UNITED STATES DISTICT COURT
SOUTHERN DISTRICT OF NEW YORK

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DAVID FLOYD *et al.*,

Plaintiffs,

- against -

08 Civ. 01034 (SAS)

Report of Jeffrey Fagan, Ph.D.

CITY OF NEW YORK *et al.*,

Defendants.

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I. OVERVIEW

A. Qualifications

I am a Professor of Law and Public Health at Columbia University, a Senior Research Scholar at Yale Law School, and a Fellow at the Straus Institute for the Advanced Study of Law & Justice at New York University School of Law. I was the Director of the Center for Community and Law at Columbia Law School from 2003 – 2009. I was a Visiting Professor of Law at Yale Law School from July 2009 – June 2010. Prior to my appointment at Columbia University, I was Professor of Criminal Justice at Rutgers -The State University of New Jersey (1989-96), and Associate Professor, John Jay College of Criminal Justice in the City University of New York. I have co-authored three books and published numerous articles on law and social policy in professional peer-reviewed journals, law reviews, and other scholarly publications. I have received honors and awards from academic and professional associations. I have been appointed to scientific committees of the National Academy of Science, the American Society of Criminology, and the National Science Foundation, and also to committees of several prestigious government agencies and private foundations. I am a Fellow of the American Society of Criminology. I have a Ph.D. in Engineering from the University at Buffalo of the State University of New York. My curriculum vitae are presented in Appendix A.

B. Summary of Issues Addressed

In this Report, I provide social science evidence to address three specific claims by Plaintiffs listed in their Second Amended Complaint in October 2008.[1] Plaintiffs allege violations by the City of New York (hereafter The City), through the New York City Police Department (hereafter, NYPD), of several sections of federal and state law: (1) 42 U.S.C. § 1983 of the Civil Rights Act of 1871, (2) the Fourth and Fourteenth Amendments of the U.S. Constitution, (3) 42. U.S.C. § 2000(d) (Title VI) of the Civil Rights Act of 1964, and violations of New York State law.

The Fourth Amendment claim alleges that the City has engaged in pattern of unconstitutional stops of City residents that are done without the requisite reasonable and articulable suspicion required under the Fourth Amendment.[2]

The Fourteenth Amendment claim alleges that the City, through the NYPD, has "often" used race and/or national origin, in lieu of reasonable suspicion, as the factors that determine whether officers decide to stop and frisk persons. Plaintiffs claim that this practice violates the Equal Protection Clause of the Fourteenth Amendment. Plaintiffs also claim that Black and Latino males are the population groups most affected by the alleged violation.[3]

I also provide evidence that addresses the intersection of the Fourth and Fourteenth Amendment claims. Specifically, I provide evidence that the NYPD has engaged in patterns of unconstitutional stops of City residents that are more likely to affect Black and Latino citizens.

C. Additional Evidence Addressed

The City has referenced on several occasions a report issued by the RAND Corporation[4] that presents social science evidence relevant to the issues raised in the Fourteenth Amendment claim in this case. The Report was completed under a contract issued by the New York City Police Foundation, and was released

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[1] Second Amended Complaint, *David Floyd et al. v. City of New York et al.*, U.S. District Court for the Southern District of New York, 08 Civ. 01034 (SAS), October 2008

[2] *Id.*, at § 2.

[3] *Id.*, at § 3.

[4] Greg Ridgeway, Analysis of Racial Disparities in the New York Police Department's Stop, Question and Frisk Practices, RAND TR534 (2007), available at: http://www.rand.org/pubs/technical_reports/2007/RAND_TR534.pdf (last visited August 17, 2010) (hereafter, RAND).

electronically and in print in November 2007. It presents results of analyses of data on the racial distribution of on stops, frisks, searches and other post-stop outcomes from 2006. The issues addressed by the RAND study comport with the legal issues in this case: "whether [stops] point to racial bias in specific police officers' decisions to stop particular pedestrians, and...whether they indicate that officers are particularly intrusive when stopping non-whites."[5]

The City has often referred to the RAND Report as exonerating it from Plaintiffs' claims of racial bias in the NYPD's patterns of stop and frisk activity, and from claims of racial bias in other post-stop outcomes of these stops.[6] The Report focuses on the substance of the Fourteenth Amendment constitutional claims and related policy questions.

Accordingly, I review the RAND report in detail, and provide an assessment of the social science reliability of the Report and its probative value as additional evidence in this case.

D. Summary of Evidence

Plaintiffs allege violations by the City of New York, through the New York City Police Department (NYPD), of several sections of federal and state law. I provide evidence that the NYPD has engaged in patterns of unconstitutional stops of City residents that are more likely to affect Black and Latino citizens. I find that:

Fourteenth Amendment Claim

- NYPD stop activity is concentrated in precincts with high concentrations of Black and Hispanic residents. The results show consistently, across the most policy-relevant and frequent crime categories, that racial composition

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[5] RAND at xi. The RAND Report included replications of analyses published by the Attorney General of the State of New York in his 1999 investigation of the NYPD's stop, question and frisk practices. See, Eliot Spitzer, The New York City Police Department's "Stop & Frisk" Practices: A Report to the People of the State of New York from the Office of the Attorney General (1999)

[6] Letter from Police Commissioner Raymond W. Kelly to Speaker Christine C. Quinn, April 29, 2009 (stating that "RAND researchers analyzed data on all street encounters between New York City Police Department officers and pedestrians that occurred during 2006, and determined that no pattern of racial profiling existed"). See, e.g., Christina Boyle and Tina Moore, *Blacks and Latinos make up about 80% stopped and questioned by NYPD, study finds*, N. Y. Daily News, January 16, 2009 (quoting Deputy Commissioner Paul Browne referring to the RAND study as showing that there is no evidence of racial profiling by the NYPD).

predicts stop patterns after controlling for the influences of crime, social conditions, and the allocation of police resources.

- NYPD stops are significantly more frequent for Black and Hispanics citizens than for White citizens, after adjusting stop rates for the precinct crime rates, the racial composition, and other social and economic factors predictive of police activity. These disparities are consistent across a set of alternate tests and assumptions.
- Blacks and Latinos are more likely to be stopped than Whites even in areas where there are low crime rates and where residential populations are racially heterogeneous or predominantly White.

Fourth Amendment Claim

- Nearly 150,000, or 6.71% of all discretionary stops lack legal justification. An additional 544,252, or 24.37% of all discretionary (non-radio run) stops lack sufficiently detailed documentation to assess their legality.
- Officers rely heavily on two constitutionally problematic stop justifications for nearly half of all stops: *furtive movements* and proximity to a *high crime area*. *High crime area* is cited in more than half the stops as an "additional circumstance" of a stop, regardless of the precinct crime rate.
- Documented stop justifications do little to explain overall variation in stop patterns. This suggests that the reasonable and articulable standards as expressed on the UF-250 form do not provide useful information regarding the individualization of suspicion.
- Stop justifications do not substantially influence the racial disparities that characterize stop practices between police precincts. Knowing the stated bases for reasonable and articulable suspicion does not explain why there are disparities in stop rates.
- Arrests take place in less than six percent of all stops, a "hit rate" that is lower than the rates of arrests and seizures in random checkpoints observed in other court tests of claims similar to the claims in this case.
- Black and Hispanic suspects are treated more harshly once the decision is made that a crime has occurred. Black and Hispanic suspects are more likely to be arrested rather than issued a summons when compared to White suspects. They are more likely to be subject to use of force.
- The rate of gun seizures is .15 percent, or nearly zero.

Additional Evidence - RAND Report

The City refers to a 2007 report published by the RAND Corporation to claim that stop and frisk practices were not racially biased during 2006. However, I find the analyses in the report are unreliable and methodologically flawed to the extent that it is not reliable evidence that racial bias is absent in NYPD stop and frisk activity.

- RAND relies on an external benchmark of suspect race (as reported by victims) in violent felony crimes to assess racial bias. However, violent felonies comprise fewer than ten percent of all crime reported in 2005-6, and also are a small fraction of the total number of stops. Therefore, violent crimes are an inadequate benchmark by which to assess racial disparities in stop rates.
- Almost half of violent crime complaints do not report a suspect race, casting serious doubts on whether statistics based on complaints where suspect race is reported can be generalized to the half of complaints where the suspect race is unknown.
- RAND's "internal benchmark" model compares a subset of officers to their colleagues to identify "outliers" who stop Blacks and Hispanics at rates significantly above or below those of their peers. However, RAND relies on a selective and non-representative sample of officers who made 50 or more stops in 2006, a fraction both of the total number of stops made and of the officers who made them. There is no basis to claim that the results for this very small group of officers apply to other officers who effect stops.
- RAND cautions that if many officers in a precinct are racially biased in their stop patterns, then none of the officers in that precinct will be flagged as problematic. The RAND design assumes low rates of bias and does not allow this assumption to be tested.
- RAND uses a matching procedure to compare stops of White and Non-Whites, and concludes that there are few significant racial differences in how suspects are treated once stopped by the NYPD. However, the matching procedure neglects several important features of stops, such as the suspected crime and the indicia of reasonable suspicion that led to the stop.
- The RAND report strongly understates the racial disparities in post-stop outcomes such as frisks and use of force.

II. DATA SOURCES AND METHODS

This preliminary section of the report describes the data sources and analytic methods that were used to compile evidence to address the claims in this case. The section begins with a description of the sources of data on (a) police stop and frisk activity and the outcomes of street encounters between citizens and police, (b) social and demographic characteristics of the places where stops occurred that may contribute to stops and other police activity independent of local crime conditions, (c) local crime conditions in the precincts where stops took place, and (d) other relevant characteristics of police precincts including police patrol strength. The analytic strategies to discuss each claim are discussed next, and the rationale for each method. The section concludes with descriptive statistics that provide an overview of SQF activity.

A. Data Sources

1. SQF Activity and Suspect Information

Data on each stop and frisk encounter documented from 2004-2009 were provided to Plaintiffs as electronic (digital) files by the NYPD. Information about each encounter was recorded on a UF-250 form, and the records entered into a digital database. A copy of the UF-250 form is attached in Appendix B. The computerized records include information on the suspect's demographic characteristics (age, gender, race or ethnicity), the date and time of the stop, the duration of the stop, the location of the stop, the suspected crime, and the outcomes of the stop. The suspected crime was recorded using individualized and often idiosyncratic notation (e.g., a Penal Law chapter, "weap", shorthand such as "CPW" for concealed weapon). These items were coded into a set of 131 specific charge categories, and then reduced to a set of homogeneous offense-specific categories (e.g., "felony violence") that were used to classify the suspected crime that motivated the stop. Detailed information about the coding system to create this classification of suspected crimes is in Appendix C.

Outcomes of each stop were also listed on the UF-250. These included whether an arrest was made or a summons issued, whether the suspect was frisked, and whether the suspect was searched. Additional factors characterizing the stop include whether any of several types of force were used, and whether contraband was seized. If a weapon was seized, the specific type of weapon was also identified. Each case included information on the precinct where the stop took place. In some instances, beat or sector information was recorded.

The UF-250 form also includes information about the reasons for the stop, or the indicia of "suspicion." More specifically, this information indicated which of a fixed list of factors motivated the stop. These include 10 specific indicia of "suspicion" (including a designation of "other"), and 10 specific indicia of "additional circumstances" that also contributed to the decision to effect a stop (again, including a category of "other"). If a frisk or search ensued from the stop, the form includes nine and four indicia of "suspicion" that motivated those outcomes, respectively. These items also were recorded into the computerized data.

For the location of the stop, the street address where the stop took place was recorded, and in some records, the precise geographical coordinates (latitude and longitude, or "x-y" coordinates) of the stop location were provided. If this information was missing but a stop address was provided, the x-y coordinates were identified using geographical mapping software.[7]

2. Demography and Socio-Economic Conditions in the City

Analyses were conducted using police precincts as the principal unit of analysis. Precincts were used instead of smaller geographical areas (e.g., beats, sectors, census block groups, census tracts) because precincts are the units where police patrol resources are aggregated, allocated, supervised and monitored. These also are the units where crime is aggregated and monitored. Precinct crime rates are the metrics for managing and evaluating police performance, and are sensitive to tactical decisions in patrol and enforcement.[8] Precincts also are widely used in research on selective enforcement in policing.[9]

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[7] ArcGIS, ver. 9.0, http://www.esri.com/software/arcview/index.html. Some locations were recorded in the SQF databases in general terms (e.g., a streetcorner), in which case the centroid of the intersection was used as the location for the stop. When yet more general location information was recorded, e.g., only the name of a street, the software returned a location based on the centroid of the for the portion of the street within that sector or beat. If only precinct information was available, the centroid of section of the street that ran through the precinct was used as the location of the stop.

[8] See, for example, Eli Silverman, THE NYPD FIGHTS CRIME (1999); William J. Bratton and Peter Knobler, TURNAROUND: HOW AMERICA'S TOP COP REVERSED THE CRIME EPIDEMIC (1998).

[9] See, e.g., Lori Fridell, BY THE NUMBERS: A GUIDE FOR ANALYZING RACE DATA FROM VEHICLE STOPS (2004); Geoffrey Alpert et al., "Police Suspicion and Discretionary Decision Making during Citizen Stops," 43 *Criminology* 407 (2005).

Data on the social and economic conditions of the precincts were compiled from ESRI,[10] a commercial service that provides population information for small geographic units across the U.S. Precinct-level demographic data were drawn from 2006 projections of U.S. Census data using ESRI's *Demographic Update Methodology: 2006/2011*.[11] 2006 was chosen as a mid-point in the 2004-9 time interval. ESRI computes projections of total population, race, ethnic, and age breakdowns, for census tract. These projections were then aggregated from tracts to police precincts.[12]

Additional data on poverty and the concentration of foreign-born population were obtained from the 2005-2007 American Community Survey (ACS).[13] ACS data were allocated to the precincts by overlaying the ACS sampling units (PUMA's) with police precincts.[14] Measures of unemployment, median household income, physical disorder, housing vacancy, and residential mobility (i.e., the percent of the population living in a different borough or city five years prior) were measured at the sub-borough level in the 2005 New York City Housing and Vacancy Survey.[15] Both PUMA and sub-borough data are allocated to police precincts based on the area containing the majority of the precinct.

The social and economic dimensions were collapsed into two dimensions in order to apply parsimonious and efficient indicators, or factors, that characterize neighborhood social and economic conditions. One factor included the disorder and poverty variables. Poverty and both social and physical disorder are robust predictors of crime rates in small areas such as neighborhoods or police precincts.[16]

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[10] ESRI, http://www.esri.com/

[11] See, ESRI, ESRI Demographic Update Methodology: 2006/2011 (2006).

[12] Because precincts do not, as a rule, share boundaries with census tracts, we allocate allocate tract populations to precincts based on the percent of each tract's area that falls into each precinct. For example, if precinct A shares area with three census tracts (A1, A2, and A3), the precinct population is estimated as:

> % of A1 falling into precinct A*population of A1 + % of A2 falling into precinct A*population of A2+% of A3 falling into precinct A*population of A3

[13] http://www.census.gov/acs/www/

[14] See, http://ftp2.census.gov/geo/maps/puma/puma2k/ny_puma5.pdf for a map of the PUMA's in New York City. PUMA's have a population of approximately 100,000, and are similar in geographical size (footprint) and population density to police precincts.

[15] http://www.census.gov/hhes/www/housing/nychvs/2005/nychvs05.html

[16] See, e.g., Wesley Skogan, DISORDER AND DECLINE: CRIME AND THE CYCLE OF DECAY IN AMERICAN CITIES (1990).

Including measures of these dimensions allow us to control for social sources of crime in determining the extent to which SQF activity is indexed uniquely to crime or its correlates. A principle components factor analysis was used to generate a composite score for the combination of these variables.[17] The second factor was a measure of the immigrant population in each precinct. The presence of concentrations of recent immigrants is a protective factor that reduces the risk of crime in a neighborhood.[18]

3. Crime Conditions

Data on crime complaints from 2004-9 were provided to Plaintiffs by the City as electronic (digital) files. Each crime complaint included a geographical location (x-y coordinates) that permitted aggregation of the counts and rates of crimes to police precincts. The detailed crime categories ("offense description") were collapsed into 16 categories based on conceptual congruity. These categories were then compiled into seven meta-categories to generate a parsimonious and coherent set of smaller categories to inform the analyses. Details of the categorizations are provided in Appendix C. The aggregated codes for the crime complaints were constructed to match the crime codes for the suspected crimes that were recorded on the UF-250 for each stop. That is, the same meta-categories are used in the analysis of suspected crimes and for local crime rates. This measurement strategy provided a foundation for benchmarking the types and rates of suspected crimes in the stops with the observed rates of reported specific crimes in each police precinct.

4. Patrol Strength

Police deployment patterns frequently involve the saturation of police patrols in crime-prone areas, which often leads to more encounters with minority citizens as compared to Whites.[19] 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

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[17] Factor analysis is a statistical technique that captures consistency among observed variables to generate a composite measure using a lower number of unobserved variables. The method produces factors that represent the correlations among the observed measures. See, for example, Jae-On Kim et al., FACTOR ANALYSIS: STATISTICAL METHODS AND PRACTICAL ISSUES (1978). The factor analysis was completed using the STATA statistical software package.

[18] See, Robert J. Sampson, "Rethinking Crime and Immigration," *Contexts*, Winter 2008. Available at http://contexts.org/articles/winter-2008/sampson/

[19] See, for example, Donald Tomaskovic-Devey, Marcinda Mason, and Matthew Zingraff, "Looking for the Driving While Black Phenomena: Conceptualizing Racial Bias Processes and Their Associated Distributions," 7 *Police Quarterly* 3 (2004)

concentrations of neighborhoods or police precincts. Greater allocation of police resources to particular neighborhoods may increase the probability or rate of contact between citizens and police, and lead to racial or ethnic differences in contact patterns. Accordingly, an analysis of stop patterns by area requires understanding of the allocation of police patrol resources in each unit of analysis.

