Public Housing, Policing, Socioeconomic Conditions, and Weapons Offenses, NYCHA Sites and Surrounding Areas, 2004–2011

	Trespass Enforcement								
	Stops			*Arrests*			*Overall Enforcement*		
Weapons Offenses	*b*	SE	p	*b*	SE	p	*b*	SE	p
Public housing	0.890	0.038	***	0.776	0.026	***	0.818	0.030	***
SES factor	0.009	0.041		0.042	0.040		0.020	0.040	
Population (logged)	0.067	0.015	***	0.147	0.015	***	0.087	0.013	***
Vertical patrols	0.001	<0.001	***	0.001	<0.001	**	0.001	<0.001	***
Patrol strength	0.001	<0.001	*	–0.002	<0.001	***	<0.001	<0.001	
Constant	–0.829	0.121	***	–1.312	0.170	***	–0.804	0.104	***
Log-likelihood	–148,459.10			–98,883.33			–163,978.84		
AIC	296,936.19			197,784.66			327,975.69		

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

sensitive to the built environment—that is, vertical patrols are more likely to be conducted in multistory residential buildings—the concentration of trespass enforcement in public housing is evident after controlling for other factors that might explain police activity in those areas compared to its immediate environs. But the effect sizes here are small,

Table 3: Negative Binomial Regressions of Trespass Enforcement by Public Housing, Policing, Socioeconomic Conditions, and Drug Offenses, NYCHA Sites and Surrounding Areas, 2004–2011

	Trespass Enforcement								
	Stops			*Arrests*			*Overall Enforcement*		
Drug Offenses	*b*	SE	p	*b*	SE	p	*b*	SE	p
Public housing	0.836	0.049	***	0.683	0.046	***	0.768	0.043	***
SES factor	–0.071	0.028	***	–0.023	0.029		–0.055	0.027	**
Population (logged)	–0.023	0.026	***	0.073	0.029	**	–0.001	0.025	
Vertical patrols	0.001	<0.001	***	0.001	<0.001	***	0.001	<0.001	***
Patrol strength	0.002	<0.001	***	<0.001	<0.001		0.002	0.001	***
Constant	–1.177	0.190	***	–1.651	0.267	***	–1.092	0.179	***
Log-likelihood	–139,342.44			–89,624.92			–152,894.80		
AIC	278,702.88			179,267.83			305,807.59		

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 4: Negative Binomial Regressions of Trespass Enforcement by Public Housing, Policing, Socioeconomic Conditions, and Violent Offenses, NYCHA Sites and Surrounding Areas, 2004–2011

	Trespass Enforcement								
	Stops			*Arrests*			*Overall Enforcement*		
Violent Offenses	*b*	SE	p	*b*	SE	p	*b*	SE	p
Public housing	1.159	0.050	***	0.948	0.071	***	1.115	0.052	***
SES factor	0.020	0.031		0.051	0.038		0.029	0.032	
Population (logged)	–0.100	0.020	***	–0.029	0.033		–0.069	0.018	***
Vertical patrols	0.001	<0.001	***	0.001	<0.001	***	0.001	<0.001	***
Patrol strength	0.004	<0.001	***	0.001	<0.001	***	0.003	<0.001	***
Constant	–1.456	0.194	***	–1.824	0.310	***	–1.470	0.172	***
Log-likelihood	–129,053.36			–84,861.04			–142,075.33		
AIC	258,124.73			169,740.09			284,168.67		

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

suggesting that the differences in enforcement rates are in turn small but statistically significant.[5]

[5]These two measures of enforcement are, as might be expected, correlated at 0.569. This is a moderate effect, but not large enough to raise concerns over multicollinearity in the models. Just to check, the models were run using only PATROL STRENGTH first, and then only with VERTICAL PATROLS. The results for the PUBLIC HOUSING variable were substantively unchanged.