Patrol strength data for each precinct and command and year were obtained by Plaintiffs from the NYPD. These data were reported by calendar quarter. Codes for each command were used to classify assignments into patrol units. Details of the command codes and the classification definitions appear in Appendix E. Housing Bureau officers in Police Service Areas (PSA's) were assigned to precincts based on the precincts that each PSA covered. The maps and precinct coverage are shown at http://www.nyc.gov/html/nypd/html/home/precincts.shtml. The officers were allocated according to the distribution of stops in each of the precincts in a PSA. Transit Bureau officers were similarly allocated based on the precinct locations of the subway stops in each Transit District. When Transit Districts crossed precinct boundaries, the officers were allocated according to the distribution of stops in each of the precincts in the relevant Transit Districts. A cross-walk of Transit Districts and Transit Stations is available at http://www.nyc.gov/html/nypd/html/transit_bureau/transit.shtml

5. Public Housing Locations

Public housing locations require special attention for several reasons. In many cities, including New York City, they are considered places with especially high risk of crime and therefore targets for special policing interventions.[20] The New York City public housing sites have received special attention from the police, as well, that produced heightened surveillance of persons coming and going from NYCHA sites, leading to frequent stops and arrests for trespass.[21] Accordingly, one of the special analyses that attempt to control for the collateral conditions that may produce higher stop rates in police precincts is the concentration of NYCHA populations in the precincts. Data were obtained from the New York City

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[20] Jeffrey Fagan, Garth Davies and Jan Holland, "Drug Control in Public Housing: The Paradox of the Drug Elimination Program in New York City," *13 Georgetown Journal of Poverty, Law & Policy* 415-60 (September 2007).

[21] Al Baker, "Of Tactics in Public Housing and Recommended Reading, *New York Times*, October 7, 2010, http://cityroom.blogs.nytimes.com/2010/10/07/of-tactics-in-public-housing-and-recommended-reading/. See, also, Jeffrey Fagan, Garth Davies and Adam Carlis, "Race and Selective Enforcement in Public Housing", Working Paper, Columbia Law School.

Department of City Planning that listed the address of all New York City Housing Authority (NYCHA) sites. Boundary maps are available from the Department at (http://www.nyc.gov/html/dcp/html/bytes/applbyte.shtml). Demographic information about the sites for 2009 was obtained by me from the NAACP Legal Defense Fund. The 2009 data were used for each year in the time series, based on the assumption that both the size and demographic characteristics of the NYCHA population changed negligibly over recent time. The total population living in NYCHA properties in each precinct was calculated and then converted to a percentage of the total precinct population.[22]

6. Land Area

The size of the land area of a precinct can influence the likelihood of contacts between officers and citizens. Officers assigned to precincts with larger "footprints" may be less likely to encounter citizens in their routine patrols – net of total population and patrol strength – simply by virtue of the number of citizens per square mile, or the population density. Conversely, densely populated areas may increase the likelihood of citizen contact with police, or the scope of police surveillance of citizens, if they have smaller "footprints" simply because there are more people crowded into smaller land areas. Under these circumstances, police and citizens will be more likely to encounter each other during their routine activities, potentially increasing the number of stops. In addition, crime rates also are sensitive to population density, so that smaller land areas together with higher population concentrations may increase the risk of crime that will lead to heightened police attention.[23]

To address this potential factor in the explanation of stop rates, specific analyses were conducted to address this potential influence on the stop rate. Data were obtained again from the New York City Department of City Planning on the land mass of each police precinct,[24] using geographical software[25] that captures land mass within the borders ("shape file") of each precinct.

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[22] There are four developments where there are more than one building and the buildings fall within different precincts. In those instances, the population was allocated equally between the two precincts.

[23] Morgan Kelly, "Inequality and Crime," 82 *Review of Economics and Statistics* 530 (2000) (showing that the risk factors for crime often are located in places with smaller areas and higher population density per square kilometer).

[24] http://www.nyc.gov/html/dcp/html/bytes/dwndistricts.shtml

[25] ArcGIS, supra note 7.

B. Analytic Methods

1. General Analytic Strategy

The general test for evidence of disparate treatment is a regression equation that takes the form:

$$\text{Outcome} = \alpha + \beta_1 * \text{ Minority} + \Sigma_i \beta_i * (\text{Plausible Non-Race Influences}) + \varepsilon,$$

Where *Outcome* is the event or status of interest, *Minority* is an indicator for the racial composition or status of the unit observed (i.e., precinct or person, depending on the outcome), *Plausible Non-Race Influences* are a set of variables representing non-race factors that also might influence the outcome, and an error term ε that captures the variation in the outcome that cannot be explained by either Minority status or the Non-Race Influences. These models may include non-race 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.[26]

Consider the following example, from *Griggs v. Duke Power Co.*, an employment discrimination case.[27] In a disparate treatment claim, one could test whether the use of a high school diploma requirement biases the hiring process since African American job applicants may be less likely to have obtained a high school diploma. Had this race-correlated control been introduced, it would likely have reduced the racial disparity in the hiring rates – for the simple reason that minority applicants at that time were less likely to have obtained a high school diploma. Should a statistical test control for whether or not an applicant had a high school diploma? As Ian Ayres points out,[28] in a disparate treatment case, the answer is yes. Under a disparate treatment theory, the critical question is whether an applicant's race was the cause of being denied employment. If applicants were rejected because the employer chose not to

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[26] For a general discussion of the specification of regression models to test for disparate treatment, see generally D. James Greiner, "Causal Inference in Civil Rights Litigation," 122 *Harvard L. Rev.* 533 (2008). For a general discussion of how regressions sort out the influences of predictors of an outcome, see Thomas J. Campbell, Regression Analysis in Title VII Cases: Minimum Standards, Comparable Worth, and Other Issues Where Law and Statistics Meet, 36 *Stanford L. Rev.* 1299 (1984).

[27] *Griggs v. Duke Power Co.*, 401 U.S. 424 (1971).

[28] Ian Ayres and Jonathan Borowsky, A Study of Racially Disparate Outcomes in the Los Angeles Police Department, at 5 (October 2008), available at http://www.aclu-sc.org/documents/view/47."

hire diploma-less applicants, the applicants' race would not be a "motivating factor" in employer's decision. The goal in specifying these models is to identify the effects of race on outcomes after simultaneously considering factors that may be relevant to race. Failure to do so raises the risk of "omitted variable bias", which could lead to erroneous conclusions about the effects of variables that do appear in a regression test.[29]

2. *Specific Types of Models*

The specific estimation technique for each analysis, or functional form of the regression equation, was responsive to the specific measure of stop activity or other dimensions of SQF activity. Models of stop activity were measured as counts over time in NYPD precincts. Accordingly, models were estimated using negative binomial regressions. This class of regression models is appropriate for counts of events, such as stops or arrests in a specific area, where assumptions about the independence of the events cannot be reliably made.[30] A specific form of negative binomial regression known as Generalized Estimating Equations (GEEs) was used.[31] GEEs are beneficial for nested or hierarchically organized data, such as years within precincts, as they allow for the specification of within-subject correlations of observations. Since the analyses include a sequence of time periods (calendar quarters), the models include an AR(1) variance estimation that adjusts for the serial correlation (or autoregression) of the counts of events within sampling units over long periods of time.[32] Since police precincts are nested within the City's

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[29] See, e.g., Ian Ayres, "Testing for Discrimination and the Problem of 'Included Variable Bias'," Yale Law School Working Paper (2010), available at http://islandia.law.yale.edu/ayers/ayresincludedvariablebias.pdf; Ian Ayres, "Three Tests for Measuring Unjustified Disparate Impacts in Organ Transplantation: The Problem of "Included Variable" Bias," 48 *Perspectives in Biology and Medicine* 68 (2005)

[30] Negative binomial regressions also are especially useful for discrete data such as event counts when the variance in the measure of activity exceeds the mean across areas. Joseph M. Hilbe, NEGATIVE BINOMIAL REGRESSION (2007). See, also, Richard Berk and John M. MacDonald, "Overdispersion and Poission Regression," 24 *J. Quantitative Criminology* 269 (2008); D. Wayne Osgood, "Poisson-Based Regression Analysis of Aggregate Crime Rates," 16 *J. Quantitative Criminology* 21 (2000); David A. Freedman, STATISTICAL MODELS: THEORY AND PRACTICE (2005); William Greene, ECONOMETRIC ANALYSIS (5TH ED.) (2003).

[31] James W. Hardin and Joseph M. Hilbe, GENERALIZED ESTIMATING EQUATIONS (2003); Gary A. Ballinger, "Using Generalized Estimating Equations for Longitudinal Data Analysis," 7 *Organizational Research Methods* 127 (2004).

[32] AR(1) adjustments reflect the reality that the best predictor of what the crime rate will be in the next month is what it was last month. This is an empirical constraint in identifying the relationship between crime and policing. Failure to correct for this temporal dependence will bias

boroughs, we included fixed effects to account for any unobserved effects of conditions in the boroughs that might influence police activity. Similarly, we included fixed effects for time (calendar quarters) to account for any variation in stop patterns (or other outcomes) that may have been the result of influences that were unique to any of the time periods.

The model fit is estimated using a Marginal R-squared statistic, which measures the amount of variance in the response variable that is explained by the fitted model. That is, this test measures the improvement in fit between the estimated model and the intercept-only (null hypothesis) model.[33] Negative values of the Marginal R-squared indicate that the estimated model does a worse job of predicting than an intercept only model.

Regression models on the specific outcomes of stops for individuals were estimated using hierarchical logistic regressions. Logistic regressions are ideal for estimating the probability that an event will occur, given a set of conditions that influence that probability.[34] For example, the probability that a person was arrested, given a stop within a police precinct, might be predicted from the person's age, sex, race or ethnicity, or from the suspected crime that led to the stop.

Hierarchical, or multilevel regression models[35] allow for the simultaneous examination of the influence of the context in which the event is nested (local crime or

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the standard errors in estimates of crime effects on policing, and this distortion remains even when fixed effects are used to control for temporal trends. See, Badi BALTAGI, Econometric Analysis of Panel Data (2001); Badi H. Baltagi and Qi Li, "Testing AR(1) Against MA(1) Disturbances in an Error Component Model," 68 *Journal of Econometrics* 133 (1995).

[33] Ballinger, *supra* note 31 at 134.

[34] William H. Greene, ECONOMETRIC ANALYSIS (5th ed.) (2003); Joseph M. Hilbe, LOGISTIC REGRESSION MODELS (2009); David W Hosmer and Stanley Lemeshow, APPLIED LOGISTIC REGRESSION (2nd ed.) (2000).

[35] See, e.g., Thomas A. DiPrete, and Jerry D. Forristal, "Multilevel Models: Methods and Substance." 20 *Annual Review of Sociology* 20:331–357 (1994). Andrew Gelman and Jennifer Hill, DATA ANALYSIS USING REGRESSION AND MULTILEVEL/HIERARCHICAL MODELS (2007); Anthony Bryk and Stephen Raudenbush, HIERARCHICAL LINEAR MODELS FOR SOCIAL AND BEHAVIORAL RESEARCH: APPLICATIONS AND DATA ANALYSIS METHODS (1992); Sophia Rabe-Hesketh and Anders Skrondal, MULTI-LEVEL MODELING, 2008; Judith D. Singer and John B. Willett, APPLIED LONGITUDINAL DATA ANALYSIS: MODELING CHANGE AND EVENT OCCURRENCE (2003); Ralph B. Taylor, "Communities, Crime, and Reactions to Crime Multilevel Models: Accomplishments and Meta-Challenges," *Journal of Quantitative Criminology* (forthcoming, 2010, available at http://www.springerlink.com/content/53l6295t7w628088/

socio-economic conditions in the crime precinct, for example, or the period of time), and individual characteristics of the event itself (e.g., the race or ethnicity of the person stopped, the specific crime). Events may be conditioned on the context in which they occur, and this strategy allows for the estimation of how one variable affects an outcome given the conditions in which the event occurs. In this case, for example, a person of racial group A may be more likely to be stopped in a neighborhood with social or crime characteristic B than in a neighborhood with characteristic C. This class of models allows for consideration of the effects of racial or ethnic group membership conditional on the place (B or C in this example) where the stop took place. In addition, these models allow for the consideration of temporal effects such as particular time periods when stops may be more or less frequent. That is, the effects of conditions B or C may be more salient in some time periods than others. So, time becomes another of the conditioning factors that can influence the rate of stops, the outcome of stops, or the relationship between *non-race influences* and the outcomes of interest.

Details of the specific regression equations are included in the presentation of evidence for each claim addressed in this report.

3. Sensitivity Analyses

In the absence of perfect information, the results of the analyses depend on assumptions about the data, about the contexts in which the events of interest take place, and about the methods that are used to test the data. The results of the analyses also may also depend assumptions about the composition of the events of interest. Accordingly, each of the analyses that are reported here are subject to a series of alternate tests that allow for the identification of a range of estimates of the effects of race or other variables of interest on the outcomes. These tests allow us to say what the effects are under a *range of* assumptions about the practices that are being observed and measured.

C. Benchmarking

The selection of a benchmark against which to assess police enforcement activity is a basic question in reliably measuring the extent of racial disparities in police-citizen interactions. A benchmark allows us to determine if police are selectively, on the basis of race or another prohibited factor, singling out persons for stops, questioning, frisk or search. So, I compare the police decision to stop someone to their availability and eligibility for stops, and compare that calculation across racial and ethnic groups. It is not hard to see that the reliability of an estimate of the extent of racial disproportionality or fairness is likely to depend on – and be particularly sensitive to – the benchmark used to measure criminal behavior.[36]

Population is one measure of the supply of people available to the police for surveillance and possibly stops. However, there are constraints on local population estimates that limit its utility as a benchmark for the behavior of the police. Residential population estimates in commercial parts of the City are often unreliable estimates of the actual composition of persons who are visible and available to the police during certain hours of the day. And, similarly, if people leave residential areas to work in commercial areas, the estimates in the residential areas will also be biased and inaccurate.

Another reason that population may not be an incomplete benchmark is that police do not stop persons randomly based on the population parameters of an area. In fact, police stop persons based on, at least in theory, their perceptions of suspected crime, or their evaluation of citizen behaviors that may provide reasonable indicia of the potential that crime has occurred or is about to take place.[37] To the extent that the rate of crime *suspicion* are correlated with the rate of crime *commission*, observed crime rates are useful candidates to serve as a component of a benchmark.[38]

Accordingly, for this analysis of police stop activity, a valid benchmark requires estimates of the supply of individuals of each racial or ethnic group who are engaged in the targeted behaviors and who are available to the police as potential targets for the exercise of their stop authority. Since police often target

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[36] The issues in benchmarking for pedestrian stops are quite different from those that influence decisions on how to benchmark for traffic stops. See, generally, Lori A. Fridell, BY THE NUMBERS: A GUIDE FOR ANALYZING DATA FROM VEHICLE STOPS, 7 (2004); Jeffrey Fagan, "Law, Social Science and Racial Profiling," 4 *Justice Research and Policy* 104 (2002); Ian Ayres, "Outcome Tests of Racial Disparities in Police Practices," 4 *Justice Research and Policy* 133 (2002); Greg Ridgeway and John MacDonald, Methods for Assessing Racially Biased Policing, in RACE, ETHNICITY AND POLICING: ESSENTIAL READINGS (S.K. Rice and M.D. White, eds.) 180 (2010); Ridgeway and MacDonald, id. See, also, Samuel Walker, "Searching for the Denominator: Problems With Police Traffic Stop Data And an Early Warning System Solution," 4 *Justice Research and Policy* 63 (2002). The Fagan and Walker articles respectively wrestle with the unique demands of benchmarking for pedestrian stops.

[37] Bernard E. Harcourt and Tracey L. Meares, "Randomization and the Fourth Amendment" (2010). Working paper, University of Chicago Law School, available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1665562.

[38] Alpert et al, Place-Based Suspicion, *supra* note 9

resources to the places where crime rates and risks are highest, and where populations are highest, some measure of population that is conditioned on crime rates is an optimal candidate for inclusion as a benchmark.

The challenge to the analyst is to identify a valid measure of crime. Ideally, we would include measures of the race-specific crime rates in each precinct (or other social area) to help construct precise benchmarks based on the participation in the behavior of interest by persons of each race and ethnicity. However, there are practical problems in this approach. For example, many crimes are unreported to the police, and there are no valid victim surveys from which we can measure crime rates. There similarly are no surveys of self-reported crimes. Race-specific arrest rates have been used as a proxy for race-specific crime rates, with a lag function that reduces the problem of correlated error terms between current enforcement and past enforcement.[39] However, there is some disagreement about the validity of prior period arrest rates, with some analysts offering positive rationales, while others have been critical.[40]

One alternate measure is crimes reported to the police. Police activity is closely linked in New York City toward crime.[41] However, crime reports don't provide a complete picture of the racial makeup of the offenders in those crimes. While crime reports may provide a snapshot of the racial composition of those involved in crime commission, it is just that: a snapshot with only partial coverage of criminal activity. In fact, there are strong limits to this benchmark. Many crimes that are reported lack a suspect identification or description. For example, fewer than one in four stops in 2009 were based on a match between the person detained and a suspect description known to the police, and the rates of unknown suspect

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[39] See, for example, Eliot Spitzer, "The New York City Police Department's 'Stop and Frisk' Practices: A Report to the People of the State of New York" (1999); Andrew Gelman, Jeffrey Fagan, and Alex Kiss, "An Analysis of the NYPD's Stop-and-Frisk Policy in the Context of Claims of Racial Bias." 102 *Journal of the American Statistical Association.* 813 (2007); Jeffrey Fagan et al., "Street stops and *Broken Windows Revisited*: *The Demography And Logic Of Proactive Policing In A Safe And Changing City,*" RACE, ETHNICITY AND POLICING: NEW AND ESSENTIAL READINGS (S.K. Rice and M.D. White, eds.) 309 (2010).

[40] Arrest data incorporate information about crime patterns, but also contain uncertainty and unobservable components because of police decisions about allocating officers to specific places. Greg Ridgeway and John MacDonald, "Methods for Assessing Racially Biased Policing," in RACE, ETHNICITY AND POLICING: NEW AND ESSENTIAL READINGS (S.K. Rice and M.D. White, eds.) 180 (2010).

[41] William J. Bratton and Peter Knobler, TURNAROUND, supra note 8. Silverman, NYPD FIGHTS CRIME, supra note _8. See, also, Letter from Commissioner Kelly to City Council Speaker Christine Quinn, *supra* note 2.

race are stable over time.[42] There is no valid basis for extrapolation of suspect race information from the small number of cases where offender race is known to the larger number of reported crimes to those cases where the suspect race is unknown. Doing so would invite a statistical bias based on assumptions and parameters that cannot be verified. So, for example, some types of suspected crimes that animate a large share of stops, such as weapons possession or drug possession, often do not follow from crime reports that identify the race of a suspect, so these base rates of offending are unknown.

Nevertheless, to the extent that observed or reported crimes are leading indicators of those behaviors that are correlated with crime, crimes known to the police are an important part of a valid benchmark. So too is population, as an index of the overall exposure of citizens to the police as available targets for surveillance and interdiction. Accordingly, these analyses use both population and reported crime as benchmarks for understanding the racial distribution of police-citizen contacts. Since the percentage of known suspects varies by crime type, the analyses in this report also include indicia of the distribution of particular types of crimes.[43]

III. Descriptive Statistics of Data Analyzed for This Report

A. Social and Demographic Characteristics

The data analyzed for this report includes 2,805,721 stops by the NYPD from 2004-9 that were recorded on a UF-250 form and provided to Plaintiffs as digital files.[44] The descriptive statistics in this section include all stops. In the multivariate models that test the legal claims, the sample excludes stops in the 22nd precinct, Central Park, since it has negligible population.

Table 1 shows the distribution of stops by year and borough. The number of stops rose from 313,047 in 2004 to 576,394 in 2009.[45] Stops were most prevalent in

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[42] See, *infra*, section VI.6.B.2

[43] Id.

[44] Fewer than .1 percent of the recorded stops did not state a valid precinct identifier. These were were excluded from the analyses.

[45] The NYPD reported over 581,000 stops in 2009 in files that were posted on the NYPD website, http://www.nyc.gov/html/nypd/html/analysis_and_planning/stop_question_and_frisk_report.shtml. The files provided to Plaintiffs included the smaller number of stops.

Table 1. Stops per Year by Borough and Citywide, 2004-9

Borough		2004	2005	2006	2007	2008	2009	Total
Bronx	N	39,051	51,520	75,824	70,987	84,732	95,784	417,898
	%	12.47	12.96	14.97	15.04	15.68	16.62	14.89
Brooklyn	N	127,485	161,545	176,119	162,788	187,142	205,588	1,020,667
	%	40.72	40.65	34.77	34.48	34.64	35.67	36.38
Manhattan	N	57,051	82,493	120,545	116,775	118,816	114,279	609,959
	%	18.22	20.76	23.8	24.74	21.99	19.83	21.74
Queens	N	78,404	91,347	114,988	100,811	117,221	131,382	634,153
	%	25.05	22.99	22.7	21.35	21.7	22.79	22.6
Staten Island	N	11,056	10,488	19,013	20,735	32,391	29,361	123,044
	%	3.53	2.64	3.75	4.39	5.99	5.09	4.39
City	**N**	**313,047**	**397,393**	**506,489**	**472,096**	**540,302**	**576,394**	**2,805,721**
	%	100	100	100	100	100	100	100

Kings County, and least prevalent in Staten Island. The percentage of stops rose over time in Bronx County, from 12.47% in 2004, to 16.62% in 2009. The share in Kings County declined over the same period, even as the actual number of stops in that borough increased from 127,485 to 205,588.

Table 2 shows the distribution of stops by calendar quarter. Stops were most common in the winter months (January-March) compared to other times of the year. The seasonal difference was most pronounced in 2004, the year when fewest stops were recorded.

The racial distribution of stops has been discussed widely, both in official reports from the City as well as a variety of secondary analyses by organizations and agencies in New York.[46] Over half the persons stopped – 51.52% – over time were African-American. Table 3 shows that both Hispanic Blacks and Non-Hispanic Blacks are included in this category. Three in ten were Hispanics, and slightly more than 10% were Non-Hispanic Whites. The age distribution of persons stopped was about evenly divided across four age categories spanning a wide band of adult ages from 16-64. These are stops, not persons, so persons stopped more than once are not described separately in this table. Nearly nine in 10 (89.48%) were males. These are stops, not individual persons, so that the counts may include repeat stops of the same person.

The age distribution of stops is evenly spread across several age categories, but diverges from the conventional age distribution of known offenders. For most crimes, the peak offending age is 16-19,[47] and slightly older (18-24) for homicide.[48] For example, according to the New York City Department of City Planning, the population of males ages 20-24 in New York City in 2005 was 292,173, or 7.48% of the male population of the City.[49] Stops of persons in this age range were 22.69% of all stops. Males 25-34 were 16.86% of the City population, but comprised 23.25% of the persons stopped. Males 35-64 were 40.62% of the male population, but 25.29% of the males stopped. So, overstopping younger persons relative to their age reflects

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[46] See, for example, Stop, Question and Frisk Policing Practices in New York: A Primer, available at www.jjay.cuny.edu/web_images/PRIMER_electronic_version.pdf

[47] The age-crime distribution has been historically stable over time. See, for example, David Farrington, "Age and Crime" 7 *Crime & Justice* 189 (1986).

[48] See, Bureau of Justice Statistics, U.S. Department of Justice, http://bjs.ojp.usdoj.gov/content/homicide/teens.cfm

[49] See, http://www.nyc.gov/html/dcp/pdf/census/projections_briefing_booklet.pdf

Table 2. Stops by Calendar Quarter (%)

		Calendar Quarter			
Year	**N**	**Jan - Mar**	**Apr - June**	**July - Sept**	**Oct - Dec**
2004	313,047	33.79	26.51	19.10	20.60
2005	397,393	27.91	28.66	20.82	22.61
2006	506,489	26.86	25.58	24.44	23.12
2007	472,096	28.61	24.41	23.69	23.29
2008	540,302	27.50	23.80	22.70	26.00
2009	576,394	29.72	24.41	23.98	21.86
Total	2,805,721	28.79	25.34	22.78	23.10

Table 3. Age, Gender and Race or Ethnicity of Persons Stopped, 2004-2009 (%)

	White	Black	Hispanic	Other	Unknown	Total
Total Stops	286,753	1,445,472	841,755	224,447	7,294	2,805,721
%	10.22	51.52	30.00	8.00	0.26	100
Age						
Less than 10	0.09	0.17	0.09	0.21	0.18	0.14
10 - 15	4.18	5.03	4.15	4.8	4.28	4.66
16 - 19	22.56	21.64	21.76	21.86	21.7	21.79
20 - 24	20.82	22.38	24.13	21.78	22.31	22.69
25 - 34	22.22	23.25	25.79	23.03	23.66	23.89
35 - 64	27.77	25.29	21.88	24.56	26.75	24.46
65 and older	0.81	0.44	0.38	0.49	0.47	0.46
Unknown	1.56	1.8	1.82	3.26	0.66	1.89
Gender						
Male	89.02	92.22	92.2	62.43	83.19	89.48
Female, Unknown, or Not Listed	10.98	7.78	7.8	37.57	16.81	10.52

the known distributions of criminal offenders, but the *extent* of over-stopping is perhaps not as great as their age-specific crime participation rates would suggest. Similarly, understopping males 35-64 relative to their age also reflects their generally lower crime risk, but the extent of understopping is less than what a stop rate indexed to that group's age-specific crime risks would suggest. In other words, the age distribution of stops in New York is not proportionately or accurately indexed to either the widely acknowledged higher crime risks of younger persons or the rapidly decreasing crime risks of persons over 35 years of age.[50]

Table 4 shows the distribution of stops by suspected crimes and suspect race or ethnicity. The crime categories were constructed from a set of 131 specific crime types that were identified in the UF-250 data. Details of the categories and the types of suspected crimes in each category are in Appendix C. The distribution by race varies by type of crime. White are less likely than Blacks and other minorities to be stopped in several crime categories: violence, weapons possession, and trespass. Whites are more likely to be stopped for property crimes and "quality of life" crimes. Stops for suspected drug crimes, including both possession and sale, are evenly distributed across racial and ethnic groups.

However, these trends should be regarded with some uncertainty due to the high number of cases where the suspected crimes were either "unknown" or unclassifiable. NYPD officers failed to accurately or usably code the suspected crime in nearly one in five stops. Examples of uncoded stops include those with notations or entries for suspected crime in the database that state "FEL" or "FELONY", or "MISD" or "MISDEMEANOR". These could not be classified. Other suspected crimes were recorded using non-existent Penal Law categories, and also could not be classified. Others were simply missing. Overall, 519,120 of the 2,805,721 records – 18.4% - were unclassifiable. The rate of unclassifiable suspected crimes was slightly higher for Black (19.68%) and Hispanic (18.27%) suspects than for Whites (16.66%) or other race (13.77%) suspects. The rate of unclassifiable cases was highest for those records where the suspect race or ethnicity also was unknown – 30.86%. As in the race of suspects in reported crimes, there is no basis on which to make assumptions about how these cases would be distributed across either race/ethnicity categories or crime categories.

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[50] See, e.g., Alfred J. Blumstein and Kiminori Nakamura, "Redemption in the Presence of Widespread Criminal Background Checks", 47 *Criminology* 1 (2009)

Table 4. Stops by Race or Ethnicity and Suspected Crime (%)

		Race				
Suspected Crime*	**N**	***White***	***Black***	***Hispanic***	***Other***	***Unknown***
Violence	410,696	10.85	14.64	15.56	16.06	11.74
Minor Violence	6,758	0.41	0.20	0.23	0.34	0.26
Felony Property	564,472	38.25	14.23	21.82	28.48	21.28
Minor Property	115,546	6.05	3.85	4.00	3.86	3.45
Weapons	531,792	8.55	21.63	18.50	16.89	13.16
Trespass	324,967	4.97	14.03	10.54	8.24	10.17
Drugs	265,585	9.48	9.93	8.80	9.08	6.09
QOL	34,040	3.06	0.76	1.20	1.82	1.70
Other Felonies	1,799	0.27	0.01	0.04	0.22	0.23
Other Misdemeanors	25,776	1.15	0.90	0.87	0.95	0.86
Other	5,170	0.32	0.15	0.17	0.29	0.19
Unknown/ Unclassifiable	519,120	16.66	19.68	18.27	13.77	30.86

* Most serious crime in each stop

B. Stops and Crime

Figures 1-8 are a series of graphs showing the basic distributions of stops arrayed across a range of benchmarks based on crime complaints for each calendar quarter. The basic comparison is stop rates per crime complaint. To provide illustrations relevant to the disparate treatment claims in the litigation, the graphs divide the City into quartiles based on the percent Black or Hispanic population, and also non-White population, and show stop rates per crime metric over time. Graphs include total crime complaints, felony violent crime complaints (murder, manslaughter, robbery, assault, rape and kidnapping), and total violent crime complaint.

The graphs show:

1. Stops per crime complaint by Black population quartiles
2. Stops per violent crime complaint by Black population quartiles
3. Stops per crime complaint by Hispanic population quartiles
4. Weapons stops per violent crime complaint by Black population quartiles
5. Weapons stops per felony violent crime complaint by Black population quartiles
6. Weapons stops per crime complaint, by non-White population quartiles
7. Weapons stops per violent crime complaint by non-White population quartiles
8. Weapons stops per felony violent crime complaint by pct non-White population quartiles

Each of the graphs shows that stop rates per crime complaint are higher, for each crime complaint and crime-specific stop metric, in the population quartile with the highest concentration of minority population. The result is consistent for both total stops and weapons stops, as well as for total and violent felony complaints. In each instance, the population with the highest quartile of minority (Black, Hispanic, or total Non-White) population has the highest stop rate per crime complaint. Although these are places where the crime rates generally are higher, the disparity in stops per crime are in some cases quite wide. The analyses in the following sections test whether these disparities are statistically significant, controlling for other characteristics in the crime precincts.

Figures 9-12 are maps that further illustrate the relationship between crime, stops, and the racial composition of precincts. Figure 9 shows all stops by precinct percent Black population. Figure 10 shows the same, but for the precinct Non-White population. Figures 11 and 12 show stops by precincts based on two measures of their crime conditions: total crime rate and both felony and misdemeanor violent crime complaints.

Fig. 1: Stops per complaint by precinct quartile % black
2004-2009

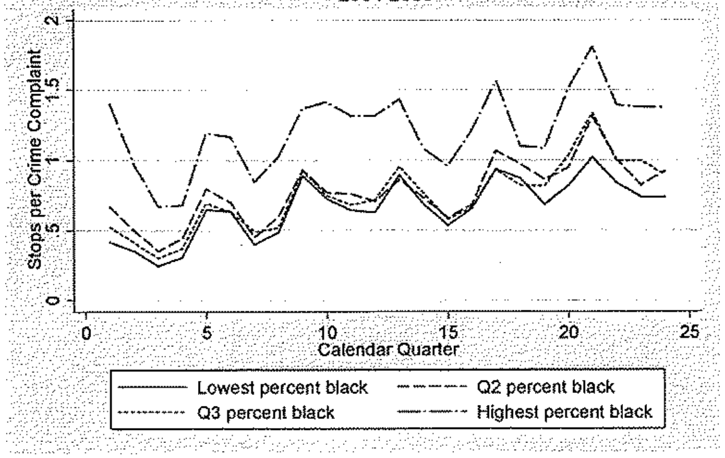


Fig. 2: Stops per violent crime complaint by quartile % black
2004-2009

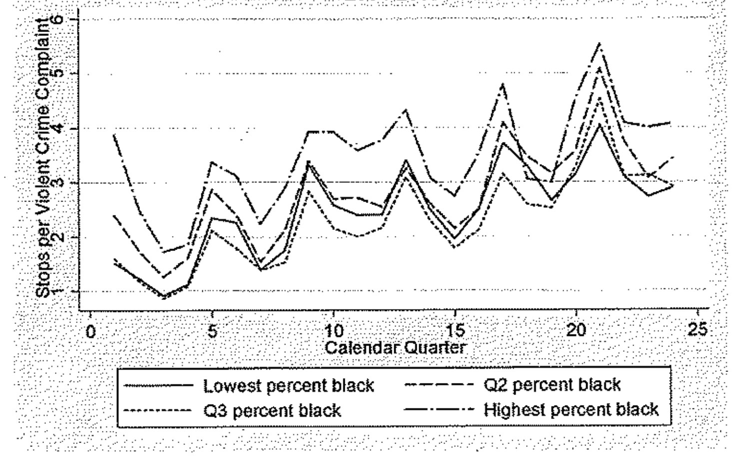


Fig. 3: Stops per complaint by precinct quartile % Hispanic
2004-2009

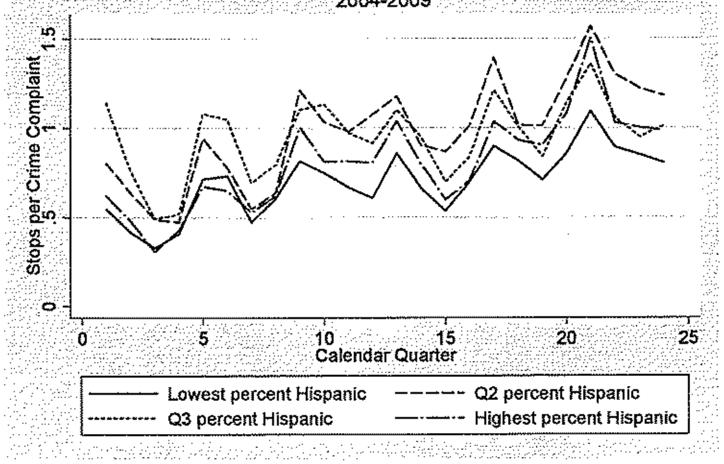


Fig. 4: Weapon stops per violent crime complaint by quartile % black
2004-2009

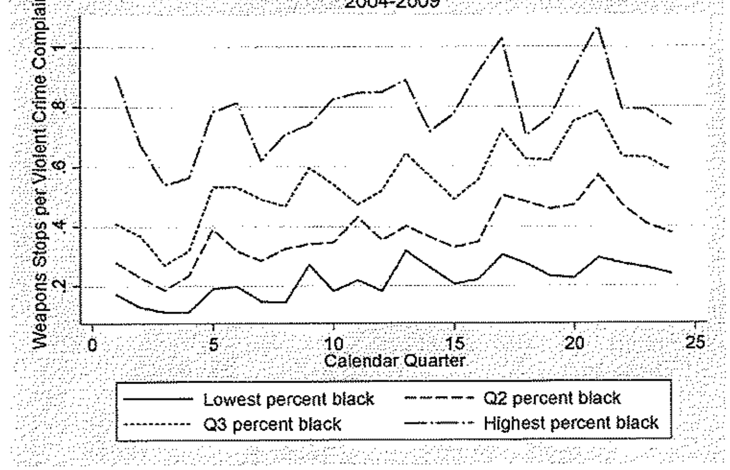


Fig. 7: Weapon stops per violent crime complaint by quartile % nonwhite 2004-2009