Table 5: Negative Binomial Regressions of Trespass Enforcement by Public Housing, Policing, Socioeconomic Conditions, and Total Offenses, NYCHA Sites and Surrounding Areas, 2004–2011

	Trespass Enforcement								
	Stops			Arrests			Overall Enforcement		
Total Offenses	*b*	SE	p	*b*	SE	p	*b*	SE	p
Public housing	1.328	0.059	***	1.086	0.068	***	1.295	0.058	***
SES factor	0.093	0.034	***	0.128	0.039	***	0.106	0.034	***
Population (logged)	−0.092	0.021	***	−0.017	0.035		−0.056	0.018	***
Vertical patrols	0.001	<0.001	***	0.001	<0.001	***	0.001	<0.001	***
Patrol strength	0.004	<0.001	***	0.002	<0.001	***	0.004	<0.001	***
Constant	−2.904	0.205	***	−3.277	0.310	***	−2.906	.0173	***
Log-likelihood	−121,637.10			−79,272.89			−132,995.27		
AIC	243,292.20			158,563.77			266,008.54		

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Table 6: Incidence Rate Ratios for Trespass Enforcement in Public Housing Versus Surrounding Area, Controlling for Policing, Crime, and Socioeconomic Conditions, 2004–2011

	Trespass Enforcement		
Crime Rate	*Stops*	*Arrests*	*Overall*
Weapons offenses	2.434	2.172	2.266
Drug offenses	2.307	1.981	2.155
Violent crimes	3.186	2.581	3.049
Total crime	3.772	2.963	3.650

*All coefficients are significant at $p < 0.001$.

Table 6 shows the extent of those disparities by converting the parameter estimates for public housing presented in Tables 2–5 to incidence rate ratios, or IRRs.[6] In a negative binomial regression, the IRR is a measure of the rate of change in a dependent variable for every unit increase in a predictor (Hilbe 2007; Hoffman et al. 2008). In these models, the IRR is the increase in enforcement per crime (the exposure variable) for each measure of trespass enforcement for the public housing sites compared to the surrounding area.

For each test, the rate of stops and arrests per crime in public housing compared to the surrounding areas is at least twice as high compared to the count of stops in the

[6]For example, in Table 2 the coefficient for PUBLIC HOUSING under the "Stops" model is 0.890. In Table 6, the value of 0.890 converted to an IRR is 2.434.

Table 7: Incidence Rate Ratios for Total Enforcement in Public Housing Versus Surrounding Area, Controlling for Policing, Crime, and Socioeconomic Conditions, 2004–2011

	Total Enforcement					
Crime Rate	*Stops*		*Arrests*		*Overall*	
Weapons offenses	1.348	***	0.908	***	1.141	***
Drug offenses	2.307	***	0.683	***	0.932	ns
Violent crimes	1.516	***	0.873	***	1.251	***
Total crime	1.761	***	0.963	ns	1.448	***

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

surrounding areas, even after controlling for the predictors in the regression equations. The IRRs vary from 2.000 to 3.716. These are large effects, especially considering the extent to which the estimates are adjusted for plausible simultaneous (policing) and lagged (crime) effects. This evidence points to targeting of public housing for trespass enforcement, consistent with a disparate treatment framework.

2. Extension to Total Enforcement

The analyses in Tables 2–5 were repeated with total enforcement as the outcome or dependent variables: that is, instead of trespass stops, trespass arrests, and overall trespass enforcement, we used total stops, total arrests, and overall total enforcement (the sum of total stops and total arrests). Since trespass enforcement in public housing is only one of several types of enforcement in those locales, these analyses examine whether the disparities between public housing and its surrounding areas are present for a broader range of police enforcement activities. Table 7 shows the IRR estimates for the public housing variable.[7]

The effects for public housing that were observed for trespass enforcement are still present, but slightly less consistently. Public housing status is significant and positive in seven of the 12 models, it is not significant in two of the 12 models, and it is negative and significant in three others. For total stops, the public housing effect is positive and significant for all four models. This suggests that there are significantly more stops in public housing, across four different crime exposure measures, after controlling for each of the crime-specific measures and three measures of police deployment. For models of overall enforcement (i.e., stops plus arrests), public housing is significant in three of the four models. The only nonsignificant effect of public housing on total enforcement is in the model with drug offenses as the exposure measure.

Overall, for both stops and overall total enforcement, there is strong and consistent evidence of greater levels of general enforcement in public housing. The differences

[7]Full model results are available from the authors.

between public housing and surrounding areas are not as large for total enforcement compared to trespass enforcement, but still large and—for stops and overall total enforcement—positive and significant. These results reflect the special emphasis on trespass enforcement in public housing. But trespass stops in public housing are still only a share—less than half—of the total amount of stops in public housing. The models in this section suggest that for stops and for overall total enforcement, these disparities are present in the totality of enforcement activities by NYPD officers. The robustness of these results to different crime exposure conditions and policing effects suggests the importance of public housing as a "hot spot" of trespass and other enforcement, net of any differences in local crime rates or other social factors.

Arrests, however, suggest fewer differences and, in some cases, a reverse effect. The public housing effect is negative and significant in three of the four models, and not significant in the fourth model. In other words, relative to the rates of violent, drug, and weapons offenses in public housing, there were significantly more arrests in the surrounding areas. However, there were more stops in public housing relative to these crimes, so the results suggest a pattern of unproductive stops relative to these two categories of crime.

C. Decomposing by Race

Tables 8–11 show results of tests for racial disparities in trespass and other enforcement domains in public housing. The regressions test for racial disparities in four types of

Table 8: Linear Mixed Effects Regressions of Differences in Trespass Enforcement Between Public Housing and Surrounding Area, by Racial Composition, Policing, and Socioeconomic Conditions, 2004–2011[a]

	Trespass Enforcement								
	Stops			*Arrests*			*Overall Enforcement*		
Difference	*b*	SE	p	*b*	SE	p	*b*	SE	p
% Black	0.457	0.268	*	1.152	0.266	***	1.027	0.292	***
% Hispanic	0.899	0.270	***	0.755	0.268	***	1.102	0.293	***
% Other race	1.785	0.446	***	1.026	0.442	**	2.076	0.486	***
Drug crimes[b]	0.035	0.006	***	0.080	0.006	***	0.058	0.006	***
Weapons crimes[b]	0.006	0.007		0.009	0.008	***	0.005	0.007	
% Minors	0.001	0.004		0.002	0.004		0.006	0.004	
Household size	–0.012	0.066		–0.044	0.066		–0.069	0.072	
Income per capita (logged)	–0.066	0.057		0.003	0.056		–0.015	0.063	
Total population (logged)	0.235	0.039	***	0.223	0.039	***	0.285	0.043	***
Vertical patrols[c]	0.146	0.006	***	0.086	0.007	***	0.149	0.007	***
Patrol strength[c]	0.404	0.006	***	0.107	0.007	***	0.377	0.007	***
Constant	0.650	0.149	***	0.372	0.149	**	0.568	0.160	***
Log-likelihood	–40,896.34			–41,521.88			–41,185.18		
AIC	82,010.68			83,261.76			82,588.37		

[a]All models estimated with fixed effects for months.
[b]Logged, lagged one month.
[c]Rate per household, logged.
***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 9: Linear Mixed Effects Regressions of Differences in Drug Enforcement Between Public Housing and Surrounding Area, by Racial Composition, Policing, and Socioeconomic Conditions, 2004–2011[a]

	Drug Enforcement								
	Stops			*Arrests*			*Overall Enforcement*		
Difference	*b*	SE	p	*b*	SE	p	*b*	SE	p
% Black	0.811	0.214	***	1.617	0.326	***	1.618	0.296	***
% Hispanic	1.126	0.217	***	0.406	0.327		0.784	0.297	***
% Other race	0.823	0.353	**	0.697	0.543		0.883	0.492	*
Drug crimes[b]	0.048	0.006	***	0.085	0.007	***	0.078	0.007	***
Weapons crimes[b]	0.009	0.008		0.041	0.008	***	0.031	0.008	***
% Minors	−0.009	0.003	***	0.005	0.005		<0.001	0.004	
Household size	0.020	0.053		0.051	0.081		0.063	0.073	
Income per capita (logged)	0.022	0.044		0.039	0.071		0.091	0.064	
Total population (logged)	0.130	0.031	***	0.084	0.048	*	0.116	0.043	***
Vertical patrols[c]	0.058	0.007	***	0.026	0.007	***	0.042	0.007	***
Patrol strength[c]	0.381	0.007	***	0.120	0.007	***	0.300	0.007	***
Constant	−0.100	0.129		−0.665	0.177	***	−0.459	0.163	***
Log-likelihood	−42,145.02			−43,216.46			−42,598.81		
AIC	84,508.04			86,650.93			85,415.62		