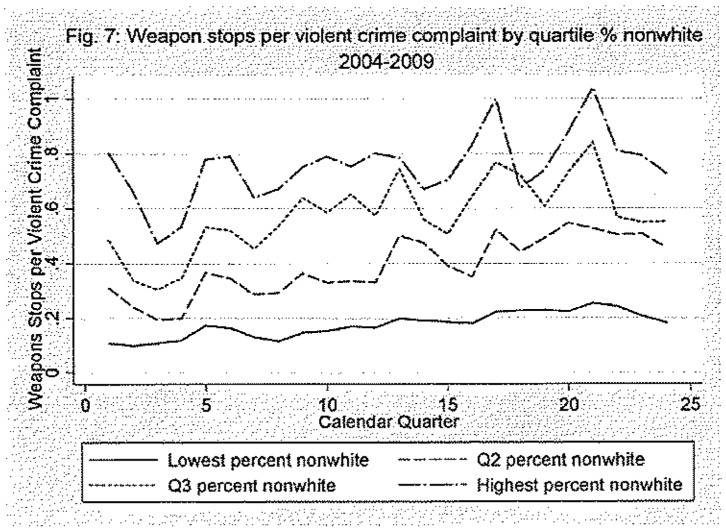


Fig. 6: Weapons stops per complaint by precinct quartile % nonwhite 2004-2009

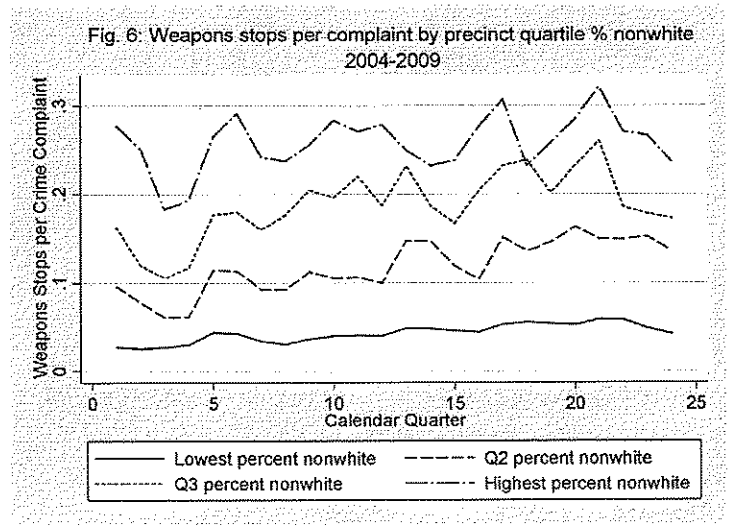


Fig. 8: Weapon stops per violent felony complaint by quartile % nonwhite 2004-2009

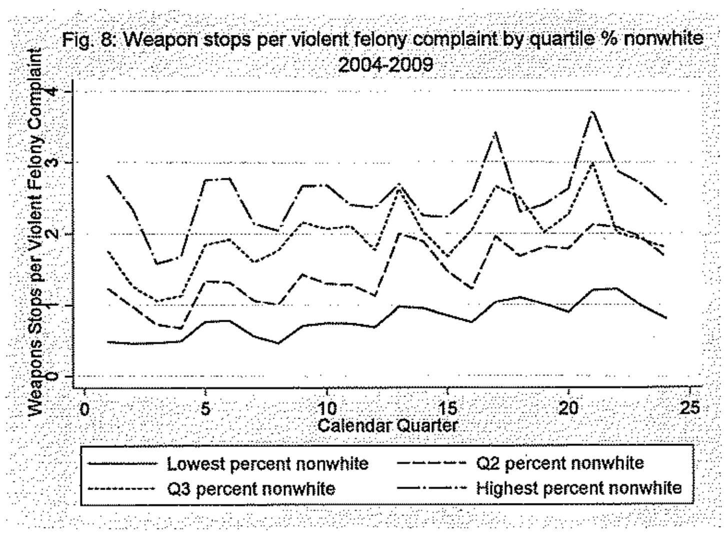


Fig. 5: Weapon stops per violent felony complaint by precinct quartile % black 2004-2009

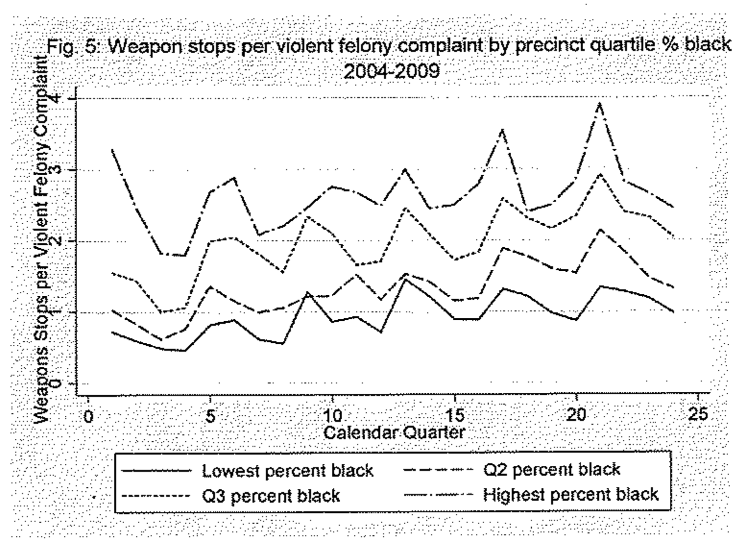


Figure 9: Stops and Precinct Population Percent Black

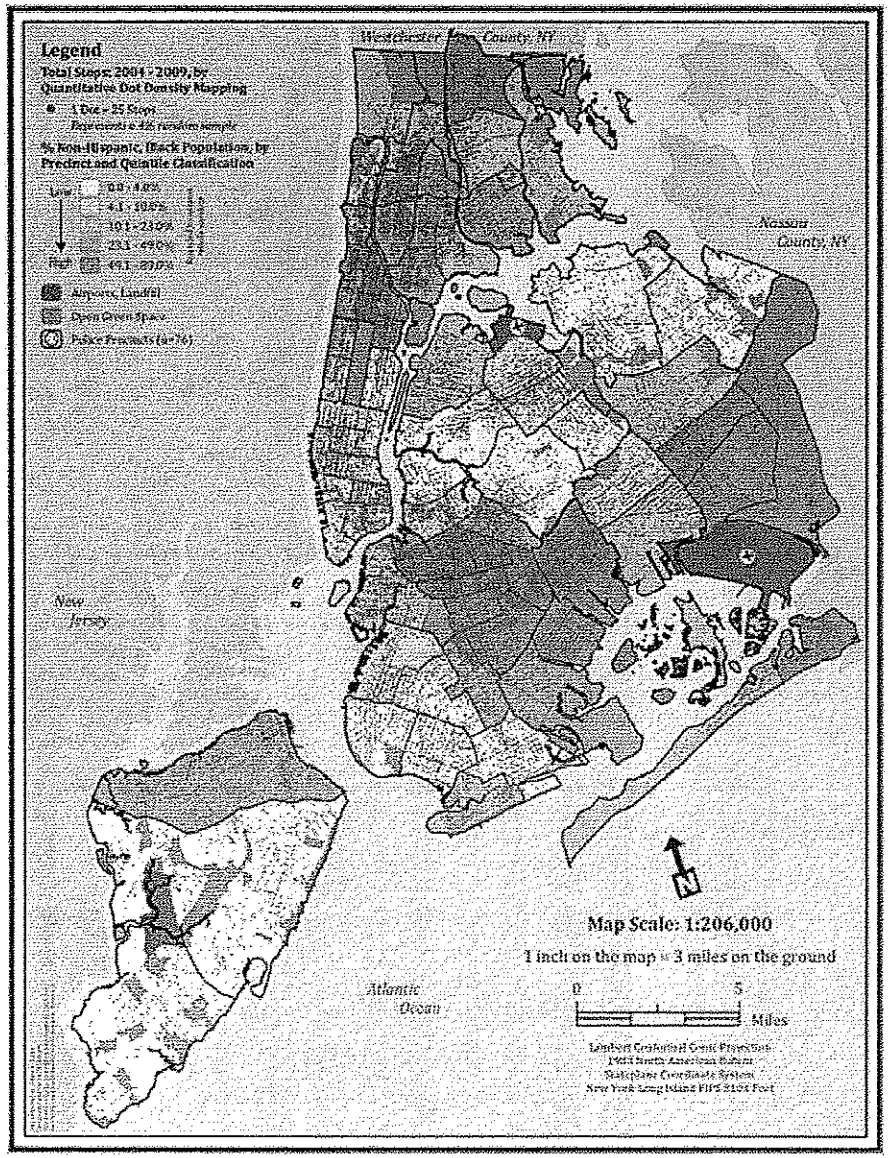


Figure 10: Stops and Precinct Population Percent Nonwhite

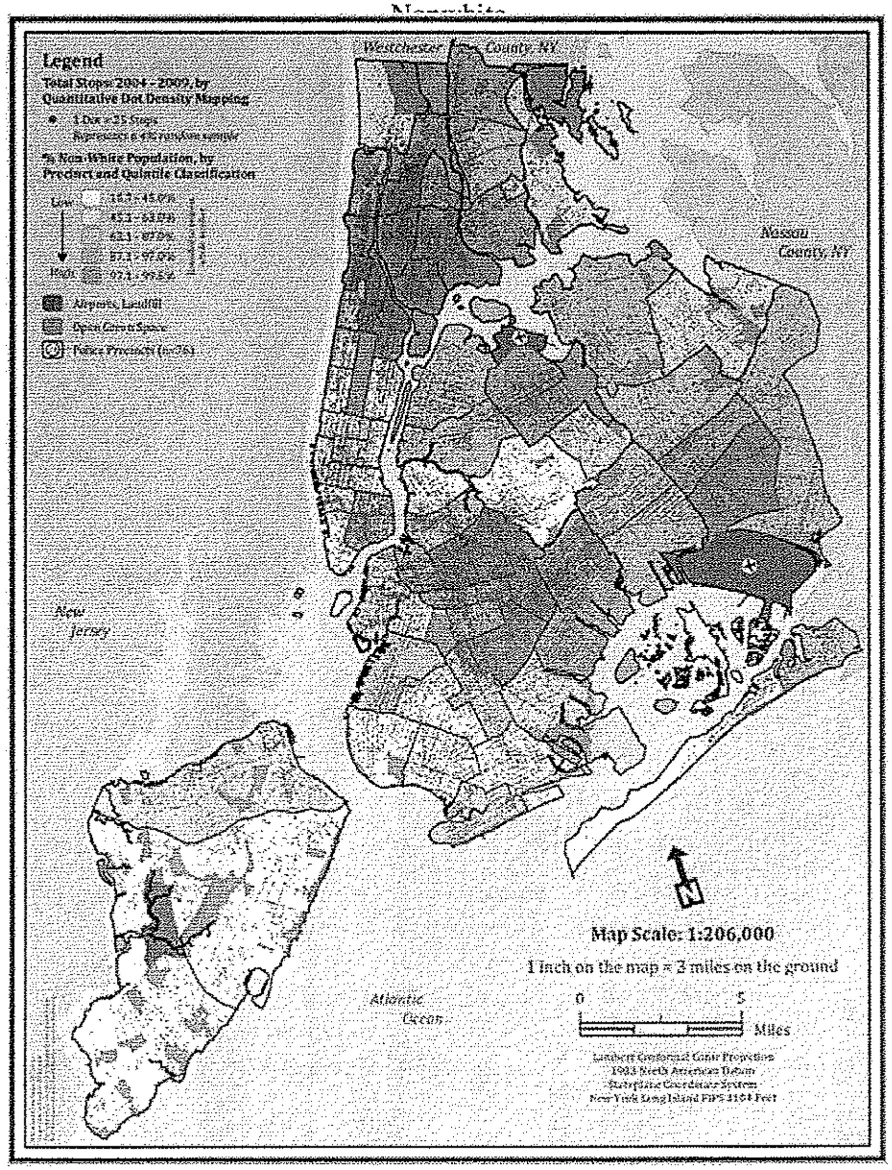


Figure 11: Stops and Crime Rates

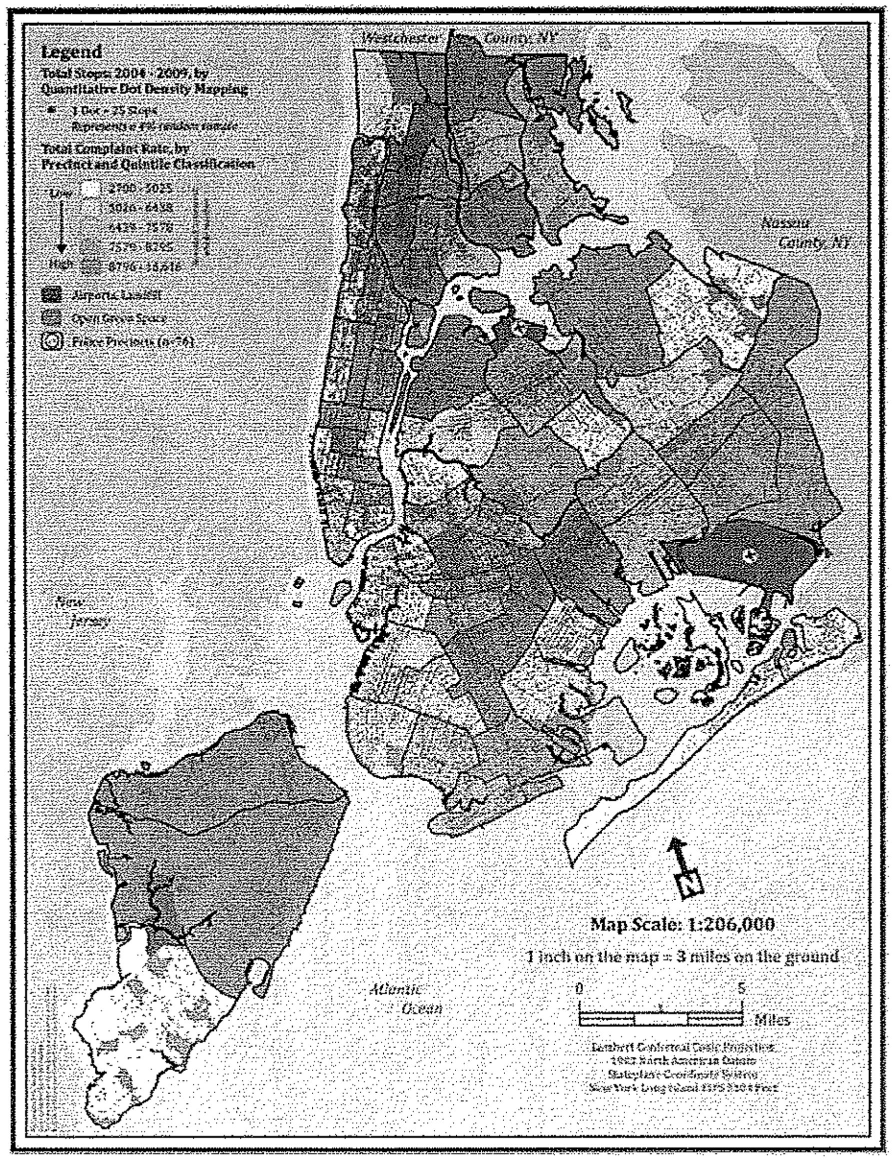
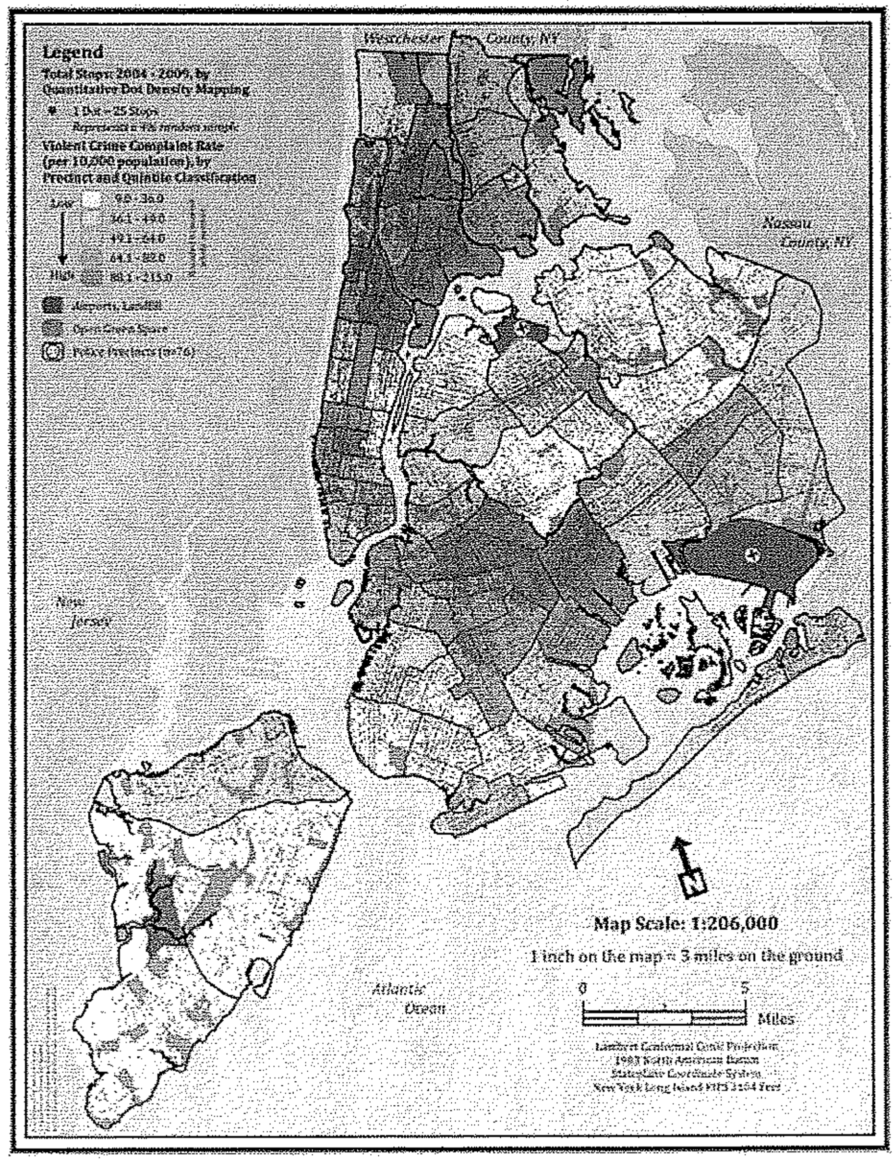


Figure 12: Stops and Violent Crime Rates



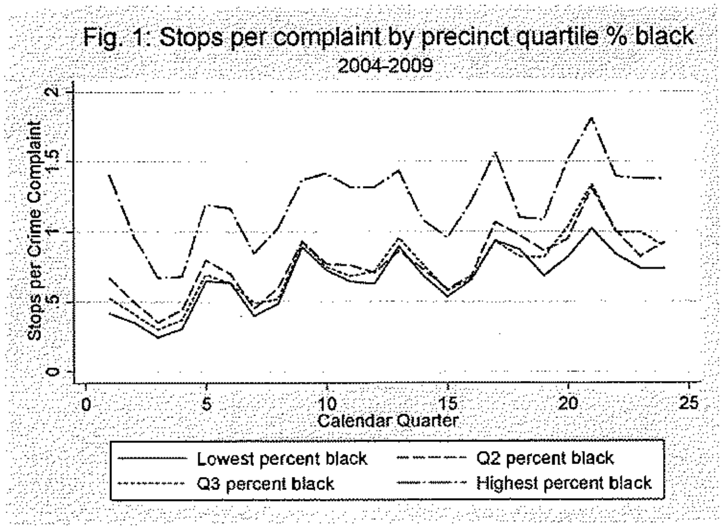


Fig. 1: Stops per complaint by precinct quartile % black
2004-2009
Stops per Crime Complaint
0
.5
1
1.5
2
0
5
10
15
20
25
Calendar Quarter
Lowest percent black
Q2 percent black
Q3 percent black
Highest percent black

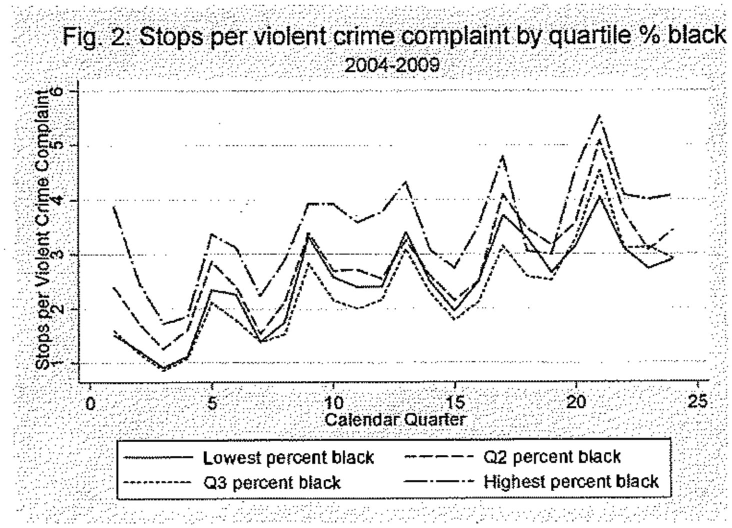


Fig. 2: Stops per violent crime complaint by quartile % black
2004-2009
Stops per Violent Crime Complaint
1
2
3
4
5
6
0
5
10
15
20
25
Calendar Quarter
Lowest percent black
Q2 percent black
Q3 percent black
Highest percent black

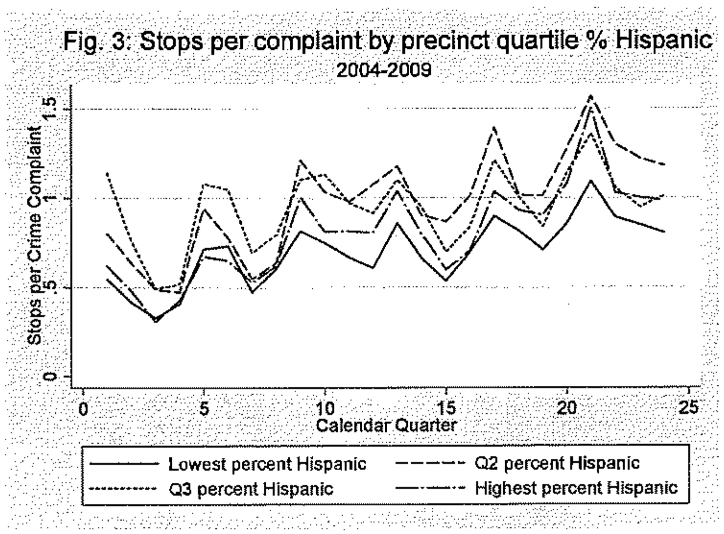


Fig. 3: Stops per complaint by precinct quartile % Hispanic
2004-2009
Stops per Crime Complaint
0
.5
1
1.5
0
5
10
15
20
25
Calendar Quarter
Lowest percent Hispanic
Q2 percent Hispanic
Q3 percent Hispanic
Highest percent Hispanic

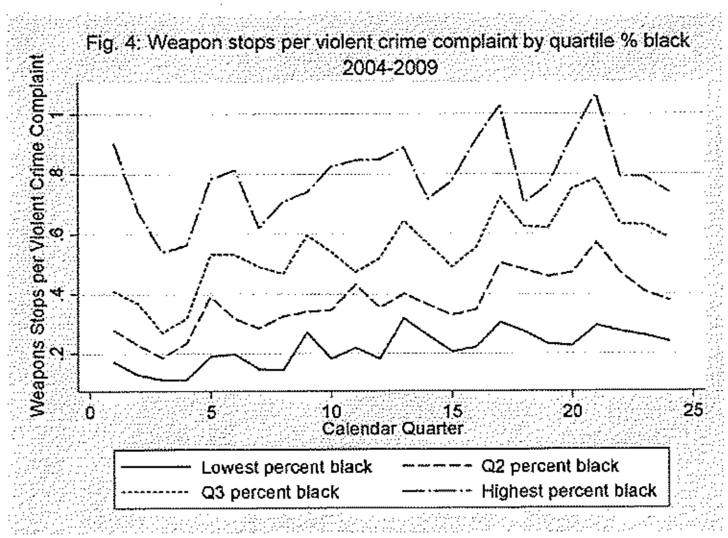


Fig. 4: Weapon stops per violent crime complaint by quartile % black
2004-2009
Weapons Stops per Violent Crime Complaint
.2
.4
.6
.8
1
0
5
10
15
20
25
Calendar Quarter
Lowest percent black
Q2 percent black
Q3 percent black
Highest percent black

IV. Claim I: Disparate Treatment

A. Overview

Plaintiffs claim that NYPD officers have used race and/or national origin as factors that determine whether officers decide to stop and frisk a person, and that Black and Latino males are the population groups most affected by the alleged violation. The analyses here begin with simple descriptions of the distribution of stops by suspect race, and then proceed to multivariate regression models to test whether there are effects on stops due to race, after adjusting for the effects of other factors that may also explain the distribution of stops.

To test these claims, a series of regression analyses were completed that followed the general analytic model discussed earlier:

$$\text{Outcome} = \alpha + \beta_1 * \text{Minority} + \beta_2 * \text{Crime} + \Sigma_i \beta_i * (\text{Plausible Non-Race Influences}) + \varepsilon,$$

Outcome is the event or status of interest, *Minority* is an indicator for the racial composition or status of the unit observed (i.e., precinct or person, depending on the outcome), *Crime* is the local crime conditions disaggregated by type of crime, *Plausible Non-Race Influences* are a set of variables representing non-race factors that also might influence the outcome, and an error term ε that captures the variation in the outcome that cannot be explained by either Crime or Minority status or the Non-Race Influences. All models are adjusted for the total population of the precinct. As discussed earlier, this is the general analytic model used to test claims of disparate treatment and discrimination in a range of policy and legal settings.

For these tests, data are analyzed at the level of the police precinct since precincts (instead of smaller units such as census tracts or police beats) since the regulation and oversight of stop and frisk policy and activities takes place at the precinct level.[51] Precinct commanders are accountable for precinct-level statistics on crime trends, though they have discretion to allocate officers tactically within precincts to specific beats or sectors. However, supervision is precinct-wide. Also, data are aggregated and reported by the NYPD at the precinct level, suggesting that this is the unit of analysis of interest to its central command.

B. Test 1

The first analysis tests whether stops in precincts are disproportionate to the racial composition of the precinct, after controlling for the known crime rate in the

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[51] See, for example, Eli Silverman, THE NYPD FIGHTS CRIME (1999); William Bratton and Peter Knobler, TURNAROUND (1998).

precinct in the previous calendar quarter,[52] and other characteristics that are correlated with crime. Here, the outcome is the number of stops for several types of suspected crime. *Minority* is the racial composition of the precinct. The *non-race influences* may be proxies for race, or they are factors that influence the crime rate. Crime and residential population characteristics – that is, the percent of residential population of each racial group – are the two benchmarks and are the *Minority* factors in the specific test design. Three race categories are included, and the category of percent White is omitted. This is done to avoid collinearity in the model estimation. So, it important to bear in mind that the coefficients for each racial group are based on comparison with the percent White in the precinct. *When a racial composition variable is significant, this means that its relationship to stop activity is significantly different from that of the White racial composition of the precinct.* A significant difference means that this finding is more than 95 percent unlikely to have occurred by chance.

Other controls include the precinct socio-economic status,[53] the percent foreign born[54] (as a proxy for immigrant populations), and the age distribution of the population. A control for patrol strength in the precinct adjusts for the number of officers who are available to make stops and also for the probability of exposure of citizens to police. Another control is a dummy variable to indicate whether

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[52] All models control for the one-calendar-quarter lag of logged crime complaints. The log transformation of the actual number of crimes is used. Log transformation is necessary to adjust when the distributions are highly skewed and non-linear. The lag reflects the planning process whereby SQF and other enforcement activity are adjusted to reflect actual crime conditions. Although COMPSTAT meetings occur more often, using a lag that is too short can confound naturally occurring spikes and declines in crime with reactions to policing. Calendar quarters in effect adjust for those naturally occurring temporal variations.

[53] Socioeconomic status is measured using a principal components factor analysis that incorporates precinct percent poverty, physical disorder, and unemployment. The combined factor explains 81.52% of their combined variance, suggesting that there is little about local poverty that is unobserved in this model.

[54] The percent foreign-born is the percent of the population born outside the 50 United States and Washington DC (i.e., considering Puerto Ricans and other born in U.S. Outlying Territories to be foreign). This population in urban areas is generally considered to present lower crime risks than other non-white populations. See, Robert J. Sampson, "Rethinking Crime and Immigration," *Contexts* (Winter 2008), available at
http://contexts.org/articles/files/2008/01/contexts_winter08_sampson.pdf

precinct contains a predominantly business district of the City.[55] These are places where the population characteristics differ between business hours and nighttime, and where residential population is less meaningful than in other parts of the City.

In addition to a general model of the total number of stops, additional models break down stops into the suspected crime that motivated the stop. For these models, a variable is included that indicates the share of crimes in the precinct in the previous period (calendar quarter) that were of the specific crime type for that model. For example, the model for stops for violent crimes includes a variable for total crime and the percentage of the total crimes that were violent crimes. This allows for estimations of any differences by race in the crime-specific patterns of stops, patterns that may be masked in the larger patterns of stops. Finally, there are controls for year and borough, to account for natural variation across boroughs that are not accounted for by precinct-specific effects.

1. Results

a. *Total and Crime-Specific Models*

Table 5 shows the results of the regressions for Total Stops and each of seven specific categories of suspected crimes. In the model for Total Stops, the percent Black population and the percent Hispanic population predict higher numbers of stops, controlling for the local crime rate and the social and economic characteristics of the precinct. The crime rate is significant as well, so the identification of the race effects suggests that racial composition has a marginal influence on stops, over and above the unique contributions of crime. It is also noteworthy that the size of the coefficients for Percent Black and Percent Hispanic are more than three times greater than the size of the coefficient for the crime rate. Patrol strength also is a significant predictor, suggesting that stops are greater when more officers are available to conduct them. This too is a marginal increase over the crime rate, suggesting that decisions on the allocation of personnel are important to understanding the frequency with which stops take place.

Among the seven crime-specific models, Percent Black is a significant predictor of stops in four of them: violent crime, drug crime, weapons stops, and trespass stops. Percent Hispanic is a significant predictor in four as well: violent crime, property crime, drug crime and weapons crimes. The crime models where

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[55] Business precincts are those with large commercial areas (i.e., the 1st, 6th, 14th and 18th), which we expect to be policed not predominantly on their residential dynamics, but also on the behavior of visitors who pass through.

Table 5. Generalized Estimating Equatiou Regression of Stops by Suspected Crime, Controlling for Precinct Characteristics and Crime Conditions in Prior Quarter [b, SE][a]

	Suspected Crime							
Predictors	*Total Stops*	*Violent Crime*	*Property*	*Drugs*	*Weapons*	*Trespass*	*Other Crimes*	*QOL/ Disorder*
Total Complaints (lagged, logged)	.280 **	.221	-.078	-.326 *	-.011	.196	.378 *	.294
	[.088]	[.150]	[.110]	[.138]	[.142]	[.255]	[.173]	[.240]
% Crime Complaints of Specific Crime Type (lagged)	N/A	-.437	3.048 ***	-.332	-3.505 *	1.849	.108	6.811 **
		[.534]	[.589]	[.757]	[1.787]	[1.373]	[.634]	[2.213]
Percent Black	.867 ***	.854 **	.291	1.926 ***	2.557 ***	1.933 **	.403	-.478
	[.190]	[.326]	[.317]	[.546]	[.336]	[.661]	[.429]	[.531]
Percent Hispanic	.994 **	1.477 **	.985 *	1.963 *	2.386 ***	1.600	.131	.055
	[.320]	[.484]	[.461]	[.779]	[.486]	[1.018]	[.539]	[.690]
Percent Otherrace	.401	1.285 *	.515	.403	.223	1.397	-.373	2.281 **
	[.379]	[.592]	[.496]	[.942]	[.481]	[1.003]	[.571]	[.805]
SES Factor	.096 *	.038	-.115	.118	.231 *	.391 *	.108	.241
	[.049]	[.091]	[.082]	[.117]	[.090]	[.166]	[.119]	[.130]
Percent Foreign Born	-.507	-.201	.051	-.580	.156	-2.171	-.440	-.669
	[.391]	[.620]	[.564]	[.991]	[.647]	[1.219]	[.791]	[.911]
Business Precinct (1st, 6th, 14th, 18th)	-.190	-.243	-.066	.243	-.096	-1.257 ***	.228	-.065
	[.190]	[.261]	[.237]	[.360]	[.246]	[.327]	[.271]	[.305]
Patrol Strength	.002 ***	.002 **	.002 ***	.002 ***	.002 ***	.002 ***	.002 **	.002 *
	[.000]	[.001]	[.001]	[.000]	[.000]	[.001]	[.001]	[.001]
Marginal R^2	.686	.444	.422	.358	.493	.313	.443	.186

Logged Population Exposure
All models include fixed effects for borough and year. Models were estimated with robust standard errors.
Significance: *= p<.05, **= p<.01, ***= p<.001

race or ethnicity is not significant predictors are low-level crimes (e.g., quality of life crimes) or other misdemeanors.

The results for violent crime deserve additional discussion, given the frequency of stops for suspected violent crimes and their importance in policy and practice.[56] In this model, neither the total crime rate nor the share of crimes that are violent are significant predictors. Stops in this model are explained by only the racial composition of the precinct and the patrol strength in the precinct. This suggests that in the search for violent crime suspects, the search seems to be based solely on the racial composition of the area.

The results for weapons stops also deserve special attention, for the same reasons. In this model, racial composition is significant, the crime rate is not significant, and the share of crime for weapons offenses is significant but negative. This suggests that the search for weapons is (a) unrelated to crime, (b) takes place primarily where weapons offenses are less frequent than other crimes, and (c) is targeted at places where the Black and Hispanic populations are highest. Similarly, for drug stops, crime is negative and significant, and the share of crime complaints for drugs also is negative and significant, while the racial composition variables are positive. This pattern suggests that the search for drug offenders is (a) negatively related to rates of crime or drug offenses specifically, and is (b) concentrated in neighborhoods with high proportions of Black and Hispanic residents. It also is noteworthy that the coefficients for the two racial composition variables are quite large.

The overall pattern in Table 5, especially for the most serious and most frequent crime and stop categories, suggests evidence of differential treatment in stop activity of police precincts based on the difference in the racial composition of the precinct between minorities and Whites. These effects are observed over and above any considerations of crime, and beyond the effects of the number of officers who are deployed and available to make stops. Perhaps most important, and in contrast to the stated policy goals of stop and frisk, these effects and are present even when crime rates are not significant predictors of stop activity.

b. Sensitivity Tests

To test the robustness of these results to alternative assumptions about the factors that explain stops, the eight models in Table 5 are replicated seven more

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[56] See, e.g., Spitzer Report, supra note 39. See, also, Letter from Commissioner Raymond Kelly to City Council Speaker Christine Quinn, supra note 6 (citing the relevance of stop and frisk activity to rates of murder and robbery, among other crimes).

times, each with a variation on the modeling assumptions. In the first sensitivity analysis, the control for patrol strength is removed. The second sensitivity analysis is limited to stops that are not radio runs, to focus on the stops that are likely to require more discretion on the part of the officer when determining suspicion. The third sensitivity analysis eliminates both "radio runs" and the control for patrol strength. Stops made pursuant to "radio runs" differ from other discretion-based stops. In "radio runs," officers are dispatched to a crime scene or location based on a citizen report or a report by another officer and where a suspect description *may* be provided by the dispatcher given (as opposed to a "crime in progress" where no description is given). Discretion may be exercised in a narrower manner in these instances, since the officer will be focused on a specific circumstance and her "gaze" is constrained in this way.

The fourth sensitivity test again includes radio runs as well as other stops, again include the control for patrol strength, but focus on more residential areas by eliminating stops made in the "business precincts" (1, 6, 14, and 18). In the fifth sensitivity analysis we return to our baseline model but add a control for the percent of the precinct population that lives in public housing. In the sixth model, the baseline models are re-estimated, splitting the crime control into separate controls for violent crime and property crime (both lagged and logged). Finally, in the seventh sensitivity analysis, we re-estimate the baseline models, but including a control for precinct land area.

The sensitivity tests basically confirm the baseline tests in Table 5, with some variations. Table 6 shows the results of these models, focusing on four critical variables: total crime, the crime-specific share of crime relevant to each model, and two racial composition variables. Recall that these are interpreted as *Percent Minority* compared to *Percent White*. The first panel in Table 6 repeats the results of the models in Table 5, to provide a comparison for interpreting the seven variations.