[a]All models estimated with fixed effects for months.
[b]Logged, lagged one month.
[c]Rate per household, logged.
$***p < 0.01$; $**p < 0.05$; $*p < 0.1$

enforcement: trespass, drugs, weapons, and total enforcement rates. Within each table, results are shown for separate regressions for stops, arrests, and total enforcement. The models control for three sets of factors that may also influence the disparities in stops: dosages of policing (vertical patrols and patrol strength), two dimensions of crime (drug offenses and weapons offenses lagged by one month), and the social and economic conditions in each place. The drugs and weapons offense categories were chosen because of their salience both in contemporary and historic enforcement rationales for the special and intensive treatment of public housing (Fagan et al. 2006). Again, these are differences, and the interpretation—as with the racial and ethnic variables—is that a positive difference in the predictor predicts a positive difference in stops.

Table 8 shows the results of three models on trespass enforcement: stops, arrests, and overall (stops plus arrests) enforcement. The first vertical panel shows the results for trespass stops. For both percent black and percent Hispanic, the difference in population between public housing sites and the surrounding areas is a significant predictor of the difference in trespass stops between those two places. The relationship is positive, as indicated by the finding in Table 2, in that there are more trespass stops in public housing.

The pattern of results in the trespass stop model in Table 8 is repeated in the second and third vertical panels that show regression results for trespass arrests and for overall

Table 10: Linear Mixed Effects Regressions of Differences in Weapons Enforcement Between Public Housing and Surrounding Area, by Racial Composition, Policing, and Socioeconomic Conditions, 2004–2011[a]

	Weapons Enforcement								
	Stops			*Arrests*			*Overall Enforcement*		
Difference	*b*	SE	p	*b*	SE	p	*b*	SE	p
% Black	1.076	0.193	***	0.980	0.153	***	1.109	0.195	***
% Hispanic	0.999	0.196	***	0.829	0.156		0.976	0.198	***
% Other race	0.899	0.320	***	0.732	0.252		0.970	0.323	*
Drug crimes[b]	0.026	0.006	***	0.044	0.006	***	0.035	0.006	***
Weapons crimes[b]	0.016	0.007	**	0.039	0.007	***	0.020	0.007	***
% Minors	–0.001	0.003	***	0.004	0.002		0.001	0.003	
Household size	–0.035	0.048		–0.085	0.038		–0.056	0.048	
Income per capita (logged)	–0.044	0.040		–0.014	0.031		–0.034	0.040	
Total population (logged)	0.101	0.028	***	0.016	0.022	*	0.103	0.028	***
Vertical patrols[c]	0.032	0.006	***	0.017	0.005	***	0.033	0.006	***
Patrol strength[c]	0.580	0.006	***	0.065	0.006	***	0.560	0.006	***
Constant	–0.473	0.116	***	–0.513	0.100	***	–0.521	0.117	***
Log-likelihood	–38,921.74			–38,447.03			–38,230.67		
AIC	78,061.49			77,112.07			78,679.34		

[a]All models estimated with fixed effects for months.
[b]Logged, lagged one month.
[c]Rate per household, logged.
$***p < 0.01$; $**p < 0.05$; $*p < 0.1$

trespass enforcement. Differences in racial composition for both percent black and percent Hispanic predict differences in trespass arrests, controlling for crime, policing, and socioeconomic conditions. The greater amounts of policing—vertical patrols and patrol strength—in public housing also predict differences in trespass enforcement. But note also that the racial differences are observed as additional significant influences even after controlling for the relevance of crime and policing.

Tables 9–11 repeat these analyses for three other dimensions of enforcement: drug enforcement, weapons enforcement, and total enforcement. The findings for the influence of racial composition on public housing are robust. The difference in percent black is a significant predictor of the difference in all three measures of enforcement in eight of the nine models in these three tables. The difference in percent Hispanic is a significant predictor in four of the nine models in these three tables. Overall, the difference in percent Hispanic population is statistically significant in seven of the 12 models, including all three trespass models and two of the three models for the important category of drug enforcement.

The consistency of the results across two different types of tests for disparate treatment suggests that, in fact, race and ethnicity play an important role in the conduct of enforcement in public housing, a role that is present after controlling for other policy-relevant factors and social conditions, as well as for the allocation of police resources and

Table 11: Linear Mixed Effects Regressions of Differences in Total Enforcement Between Public Housing and Surrounding Area, by Racial Composition, Policing, and Socioeconomic Conditions, 2004–2011[a]

	Total Enforcement								
	Stops			*Arrests*			*Overall Enforcement*		
Difference	*b*	SE	*p*	*b*	SE	p	*b*	SE	p
% Black	0.044	0.052		1.415	0.383	***	1.036	0.267	***
% Hispanic	0.056	0.053		−0.046	0.381		−0.197	0.266	
% Other race	0.188	0.087	**	0.239	0.630		0.901	0.440	**
Drug crimes[b]	0.005	0.001	***	0.059	0.006	***	0.028	0.004	***
Weapons crimes[b]	−0.001	0.002		0.035	0.007	***	0.012	0.005	**
% Minors	−0.001	0.001		0.002	0.005		0.005	0.003	
Household size	0.022	0.013		0.085	0.096		0.048	0.067	
Income per capita (logged)	−0.012	0.011		0.108	0.089		0.050	0.062	
Total population (logged)	0.066	0.008	***	0.047	0.057		0.005	0.040	
Vertical patrols[c]	0.011	0.001	***	0.042	0.007	***	0.026	0.005	***
Patrol strength[c]	1.054	0.001	***	0.142	0.006	***	0.631	0.005	***
Constant	0.071	0.030	**	−0.755	0.200	***	−0.337	0.140	**
Log-likelihood	−3,117.05			−40,325.80			−31,892.37		
AIC	6,452.10			80,869.59			64,002.74		

[a]All models estimated with fixed effects for months.
[b]Logged, lagged one month.
[c]Rate per household, logged.
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

the intensity of policing tactics. This comports with other analyses of the effects of the OMP regime, and its heavy emphasis on stops and frisks. Blacks are stopped at far higher rates than are Hispanics (Gelman et al. 2007; Fagan et al. 2010). They also are more likely to be frisked once stopped, and arrested as well (Ridgeway 2007).

Still, these results have their limitations, and the limitations reflect the difficulty of research in policing when comparing areas to detect possibly disparate treatment. Research on public housing in particular faces considerable challenges in identifying a set of unconfounded and unbiased factors that can explain differences in how these places are regarded by police relative to similarly situated places nearby. Beyond the difficulty of establishing or approximating experimental conditions, crime and enforcement raise endogeneity concerns, and lagging crime or using first differences approaches are only partial solutions to these problems (Manski & Nagin 1998). One can control for many concurrent and plausible explanations that may explain disparate treatment, and limit the uncertainty of unobservables and estimators whose distributions are not fully known. That is the strategy in this article. The challenge empirically is to move beyond a descriptive analysis to a quasi-experimental design that exploits the proximity-neighbor function of the adjacent block groups.

One way to do that is to uncover counterfactuals that might arbitrate between competing explanations. Those are not readily available in this context. Given the persistently higher rates of violence and drug crimes in public housing, it is hard to conclude—as one might in research on vehicle stops—that an equilibrium has been reached between policing and crime, and that things might be even worse for public housing residents should the police back off in trespass enforcement. Still, beyond the test for discrimination in stops as an outcome, other tests such as drug or gun seizures might well serve as a counterfactual to supplement the outcomes analysis and suggest other benchmarks for this analysis. But the OMP regime in New York is remarkably inefficient in producing either gun or drug seizures, or even limiting shootings. Seizure rates for drugs are below 2 percent of all stops, and gun seizures at less than 1 percent of all stops (Fagan et al. 2010). Even small effects would be difficult to detect and interpret given these low base rates. Our results thus describe a pattern of bias in trespass and other enforcement, and take measured steps toward eliminating the competing explanations.

V. Conclusion

Notwithstanding any advantages or disadvantages in public safety that may accrue from this process over time, trespass enforcement seems to be structured into the fabric of public housing, especially those places where black residents are the majority population group, placing both its residents and visitors under a firm police gaze.