Variant 1 omits Patrol Strength. The racial composition variables are significant for five of the eight models. This result is observed for crime-specific models of stops for violent crime, drug crime, weapons stops, and trespass (for Percent Black only). A nearly identical pattern results in Variant 2, where radio runs are omitted. This is important, since the non-radio run stops are those instances where officers exercise their discretion and their "search" is not constrained by either the urgency of a crime in progress or by the contours of a specific suspect description. In several of these models, crime is significant, but the pattern of racial composition effects remains significant. So, when looking only at stops where officers have complete discretion, the patterns of racial composition effects that exceed crime effects persist.

Table 6. Sensitivity Analyses for Negative Binomial Regresssions on Stop Counts by Type of Suspected Crime [b, SE]*

	Suspected Crime							
Predictors	*All Crimes*	*Violent Crime*	*Property*	*Drugs*	*Weapons*	*Trespass*	*Other Crimes*	*QOL/ Disorder*
Baseline Models (from Table XX)								
Total Complaints (lagged, logged)	.280 **	.221	-.078	-.326 *	-.011	.196	.378 *	.294
	[.088]	[.150]	[.110]	[.138]	[.142]	[.255]	[.173]	[.240]
% Crime Complaints of Specific Crime Type (lagged)	N/A	-0.437	3.048 ***	-0.332	-3.505 *	1.849	0.108	6.811 **
		[.534]	[.589]	[.757]	[1.787]	[1.373]	[.634]	[2.213]
Percent Black	.867 ***	.854 **	.291	1.926 ***	2.557 ***	1.933 **	.403	-.478
	[.190]	[.326]	[.317]	[.546]	[.336]	[.661]	[.429]	[.531]
Percent Hispanic	.994 **	1.477 **	.985 *	1.963 *	2.386 ***	1.600	.131	.055
	[.320]	[.484]	[.461]	[.779]	[.486]	[1.018]	[.539]	[.690]
Marginal R^2	.686	.444	.422	.358	.493	.313	.443	.186
Variant 1: Omitting Patrol Strength Control								
Total Complaints (lagged, logged)	.548 ***	.462 **	.213	-.059	.146	.485 *	.603 **	.547 **
	[0.106]	[.157]	[.162]	[.151]	[.147]	[.215]	[.159]	[.194]
% Crime Complaints of Specific Crime Type (lagged)	N/A	-.498	2.904 ***	-.031	-3.073	1.642	.061	7.066 ***
		[.514]	[.565]	[.760]	[1.766]	[1.331]	[.638]	[2.187]
Percent Black	1.080 ***	1.008 **	.535	2.177 ***	2.789 ***	2.161 ***	.576	-.361
	[.217]	[.333]	[.345]	[.563]	[0.369]	[.675]	[.444]	[.522]
Percent Hispanic	1.229 **	1.661 **	1.311 *	2.244 **	2.605 ***	1.768	.348	.183
	[.368]	[.520]	[.579]	[.815]	[.559]	[1.027]	[.585]	[.678]
Marginal R^2	.566	.374	.372	.303	.393	.219	.399	.399
Variant 2: Omitting Radio Runs								
Total Complaints (lagged, logged)	.487 ***	.416 **	.441 ***	.316 *	.268	.813 **	.347 *	.519 *
	[.083]	[.125]	[.093]	[.139]	[.146]	[.286]	[.157]	[.219]
% Crime Complaints of Specific Crime Type (lagged)	N/A	.729	1.359 **	2.546 **	2.569	-.899	-.129	-.708
		[.574]	[.507]	[.818]	[1.976]	[1.186]	[.653]	[2.616]
Percent Black	1.187 ***	.958 **	.249	1.814 ***	2.672 ***	2.020 *	.975 *	-.272
	[.241]	[.332]	[.324]	[.555]	[.375]	[.821]	[.447]	[.519]
Percent Hispanic	1.491 ***	1.837 ***	1.323 **	2.231 **	2.638 ***	2.011	.787	.407
	[.376]	[.501]	[.439]	[.834]	[.526]	[1.238]	[.607]	[.704]
Marginal R^2	.672	.433	.359	.371	.492	.337	.475	.160

Variant 3: Omitting Patrol Strength and Radio Runs								
Total Complaints (lagged, logged)	.668 ***	.616 ***	.603 ***	.421 **	.378 **	.952 ***	.527 **	.658 ***
	[.098]	[.127]	[.125]	[.135]	[.140]	[.258]	[.164]	[.174]
% Crime Complaints of Specific Crime Type (lagged)	N/A	0.604	1.334 **	2.586 ***	2.417	-1.096	-0.049	-0.658
		[.558]	[.503]	[.812]	[2.091]	[1.155]	[.623]	[2.585]
Percent Black	1.392 ***	1.146 **	.418	1.964 ***	2.870 ***	2.209 **	1.239 **	-.193
	[.267]	[.348]	[.342]	[.564]	[.398]	[.814]	[.468]	[.523]
Percent Hispanic	1.702 ***	2.050 ***	1.533 **	2.369 **	2.820 ***	2.165	1.056	.493
	[.425]	[.532]	[.510]	[.846]	[.569]	[1.213]	[.680]	[.691]
Marginal R2	.523	.347	.274	.318	.391	.231	.413	.173
Variant 4: Omitting business districts (1st, 6th, 14th, 18th)								
Total Complaints (lagged, logged)	.300 ***	.246	-.068	-.355 *	-.028	.192	.411 *	.352
	[.088]	[.148]	[.112]	[.142]	[.145]	[.252]	[.174]	[.249]
% Crime Complaints of Specific Crime Type (lagged)	N/A	-.384	3.359 ***	-.379	-3.600 *	1.579	.004	7.607 ***
		[.539]	[.607]	[.776]	[1.785]	[1.363]	[.676]	[2.248]
Percent Black	.906 ***	.917 **	.329	1.958 ***	2.574 ***	2.203 *	.432	-.439
	[.191]	[.327]	[.320]	[.557]	[.340]	[.668]	[.434]	[.529]
Percent Hispanic	1.066 **	1.611 **	1.035 *	1.976 *	2.397 ***	1.731	.216	.075
	[.322]	[.485]	[.478]	[.799]	[.496]	[1.035]	[.547]	[.695]
Marginal R2	.685	.449	.415	.349	.484	.370	.440	.197
Variant 5: Controlling for Public Housing Population								
Total Complaints (lagged, logged)	.317 ***	.218	-.094	-.331 *	.002	.062	.376 *	.293
	[.080]	[.150]	[.109]	[.144]	[.142]	[.217]	[.175]	[.240]
% Crime Complaints of Specific Crime Type (lagged)	N/A	-.482	3.273 ***	-.501	-4.079 *	1.434	.145	6.823 **
		[.535]	[.604]	[.797]	[1.987]	[2.812]	[.639]	[2.215]
Percent Black	.714 ***	.821 *	.253	1.818 ***	2.371 ***	1.609 **	.382	-.488
	[.166]	[.328]	[.313]	[.523]	[.304]	[.555]	[.428]	[.536]
Percent Hispanic	.762 ***	1.420 **	.873	1.686 *	2.077 ***	.641	.096	.031
	[.239]	[.498]	[.466]	[.698]	[.427]	[.837]	[.533]	[.664]
Marginal R2	.738	.447	.420	.345	.576	.459	.441	.187

Variant 6: Splitting Complaints								
Total Violent Crime Complaints (lagged, logged)	.002	-.240	-.339 **	-.220	.010	-.296	.064	-.168
	[.097]	[.190]	[.131]	[.131]	[.111]	[.177]	[.175]	[.261]
Total Nonviolent Crime Complaints	.203 ***	.413 ***	.340 *	-.049	-.035	.602 ***	.223 *	.123
	[.054]	[.097]	[.135]	[.090]	[.063]	[.179]	[.094]	[.169]
% Crime Complaints of Specific Crime Type (lagged)	N/A	.648	.686	-.761	-3.655	3.555 *	.429	6.741 ***
		[.853]	[1.115]	[.792]	[1.870]	[1.589]	[.674]	[2.116]
Percent Black	1.029 ***	1.050 **	.339	1.980 ***	2.542 ***	2.402 **	.604	-.369
	[.219]	[.344]	[.327]	[.580]	[.349]	[.738]	[.441]	[.635]
Percent Hispanic	1.135 ***	1.642 ***	1.051 *	2.006 *	2.364 ***	2.040	.299	.030
	[.355]	[.504]	[.459]	[.804]	[.494]	[1.198]	[.568]	[.777]
Marginal R2	.669	.435	.436	.358	.494	.239	.433	.171
Variant 7: Controlling for Land Area								
Total Complaints (lagged, logged)	.284 ***	.246	-.099	-.331 *	.030	.276	.353 *	.323
	[.087]	[.151]	[.110]	[.132]	[.144]	[.255]	[.174]	[.244]
% Crime Complaints of Specific Crime Type (lagged)	N/A	-.434	3.073 ***	-.340	-3.528 *	2.326	.095	6.980 **
		[.531]	[.593]	[.758]	[1.792]	[1.373]	[.641]	[2.235]
Percent Black	.869 ***	.856 **	.276	1.928 ***	2.562 ***	1.915 **	.387	-.464
	[.189]	[.321]	[.319]	[.552]	[.329]	[.638]	[.446]	[.530]
Percent Hispanic	.989 **	1.425 **	1.024 *	1.972 *	2.303 ***	1.432	.163	.011
	[.322]	[.490]	[.468]	[.777]	[.489]	[.980]	[.535]	[.685]
Marginal R2	.687	.444	.433	.356	.497	.343	.459	.182

All models controlled for % of Crime Complaints Specific to Crime Type, Precinct Social and Economic Conditions, and Time
Logged Population Exposure
All models include fixed effects for borough and year. All models estimated with robust standard errors.
Significance: * = p< .05, **= p < .01, ***= p < .001

Variant 3 compounds Variants 1 and 2, omitting both patrol strength and radio runs. Not only are the results the same, but the coefficients for the two racial composition variables are larger.

Variant 4 omits business districts. In the City's primarily residential areas, the racial composition variables again are significant for models of total crime, violent crime, drug crimes, and weapons stops. The same pattern is observed in Variant 5 (when a covariate is added to the model to control for the percentage of the precinct population living in public housing), and in Variant 7, which controls for land area and, in effect, population density and police-citizen exposure.

Variant 6 splits total crime between violent and non-violent crime complaints, to focus specifically on the category of crime that receives the most attention in terms of policy and strategy. The same pattern of effects for the racial composition variables is observed: controlling for a wide variety of social and legally-relevant factors, including crime, the Percent Black and Percent Hispanic composition of the precinct (compared to the Percent White) predicts the stop rate for total crime, violent crime, weapons and drug stops. But what is interesting here and important is the seeming statistical irrelevance of violent crime as a predictor of stop patterns. Stop patterns instead are predicted efficiently by non-violent crimes. Given the emphasis in narrative and in various policy documents on violent crime, this is an unanticipated set of results.

2. Summary

A set of regressions tested whether stop patterns are explained by crime (controlling for population size), and whether the racial contribution of the precinct explains the stop patterns net of crime and other legally and socially relevant control variables. The results show consistently, across the most policy-relevant and frequent crime categories, that racial composition predicts stop patterns over and above any predictions made by crime or other factors. In effect, overall stop patterns in the precincts are predicted more by the Percent Black and Percent Hispanic (compared to Percent White) than by observed crime. These results are robust to a set of alternate controls and alternate set of conditions and contexts. The durability of the results across both crime types in the baseline models and across variations in suggests that in fact, the racial composition of an area plays an important role in conduct of stops that exceeds the role of crime, social conditions, or the allocation of police resources.

C. Test 2

1. Analytic Design

Test 2 presents an alternate strategy to identify the effects of race on patterns of stops. The additional dimension of this test is an analysis of individual effects by racial groups within precincts. The test uses the multilevel modeling strategy described in Section II.B.2. In this test, the data are structured so that individual racial groups (referred to as "Level 1") are nested within each precinct ("Level 2"). Precincts are, in turn, nested within the 24 calendar quarters of the analysis ("Level 3"). The outcome of interest is the number of stops made of suspects of each racial group, in each precinct, in each calendar quarter, or *total stops* of each group-precinct-quarter observation. The racial differences in stop patterns are estimated at level one, with a series of dummy variables to indicate each group ("Black", "Hispanic", and "Other Race", with Whites omitted to serve as a basis for comparison). Coefficients on the dummy variables represent the different prevalence of stops among each racial group. The availability of suspects to be stopped, and other factors that might predict police activity, are controlled with Level 2, or precinct level, characteristics. The same set of covariates that were used in the previous set of analyses is used here to test the contributions of precinct crime and social conditions on stop patterns. In addition, a set of seasonality controls is included to adjust the estimates for differences in crime rates by time of the year.[57]

There are two parameters that convey information about the racial distribution of the stops. The first is a test of the significance of the individual-level race predictors described above. Because stops of Whites are the omitted group, the Black, Hispanic, and Other coefficients represent differences between Whites and each group. A positive value of a group's regression parameter (unstandardized coefficient, or *b* in the model results) means that the stop count for that group is greater than that of whites – in other words, that controlling for precinct crime and demographic conditions, persons in this racial or ethnic group are more likely to be stopped. As in any other significance test: a p-value of less than .05 shows the finding to be systematic and not a chance occurrence.

The second test assesses whether, in addition to the comparison of minority groups to Whites, stop patterns of individual minority groups differ systematically

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[57] There is a long tradition of studies of the seasonality of crime and the theoretical explanations for why crime varies by season. See, e.g., John R. Hipp et al., "Crimes of Opportunity or Crimes of Emotion? Testing Two Explanations of Seasonal Change in Crime," 82 *Social Forces* 1333 (2004).

from each other.[58] To do this, we test for equivalence of the race coefficients, in the form:

$$H_0: \gamma_{01} = \gamma_{11} = 0$$

where γ_{01} is the effect of Black (compared to White) on number of stops and γ_{11} is the effect of Hispanic (compared to White) on the number of stops. If there is no difference, the result of the Chi-square test of the differences will be not significant. No difference in this case would mean that there are no differences by race among Blacks, Whites and Hispanics. The results of the test are reported at the bottom of each table.

As before, models are estimated first for all stops, and then crime-specific models are estimated that control for the portion of all crimes specific to the crime-specific stops for each model. Sensitivity analyses test the robustness of general findings to varying model assumptions (i.e., which variables are included or how they are measured) and to varying but legally or statistically important subsamples of study populations.

2. *Results*

a. *Total and Crime-Specific Models*

In Tables 7-10, the results are divided into two "panels." The top panel compares the stop patterns of each race group within precincts. The regression coefficients for Black, for example, show the significance and effect size of stops of Blacks on the total number of stops in the precinct from 2004-9. The lower panel shows the effects of the precinct-level variables, similar to the variables that were tested in Test 1. The effects in the upper panel are conditional on (or net of) the effects in the lower panel.

Table 7 shows results from the models predicting stops, by race, per precinct-quarter. As in Tables 5 and 6, the first column presents estimates from the model examining total stops, and subsequent columns represent crime-specific stops. Each model's results indicate that stops of Black and Hispanic suspects are more common by precinct, controlling for the precinct context in which stops take place. For example, the coefficients on precinct characteristics in Table 7's "total stops" model indicate that stops, on average, are more prevalent in high-crime and high-population precincts and calendar quarters, in precincts with large Black and

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[58] Technically, this is a test of whether the effects of each parameter (race group) on the slope outcome are the same or different.

Table 7. Multilevel Poisson Regressions on Stops by Suspected Crime, Controlling for Precinct Characteristics and Crime Conditions in Prior Quarter* (b, SE)

	Suspected Crime						
	Total	Violent Crime	Property	Drugs	Weapons p	Trespass	QOL/Disorder
Race-Group Indicators (as compared to whites)							
Blacks	1.613 ***	1.927 ***	.617 ***	1.648 ***	2.535 ***	2.643 ***	.176 ***
	[.002]	[.006]	[.004]	[.007]	[.007]	[.009]	[.014]
Hispanics	1.070 ***	1.439 ***	.504 ***	.986 ***	1.838 ***	1.807 ***	.114 ***
	[.002]	[.006]	[.004]	[.007]	[.007]	[.009]	[.015]
Others	-.281 ***	.127 ***	-.579 ***	-.348 ***	.391 ***	.194 ***	-.804 ***
	[.003]	[.008]	[.005]	[.010]	[.008]	[.012]	[.019]
Precinct-Level Characteristics							
Total Complaints (lagged, logged)	.257 ***	.079	.099	.448 **	.503 ***	.781 ***	.791 ***
	[.063]	[.124]	[.133]	[.138]	[.116]	[.164]	[.148]
Percent Crime-Specific Complaints (lag	N/A	4.371 ***	-0.48	2.759 ***	11.504 ***	10.175 ***	-0.784
		[.594]	[.588]	[.738]	[2.392]	[2.010]	[1.953]
Percent Black	.935 ***	.459 **	-.128	1.094 ***	1.936 ***	1.080 ***	-.753 ***
	[.076]	[.163]	[.169]	[.171]	[.154]	[.201]	[.180]
Percent Hispanic	.565 ***	.652 **	.101	1.165 ***	1.793 ***	.408	-.566 *
	[.107]	[.213]	[.236]	[.240]	[.208]	[.289]	[.254]
Percent Other Race	.731 ***	2.054 ***	.970 **	.947 **	.869 **	2.123 ***	1.963 ***
	[.150]	[.295]	[.322]	[.331]	[.283]	[.393]	[.352]
Low SES Factor	-.011	-.138 **	-.419 ***	-.119 *	.022	.230 ***	.007
	[.022]	[.043]	[.048]	[.050]	[.041]	[.058]	[.000]
% Foreign Born	.133	.941 **	1.394 ***	-.785 *	.264	-1.967 ***	.020
	[.159]	[.315]	[.345]	[.353]	[.303]	[.422]	[.377]
Patrol Strength	.003 ***	.004 ***	.004 ***	.003 ***	.003 ***	.004 ***	.001 *
	[.000]	[.000]	[.000]	[.000]	[.000]	[.001]	[.000]
Population (logged)	.104 *	-.187 *	-.131	-.491 ***	-.275 **	-.557 ***	-.237 *
	[.044]	[.088]	[.095]	[.097]	[.083]	[.117]	[.108]
Business Precinct (1st, 6th, 14th, 18th)	-.441 ***	-.301 *	-.573 **	-1.135 ***	-.759 ***	-2.193 ***	-.660 ***
	[.073]	[.147]	[.165]	[.161]	[.139]	[.194]	[.171]
Seasonality Parameters (Q4=comparison group)							
Q1	.333 *	.282 *	.360 **	.365 **	.250 **	.512 ***	.335 *
	[.146]	[.106]	[.089]	[.109]	[.068]	[.112]	[.154]
Q2	.167	.155	.252 **	.348 **	.209 **	.185	.490 **
	[.139]	[.102]	[.086]	[.105]	[.066]	[.111]	[.147]
Q3	.032	-.026	.098	.195	.196 **	-.075	.108
	[.139]	[.101]	[.085]	[.104]	[.065]	[.108]	[.147]
Test (black=hispanic)							
Chi-Squared, p	150757.4 ***	18824.566 ***	1192.995 ***	20044.77 ***	48561.757 ***	39859.961 ***	19.115 ***

Poisson models predict stop totals by race group, within precinct and calendar quarter
Unit-Specific Estimates, Nonrobust Standard Errors
Significance: * p <.05, ** p <.01, *** p <.001

Hispanic populations, and precincts where more officers are deployed. The coefficients on the race-group indicators indicate that after controlling for these precinct characteristics, Blacks and Hispanics are stopped in greater numbers than Whites, and suspects of other races are stopped less.