Distributive concerns predict that public housing residents would enjoy the benefits of vertical patrol, and they would welcome the increased attention. In a contest between de-policing and policing, policing usually wins. Even the much more intrusive searches associated with Operation Clean Sweep in Chicago—during which systematic suspicionless searches of residents' apartment buildings were conducted—garnered a surprising amount of community support (Yarosh 1992). Accordingly, we expect at least some support from the community (Johnson 1989). Yet numbers matter too, and for residents, especially those uninvolved in the drug trade, the frequency of vertical patrol is daunting. Given that there are more than 25,000 vertical patrols per month in public housing in New York, it is quite possible for a resident to be stopped and questioned multiple times in the same week. In fact, Carlis (2009) cites recent survey data showing that 24 percent of public housing residents surveyed reported being stopped more than 20 times in the past year, and only about one in four (28 percent) reported no stops in the previous year. According to the same survey, in the Thomas Jefferson Homes, 14.7 percent had been arrested for trespass.

Public housing residents' frustration is compounded by the fact that the patrols only indirectly target the most serious crimes. The vast majority of arrests are for trespass, and the connection to more serious crime is not apparent to residents (Carlis 2009). As a result of the frequency of stops, their tangential relationship to serious criminal conduct, and occasional mistreatment by NYPD officers, public housing residents are ambivalent about the appropriateness and desirability of vertical patrols. In weighing the tradeoff between liberty and security for public housing residents, the way vertical patrols are conducted troubles residents.

Vertical patrols regard residents and visitors alike as criminal suspects merely for being present within their own apartment buildings. Their status of simply being in the contested space of public housing exposes them and their friends and kin to legally questionable stops and arrests. The racialization of this process compounds other racial tensions that create legitimacy deficits that in turn complicate the project of police-citizen cooperation in the pursuit of security. Policing in public housing has the potential to be a transformative force, ensuring building residents feel safe and secure in their homes and broadening the ties between citizens and police. It also has the potential to redistribute the benefits and burdens of patrol by seeking balance in how vertical patrol is conducted. However, this process will have to reverse decades of cognitive bias about public housing and its residents and policy entropy that seems to move only in one direction.

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Appendix: Descriptions of Variables

Variable	*Definition*	*Type*	*Table Reference*
Public housing	Indicator for public housing & surrounding areas	Dichotomous (public housing = 1)	All results tables
Stops			
Total	Total stops for all offenses	Count	Tables 7 & 11
Weapons	Stops for weapons offenses	Count	Table 10
Trespass	Stops for trespass offenses	Count	Tables 2–6, 8
Drugs	Stops for drug offenses	Count	Table 9
Arrests			
Total	Total arrests for all offenses	Count	Tables 7 & 11
Weapons	Arrests for weapons offenses	Count	Table 10
Trespass	Arrests for trespass offenses	Count	Tables 2–6, 8
Drugs	Arrests for drug offenses	Count	Table 9
Overall enforcement			
Total	Total stops + Total arrests	Summed count	Tables 7 & 11
Weapons	Weapons stops + Weapons arrests	Summed count	Table 10
Trespass	Trespass stops + Trespass arrests	Summed count	Tables 2–6, 8
Drugs	Drug stops + Drug arrests	Summed count	Table 9
Crime rates			
Total	Total crime complaints	Count (logged and lagged)	Tables 5–7
Weapons	Crime complaints for weapons offenses	Count (logged and lagged)	Tables 2, 6–11
Drugs	Crime complaints for drug offenses	Count (logged and lagged)	Tables 3, 6–11
Violent	Crime complaints for violent offenses	Count (logged and lagged)	Tables 4, 6 & 7
Policing			
Vertical patrols	Number of vertical patrols reported by police per unit of analysis, year, month	Count	All results tables
Patrol strength	Number of unique police officers recording an arrest per unit of analysis, year, month	Count	All results tables
Demography			
SES factor	PCA score comprised of: % nonwhite, % minors, average household size, and per-capita income	Continuous	Tables 2–7
Total population	Total population (logged)	Continuous	All results tables
% black	% of population that is black	Continuous	Tables 8–11
% Hispanic	% of population that is Hispanic	Continuous	Tables 8–11
% white	% of population that is white	Continuous	Tables 8–11
% other race/ethnicity	% of population that is other race/ethnicity	Continuous	Tables 8–11
% minors	% of population that is under 18 years old	Continuous	Tables 8–11
Average household size	Average household size	Continuous	Tables 8–11
Per-capita income	Per-capita income (logged)	Continuous	Tables 8–11