In the crime-specific stops in subsequent models, the precinct characteristics that predict stop patterns vary slightly by type of suspected crime, with (lagged and logged) crime complaints predicting drug stops, weapon stops, trespass stops, and quality-of-life stops, but not violent or property crime stops. Precinct percent Black is associated with more stops on suspicion of violent, drug, weapons, and trespass arrests, but fewer stops on suspicion of quality-of-life offenses. Precinct percent Hispanic is associated with more stops on suspicion of violent, drug, and weapons offenses, and fewer stops on suspicion of quality-of-life offenses. However, while the precinct-level relationships vary, the "Level One" relationship is robust: controlling for precinct characteristics – including crime levels and the relative availability of individuals of each racial group to be stopped (based on their population representation) – Blacks and Hispanics are stopped more often than Whites are. Moreover, the larger magnitude of the Black coefficient, combined with the significant chi-squared test comparing Black and Hispanic stop levels, indicate that Blacks are stopped more frequently than both Whites and Hispanics.

b. Specific Subsets of Precincts

Tables 8, 9, and 10 show similar results when narrowing the focus by three sets of precinct characteristics: residential areas, commercial areas, and precincts that are racially mixed or predominantly white. Table 8 shows the results for tests excluding the four "commercial" precincts, and focus exclusively on places that are primarily residential. Table 9 analyzes only those four precincts that are intensive commercial areas. These are areas where residential population is less important than residential areas in local crime conditions. Table 10 examines predominantly White or racially heterogeneous precincts.

Table 8 shows the results for the models excluding the four commercially-dominated precincts. For Total Stops, Blacks and Hispanics are significantly more likely to be stopped than Whites, net of the other crime and social contextual factors in the precinct. The results of the hypothesis tests confirm what the individual regression parameters show. This finding is reproduced in each of the crime-specific models. The effect sizes vary: they are largest for Blacks and Hispanics for violent crimes, trespass, and weapons offenses. The effects are smaller but still significant for property offenses and disorder or quality of life offenses, offenses that are less typically associated with any particular type of place or population

Table 8. Multilevel Poisson Regression on Stops by Suspected Crime, Controlling for Precinct Characteristics and Crime Conditions in Prior Quarter, Excluding Commercial Precincts [b, SE]*

	Suspected Crime						
	Total	*Violent Crime*	*Property*	*Drugs*	*Weapons*	*Trespass*	*QOL/ Disorder*
Race-Group Indicators (Whites=Reference Group)							
Blacks	1.627 ***	1.941 ***	.567 ***	1.679 ***	2.592 ***	2.681 ***	.121 ***
	[.002]	[.006]	[.004]	[.007]	[.007]	[.009]	[.015]
Hispanics	1.094 ***	1.464 ***	.501 ***	1.022 ***	1.892 ***	1.844 ***	.115 ***
	[.002]	[.007]	[.004]	[.007]	[.007]	[.009]	[.015]
Others	-.263 ***	.144 ***	-.581 ***	-.326 ***	.439 ***	.225 ***	-.822 ***
	[.003]	[.008]	[.005]	[.010]	[.009]	[.012]	[.020]
Precinct-Level Characteristics							
Total Complaints (lagged, logged)	.192 **	.187	.075	.532 ***	.619 ***	1.145 ***	.784 ***
	[.067]	[.133]	[.144]	[.147]	[.125]	[.176]	[.160]
Percent crime-specific complaints (lagged)	N/A	4.513 ***	-.268	1.914 *	10.799 ***	9.236 ***	-.556
		[.609]	[.621]	[.774]	[2.443]	[2.038]	[2.058]
Percent Black	1.023 ***	.408 *	-.077	1.145 ***	1.908 ***	.868 ***	-.748 ***
	[.078]	[.169]	[.179	[.175]	[.16]	[.207]	[.187]
Percent Hispanic	.677 ***	.660 **	-.037	1.226 ***	1.785 ***	.275	-.549 *
	[.109]	[.220]	[.246]	[.245]	[.215]	[.295]	[.262]
Percent Other Race	.840 ***	2.140 ***	1.000 **	1.057 **	.922 **	2.133 ***	1.983 ***
	[.151]	[.303]	[.332]	[.334]	[.291]	[.399]	[.361]
Low SES Factor	.003	-.180 ***	-.409 ***	-.113 *	-.009	.126 *	.003
	[.023]	[.046]	[.051]	[.052]	[.044]	[.061]	[.055]
% Foreign Born	-.069	1.055 **	1.294 ***	-.864 *	.396	-1.417 **	.033
	[.165]	[.330]	[.365]	[.365]	[.319]	[.438]	[.397]
Patrol Strength	.002 ***	.004 ***	.003 ***	.003 ***	.003 ***	.005 ***	.001 *
	[.000]	[.000]	[.000]	[.000]	[.000]	[.001]	[.001]
Population (logged)	.198 ***	-.323 **	-.090	-.544 ***	-.403 ***	-1.009 ***	-.246
	[.052]	[.104]	[.114]	[.116]	[.100]	[.139]	[.131]
Seasonality Parameters (Q4=Reference Group)							
Q1	.334 *	.301 *	.356 ***	.357 **	.267 ***	.561 ***	.319 ***
	[.145]	[.109]	[.091]	[.105]	[.069]	[.121]	[.160]
Q2	.159	.179	.252 **	.356 **	.233 **	.243	.479 ***
	[.138]	[.105]	[.088]	[.102]	[.067]	[.117]	[.153]
Q3	.026	-.021	.102	.205	.209 **	-.055	.100 ***
	[.138]	[.103]	[.087]	[.100}	[.065]	[.114]	[.152]
Test (black=hispanic)							
Chi-Squared	140691.21	17650.406	377.639	19263.026	48433.713	39773.64	0.153
p	***	***	***	***	***	***	

Poisson models predict stop totals by race group, within precinct and calendar quarter
Unit-Specific Estimates, Nonrobust Standard Errors
Significance: * p<.05, **p<.01, ***p<.001

group. The effects for the Level 2 precinct characteristics are similar to the effects reported in the regression models in Test 1.

To some extent, these results are simple reflections of the overall tendency for the number of stops of Blacks to exceed stops of Whites. But the regression coefficients in the upper panel are adjusted for the coefficients or effects in the lower panel, which are the precinct-level effects. Controlling for crime levels and other non-racial characteristics, there are statistically significant differences between Blacks, Hispanics and Whites across all crime types, regardless of the characteristics of the places where these stops take place.

Table 9 shows the same models for the commercial precincts, where racial composition of the population has a different meaning and structure than in the City's residential areas. Since the local racial composition and other social contextual factors are less relevant to local conditions in these precincts than are crime conditions, they were omitted from the models. The tests here, then, are limited solely to the precinct crime conditions and patrol strength. The models produce the same results in these precincts, using a simple set of controls for crime, crime-specific events, and patrol strength. Blacks and Hispanics are consistently more likely to be stopped than are Whites in these places, both for total stops and for each of the crime-specific categories. Both the regression coefficients and the hypothesis tests are significant, and confirm the disparity.

Table 10 shows the same models examining the 32 precincts with the upper 50 percent of White population in the City in 2006.[59] These precincts are either racially heterogeneous or predominantly White.[60] Focusing on these areas reduces the risk that observed racial disparities in stop rates are driven solely by the elevated stop levels in predominantly Black precincts, reported in Tables 5 and 6. In the subsample of White and mixed race precincts, Blacks are stopped significantly more often than are Whites or Hispanics, a pattern that is also present when focusing on stops for violent crime, drug offenses, weapons possession, or trespass offenses. On the other hand, Whites in these precincts are more likely than Blacks to be stopped for property or quality of life offenses.

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[59] These 32 precincts span all five boroughs, and include 9, 10, 13, 17, 19, 20, 24,45, 49, 50, 60,61, 62, 63, 66, 68, 70, 76, 78, 84, 90, 94, 100, 104, 106, 107, 109, 111, 112, 120, 122, 123. The four business precincts – 1, 6, 14, 18 – are excluded from this analysis, and are treated separately in other analyses.

[60] The average percent of the population that is White in these precincts is 51 percent, and ranges from 30 to 84 percent. The average percent Black population in these precincts is 11 percent, ranging from less than one percent to 41 percent.

Table 9. Multilevel Poisson Regression on Stops by Suspected Crime, Controlling for Precinct Characteristics and Crime Conditions in Prior Quarter, Commercial Precincts Only*

	Suspected Crime						
	Total	*Violent Crime*	*Property*	*Drugs*	*Weapons*	*Trespass*	*QOL/ Disorder*
Race-Group Indicators (as compared to whites)							
Blacks	1.296 ***	1.525 ***	1.539 ***	.925 ***	.635 ***	.403 ***	1.096 ***
	[.010]	[.031]	[.019]	[.031]	[.031]	[.055]	[.067]
Hispanics	.419 ***	.609 ***	.594 ***	.082 *	.224 ***	-.169 **	.092
	[.011]	[.035]	[.022]	[.036]	[.034]	[.062]	[.080]
Others	-.705 ***	-.387 ***	-.517 ***	-.800 ***	-.841 ***	-1.076 ***	-.396 ***
	[.015]	[.044]	[.028]	[.046]	[.046]	[.084]	[.091]
Precinct-Level Characteristics							
Total Complaints (lagged, logged)	-1.486 **	-1.212 *	-.500	2.270 **	-.641	-1.075	1.591
	[.468]	[.535]	[.449]	[.783]	[.500]	[.726]	[.908]
Percent crime-specific complaints (lagged)	N/A	-2.220	-5.236 ***	26.479 ***	26.572 *	30.439	-5.537
		[1.919]	[1.03]	[2.616]	[10.728]	[38.643]	[6.207]
Patrol Strength	.007 ***	.005 ***	.005 ***	.002	.005 ***	.006 ***	.000
	[.001]	[.001]	[.001]	[.002]	[.001]	[.002]	[.002]
Population (logged)							
Seasonality Parameters (Q4=reference group)							
Q1	.209	.164	.483 **	.768 ***	.121	.254	.564 *
	[.127]	[.138]	[.13]	[.198]	[.124]	[.187]	[.234]
Q2	-.062	-.085	.122	.609 *	-.065	-.059	.743 **
	[.136]	[.148]	[.134]	[.213]	[.136]	[.203]	[.254]
Q3	.061	.038	.017	.147	.104	.026	.247
	[.122]	[.131]	[.121]	[.191]	[.118]	[.180]	[.225]
Test (black=hispanic)							
Chi-Squared	11298.7	1414.448	3906.178	806.99	197.162	98.895	242.769
p	***	***	***	***	***	***	***

Poisson models predict stop totals by race group, within precinct and calendar quarter
Unit-Specific Estimates, Nonrobust Standard Errors
Significance: * p<.05, **p<.01, ***p<.001

Table 10. Multilevel Poisson Regression on Stops by Suspected Crime, Controlling for Precinct Characteristics and Crime Conditions in Prior Quarter*
(Predominantly White and Racially Heterogeneous Precincts)

	Suspected Crime						
	Total	Violent Crime	Property	Drugs	Weapons	Trespass	QOL/ Disorder
Race-Group Indicators (as compared to whites)							
Blacks	.394 ***	.961 ***	-.346 ***	.389 ***	1.292 ***	1.598 ***	-.862 ***
	[.003]	[.008]	[.005]	[.010]	[.009]	[.012]	[.021]
Hispanics	.219 ***	.660 ***	-.082 ***	.070 ***	.774 ***	.848 ***	-.524 ***
	[.003]	[.008]	[.005]	[.010]	[.010]	[.013]	[.019]
Others	-.959 ***	-.454 ***	-1.034 ***	-1.291 ***	-.800 ***	-.755 ***	-1.535 ***
	[.004]	[.011]	[.007]	[.016]	[.015]	[.019]	[.028]
Precinct-Level Characteristics							
Total Complaints (lagged, logged)	.574 ***	.501 **	.156	.745 ***	.852 ***	1.144 ***	1.179 ***
	[.086]	[.186]	[.210]	[.186]	[.167]	[.222]	[.225]
Percent of (past-quarter) complaints of specific crime type	N/A	3.247 ***	-3.655 ***	23.354 ***	22.468 ***	37.834 ***	5.925 *
		[.981]	[.805]	[1.948]	[4.619]	[5.443]	[3.003]
Percent Black	.439 *	-1.231 *	-3.824 ***	-1.333 **	2.104 ***	.852	-2.601 ***
	[.214]	[.538]	[.566]	[.484]	[.433]	[.579]	[.575]
Percent Hispanic	.774 ***	1.150 **	.231	.107	1.928 ***	1.503 **	-1.580 ***
	[.176]	[.396]	[.448]	[.413]	[.363]	[.481]	[.479]
Percent Other Race	.629 *	1.485 *	.098	-1.796 **	-.209	-.022	-.554
	[.303]	[.681]	[.776]	[.684]	[.615]	[.818]	[.799]
Low SES Factor	.119 **	-.065	-.459 ***	-.448 ***	.090	.240 *	-.165
	[.041]	[.097]	[.107]	[.096]	[.085]	[.113]	[.113]
% Foreign Born	.364	2.027 **	2.819 ***	3.076 ***	1.533 **	.972	2.099 **
	[.281]	[.628]	[.711]	[.632]	[.578]	[.756]	[.743]
Patrol Strength	.001 **	.007 ***	.007 ***	.005 ***	.004 ***	.009 ***	.004 ***
	[.000]	[.001]	[.001]	[.001]	[.001]	[.001]	[.001]
Population (logged)	.147 *	-.429 **	-.291	-.298 *	-.368 **	-.621 ***	-.446 **
	[.059]	[.133]	[.149]	[.136]	[.120]	[.157]	[.168]
Seasonality Parameters (Q4=reference group)							
Q1	.355 *	.289 **	.444 ***	.326 **	.288 **	.439 ***	.321
	[.166]	[.112]	[.118]	[.104]	[.094]	[.125]	[.241]
Q2	.217	.178	.278 *	.270 **	.266 **	.218	.431
	[.158]	[.109]	[.115]	[.103]	[.092]	[.123]	[.231]
Q3	.044	-.051	.062	.187	.223 *	-.077	.018
	[.158]	[.107]	[.113]	[.099]	[.090]	[.120]	[.230]
Test (black=hispanic), Chi-Squared	4327.183	2247.190	2409.942	1132.826	5235.136	1417.607	206.810
p	***	***	***	***	***	***	***

Poisson models predict stop totals by race group, within precinct and calendar quarter
Unit-Specific Estimates, Nonrobust Standard Errors
Significance: * P <.05, ** P <.01, *** P <.001

V. Claim 2 – Lack of Reasonable and Articulable Suspicion

A. Overview

Plaintiffs cite two specific Fourth Amendment violations. First, they allege that there is a pattern of stops of City residents (and presumably visitors) that are done outside the parameters of "reasonable and articulable suspicion" as set forth under the Fourth Amendment and subsequent caselaw.[61] In addition to reviewing the empirical evidence for these claims, I also examine evidence regarding the intersection of the Fourth and Fourteenth Amendment claims. Specifically, I assess whether each of these claims are more likely to affect Black and Latino citizens.

B. Reasonable and Articulable Suspicion

1. Standards and Thresholds

Fourth Amendment jurisprudence demands that a suspect's behavior reach a threshold of reasonable and articulable suspicion (RAS) that justifies the police intervention.[62] Under New York law, police need an "articulable reason" to justify approaching a suspect for the purpose of requesting background information or to ask "basic, nonthreatening questions", applying the familiar *DeBour* standard for searches and seizures.[63] To ask "more pointed" questions indicating that the suspect is under suspicion of violating the law requires a "founded suspicion that criminal activity is afoot."[64] Current practice, as reflected in the UF-250 data, is for an officer to first determine that the circumstances of the encounter with an individual meets the standards for RAS before proceeding to detain and question that person, and then to record the bases for RAS within the catergories listed on the form. This categorization of information takes place after the stop has been completed.

The categories available for NYPD officers to record the bases of RAS are a set of indicia derived from aggregate experiences of officers in conducting stop and

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[61] Second Amended Complaint, *David Floyd et al. v. City of New York et al.*, U.S. District Court for the Southern District of New York, 08 Civ. 01034 (SAS), October 2008, at § 2.

[62] See, Barry Kamins, NEW YORK SEARCH & SEIZURE § 2.04 (Matthew Bender, Rev. Ed. 2009),

[63] See generally *People v. De Bour*, 352 N.E.2d 562 (1976) (articulating the standard for search and seizure under New York common law).

[64] Id.

frisks over many years, and cabined by both federal and New York State caselaw. Accordingly, the most natural way to think about these indicia of suspicion is that they are group-based identifiers rather than markers of individual behavior. For the most part, suspicion attaches to group-based traits, conditions, and behaviors: the police identify sets of individuals with motives, such as individuals who match a drug courier profile, individuals whose behavior fits a patter of someone casing a store for a possible burglary, individuals who fit an eye-witness description, individuals who occupy a specific location where crimes may be prevalent, or individuals whose movements signal that they are concealing contraband. These are not individual markers of suspicion, but in fact are constructed categories that the officer who has determined that a suspect is "suspicious" must use as an organizing scheme to express the bases of suspicion. In other words, if a suspect "looks like a perp", as former NYPD officer Perry Bacon[65] characterized as the basis for many stops, the categories of RAS on a UF-250 provide an institutional mechanism for re-organizing the behaviors or other information that formed that signal.

2. Implementation of the Legality Standards

The constitutional sufficiency of stops was determined from the primary "circumstances of the stop" and the "additional circumstances" noted for each record in the UF-250 database. Stops are classified as either "legally justified", "unjustified" based on noted justifications, or of indeterminate legality. Based on the memorandum in Appendix D, each of the nine "circumstance" categories was analyzed to determine whether it would be sufficient to justify a stop on its own, or if it would be legally sufficient only when applied in conjunction with other stop factors or additional circumstances that were present in the case.

Because stop circumstances are listed in a check-box format on the back of the UF-250 form, officers may indicate any number of the 10 circumstances listed, or that "other" circumstances apply. There are therefore 1,024 possible combinations of primary circumstances that could be indicated, a number that grows exponentially when considering the 1,024 possible combinations of "additional circumstances" that could apply (plus "other additional circumstances). The enormous number of combinations of circumstances made an analysis of the legal sufficiency of individual cases extremely difficult, unwieldy and uninformative.

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[65] Perry Bacon, BAD COP: NEW YORK'S LEAST LIKELY POLICE OFFICER TELLS ALL (2009).

Instead, using the analyses of prima facie sufficiency or conditional sufficiency of each stop circumstance discussed in Appendix D, stops were classified as justified, unjustified, or indeterminate, according to the following criteria:

1. Stops are **justified** if the circumstances provided are considered sufficient as the sole rationale for the stop and need no additional information or qualification (i.e., Casing, Drug Transactions, or Violent Crime)
2. Stops are **justified** if the circumstances listed are conditionally justified (e.g., carrying a suspicious object, fitting a suspect description, acting as a lookout, wearing clothing indicative of a violent crime, furtive movements, or a suspicious bulge in one's clothing), and an "additional circumstance" is also indicated.
3. Stops are **unjustified** if no primary stop circumstances are provided. For example, stops are **unjustified** if the only listed circumstances is that the suspect was present in a high crime area. Stops that list "Other Stop Factors" only are unjustified.
4. Stops are of **indeterminate** legality if the circumstance or circumstances listed are (all) conditionally justified, and no additional circumstances are provided.
5. Stops are of **indeterminate** legality if the only circumstances listed are "other circumstances" or if no additional circumstances are indicated.

The estimates of legal sufficiency are most likely generous. That is, this coding scheme overestimates the extent to which stops are legally justified since some of the combinations of "conditionally legal circumstances" and "additional circumstances" are still insufficient to justify a stop without detailed circumstantial information. [66]

3. Descriptive Statistics

a. Stop Factors by Crime Type

Table 11 shows the percentage of cases citing each stop factor and additional circumstance, by category of suspected crime. Radio runs are excluded from this table, since these are instances where officers are responding either to specific circumstances or other information that narrows their discretion with respect to RAS. With the exception of *furtive movements* and *high crime area*, the stop factors and additional circumstances are cited unevenly across the crime categories, though

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[66] See Appendix D for discussion of the subjective and conditional nature of each Stop Circumstance.

Table 11. Percent of Stops with Each Stop Justification by Crime Suspected, Excluding Radio Runs*

	Suspected Crime							
	All Stops	*Violent*	*Property*	*Drug*	*Weapons*	*Trespass*	*QOL*	*Other*
Stop Circumstances								
Suspicious Object	2.8	0.8	5.1	1.6	2.2	0.3	9.1	4.2
Fits Description	13.6	31.7	10.5	6.5	13.5	3.7	12.1	13.7
Casing	26.5	47.0	49.4	6.7	9.9	11.9	26.9	26.4
Acting as Lookout	16.0	20.9	24.0	16.8	8.5	10.4	20.4	15.3
Clothing	3.9	6.0	2.9	1.5	5.6	1.4	5.0	4.3
Drug Transaction	11.5	1.2	0.9	68.5	5.2	5.8	2.5	9.9
Furtive Movements	42.3	38.7	34.4	39.5	60.0	27.3	35.8	44.3
Actions of Violent Crime	6.3	14.6	4.9	1.7	7.4	1.6	2.1	6.2
Suspicious Bulge	10.4	2.9	1.2	1.5	34.4	1.3	2.0	10.2
CS- Other	21.7	9.4	23.3	13.7	10.0	60.0	32.0	21.8
Additional Circumstances								
Report of Witness	9.4	16.1	7.3	7.1	9.0	5.1	10.3	10.3
Ongoing Investigation	12.2	25.5	14.9	5.8	10.1	3.8	9.5	11.3
Proximity to Crime Scene	17.2	26.1	13.6	13.1	19.5	12.4	17.7	17.0
Evasive Response	16.2	16.3	14.5	16.6	18.3	7.1	14.2	19.9
Associating with Known Criminals	3.5	3.3	2.4	6.5	4.0	2.0	6.0	3.5
Changed Direction	24.7	25.1	23.5	27.8	29.5	13.1	25.5	25.5
High Crime Area	55.4	52.1	60.6	59.9	49.4	62.5	54.3	53.3
Time of Day	34.1	34.8	38.3	30.9	30.6	35.8	30.8	34.2
Sights and Sounds of Criminal Activity	1.8	2.0	3.3	1.5	1.2	0.4	2.9	2.0
AC - Other	4.5	3.5	4.7	4.4	3.9	5.6	7.3	4.6

N=2,233,027 stops from 2004-9, excluding Radio Runs
* Totals exceed 100% due to multiple justifications per stop

with some correspondence to the suspected crime. For example, drug transaction is cited in more than two stops in three where the suspected crime is a drug transaction. And casing is cited in nearly half the stops where a property crime was suspected. *Fits description* was cited in about one third of the cases where violent crime was suspected.

However, there also are several circumstances where the substantive meaning of the stop factor or additional circumstance does not match the crime category. For example, *casing* is cited in nearly half the cases where a violent crime is suspected. *Furtive movements* are checked off in more than one third of the stops where other crimes are suspected, and nearly half the quality of life offenses. And high crime area is checked off in more than half the cases.

In fact, *furtive movements* and *high crime area* are the two most common items checked off on the UF-250. As discussed in Appendix D, these two categories are notable in two ways: they both are subject to subjective and highly contextualized interpretation, and they both – either separately or in conjunction with one another – are legally insufficient to justify a stop. Both *high crime area* and *furtive movement* in fact turn out to be poor indicia that "crime is afoot", to use the language and jurisprudential meaning in *Terry*, or the notion of high crime area as articulated in *Wardlow*.[67] In cases where officers checked off "high crime area" as an additional circumstance, the hit rate – that is, the number of cases resulting in arrest – was 5.14 percent. But in cases where high crime area was <u>not</u> checked, the hit rate was 6.27 percent, or 22 percent higher. In other words, although *high crime area* is the most often cited circumstance, it is cited in cases where the RAS was more than 20 percent more likely to be unfounded. The efficiency of stops in fact declines when this broad and subjective net of suspicion is applied.

The same problem arises with *furtive movements*. The arrest rate in cases where furtive movement was checked was 5.11 percent, compared to 6.03 percent in cases where it is not checked, a difference of 18 percent. This commonly cited factor of individualized suspicion in fact, as practiced by the City, is also an inefficient marker in the search for criminal offenders. It seems to be invoked so often and in such disparate circumstances to suggest that it is almost meaningless.

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[67] *Terry v. Ohio*, 392 U.S. 1 (1968); *Illinois v. Wardlow*, 120 S. Ct. 673 (2000). See, also, Andrew Guthrie Ferguson & Damien Bernache, "The 'High-Crime Area' Question: Requiring Verifiable and Quantifiable Evidence for Fourth Amendment Reasonable Suspicion Analysis," 57 *American University Law Rev.* 1587, 1588 (2008) (demonstrating current Supreme Court jurisprudence provides those stopped in "high-crime area" with less robust Fourth Amendment protections).

For example, retired NYPD officer Peter Mancuso, speaking at a New York City Bar Association forum on "stop and frisk" in March 2010, said that the high rate of checking off furtive movements on the UF-250 suggests that RAS standards are not being used to select individuals for stops. Mr. Mancuso stated that:

> "Furtive movements ... tells me that the cops are out there winging it a bit ..... they're really not looking for individuals".[68]

Figure 13 seems to support Mr. Mancuso's characterization, and by extension, the use of high crime area as an additional circumstance. The figure shows that both furtive movements and high crime area are used somewhat promiscuously and indiscriminately. When the precincts are divided into five groups based on their average crime rate (from crime complaints) over the 2004-9 analysis period for this report, the percentage of cases where high crime area is checked off is constant, even as the average number of stops increases across the quintiles. In other words, there is no sensitivity in the use of this marker of RAS to the actual crime rates in the area. No doubt there are high crime pockets in each of the precincts, regardless of the precinct's overall crime rate, but most likely there are more of them in precincts with higher crime rates, and – more importantly – far fewer of them in low crime precincts.[69] The pattern of cases where furtive movements are checked off suggests a similar pattern of indiscriminate use of this criterion to justify stops.

The broad and indiscriminate use of *furtive movement* or *high crime area* – the two most commonly cited factors – and the loss of crime detection efficiency in cases where either are checked off – raises doubts about whether stops based on these factors are valid markers of RAS. Recall that the stop factors are entered onto the UF-250 form **after** the stop is completed. If the initial basis for suspicion leading to the stop was thin, then adding on either of these subjective and ill-defined factors, both of which are constitutionally problematic[70], provides a post hoc justification to

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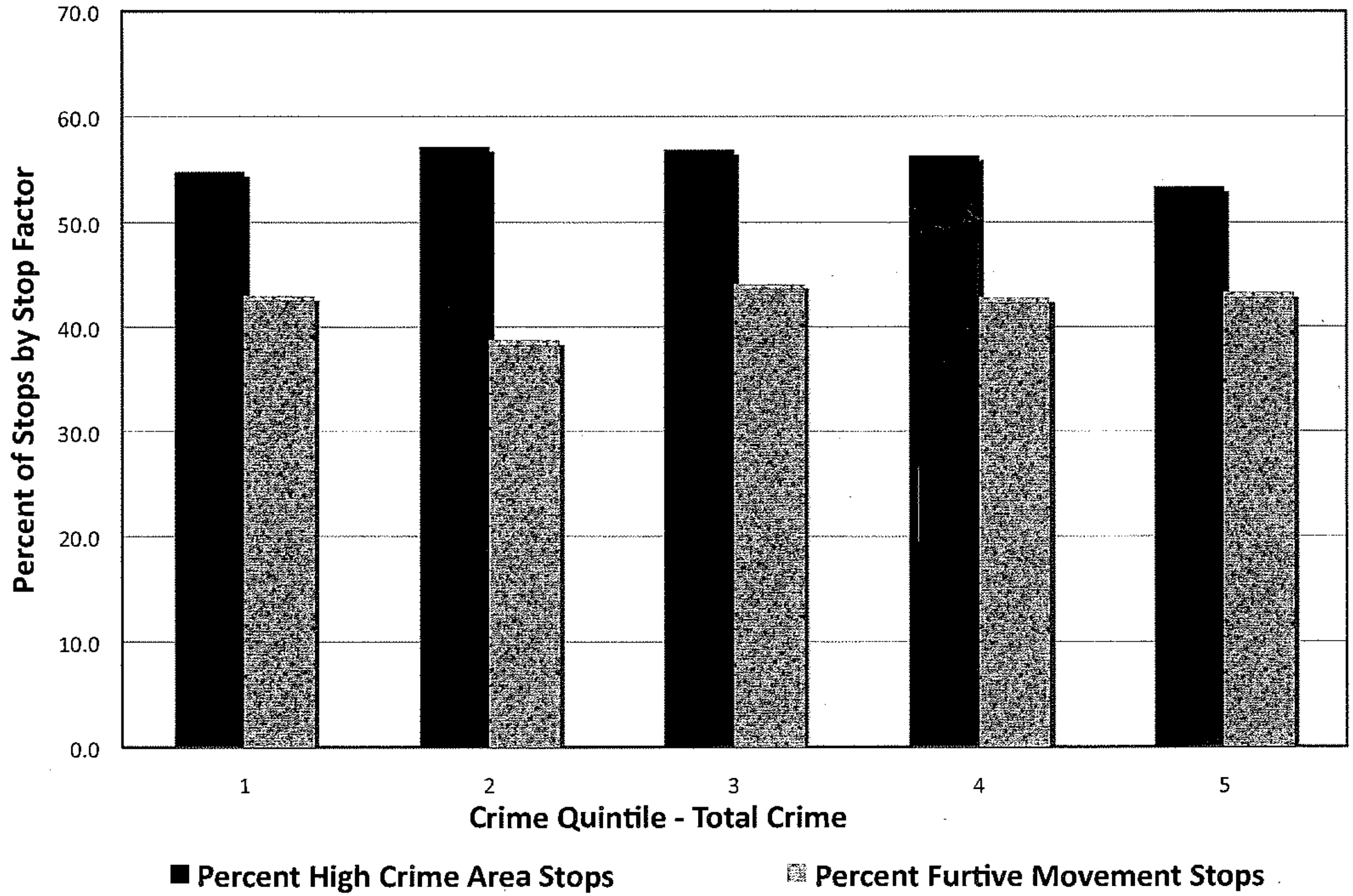
[68] See, John Jay College of Criminal Justice, The New York Police Department's Stop and Frisk Policies (transcript), 40-41, March 9, 2010, Association of the Bar of the City of New York.

[69] See, David Weisburd et al., "Trajectories of Crime at Places: A Longitudinal Study of Street Segments in the City of Seattle." 42 *Criminology* 283 (2004).

[70] *See People v. Powell*, N.Y.S.2d 725, 727-28 (1st Dep't 1998) (holding that officers did not have reasonable suspicion to frisk a suspect walking with his arm stiffly against his body in a high crime area); *United States v. McCrae*, 2008 U.S. Dist. LEXIS 2314, *9-*10 (E.D.N.Y. January 11, 2008) (holding that an officer did not have reasonable suspicion to stop a suspect who moved his hand from the center of his stomach to the left side of his waist in a manner that the officer claimed was similar to how an officer handles firearms while in plain clothes); *United*

Figure 13. Percent High Crime Area Stops by Total Crime Quintile



a stop that was most likely erroneous with respect to whether crime was afoot, and might have been based on a threshold of suspicion that otherwise would have been legally insufficient to justify the stop.

b. Stops by Legal Sufficiency

The stop factors and additional circumstances were classified into three categories of legal sufficiency as described above, applying the caselaw standards discussed in Appendix D. Overall, 68.9 percent of all stops were classified as legally justified. About one in four (24.4 percent) were classified as indeterminate, with too little information to classify the stop as justified, and 6.7 percent were legally insufficient. Overall, nearly 30 percent of all stops appear to be either facially unconstitutional, or lacking sufficient information to make a complete determination.

These results challenge the viability of the current regulatory regime for assessing the presence of reasonable and articulable suspicion in a pedestrian stop.[71] The fact that the legal sufficiency of 31 percent of all stops cannot be shown suggests that the current regime for regulating the constitutional sufficiency of the huge volume of stops is ineffective and insensitive to the actual conduct of stops.

Legal sufficiency also varies by the suspected crime. Table 12 shows the results of the classification of stops by legal sufficiency disaggregated by suspected crime. Radio runs are analyzed separately from other stops, since radio runs may be less likely to be based on individualized suspicion than other exigencies or circumstances, and afford the police officer less discretion. For non-radio runs, in the lower panel of Table 12, the percentage of justified stops ranges from a low of 38.56 in trespass stops to a high of 85.84 percent for drug stops.

The high rate of indeterminate legality in trespass stops may result from the design of the stop factors, since "other" was checked off in 60 percent of the stops for this suspected crime. On the other hand, it could also reflect serious constitutional problems in the legal sufficiency of vertical patrols in public housing that typify trespass enforcement in New York City.[72] State courts have treated trespass

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[71] See, e.g., William Stuntz, "Terry's Impossibility," 72 *St. John's Law Review* 1213 (1998); See, also, Bernard E. Harcourt and Tracey L. Meares, "Randomization and the Fourth Amendment," Working Paper, University of Chicago Law School, available at http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1665562

[72] Adam Carlis, "The Illegality of Vertical Patrols," 109 *Columbia Law Review* 2002 (2009).

Table 12. Legal Sufficiency of Stops by Suspected Crime (% of Stops)

		Legal Sufficiency		
Radio Runs	N	*Justified*	*Indeterminate*	*Unjustified*
Total Stops	572,694	68.03	26.71	5.26
Violent Crime Stops	105,405	77.60	17.50	4.90
Property Crime Stops	149,763	71.36	25.01	3.62
Drug Stops	35,732	82.17	13.15	4.68
Weapon Stops	83,387	60.96	29.70	9.34
Trespass Stops	60,686	43.11	51.64	5.25
QOL Stops	8,464	64.09	30.45	5.46
Other Stops	129,257	68.99	26.05	4.96
No Radio Runs	N	*Justified*	*Indeterminate*	*Unjustified*
Total Stops	2,233,027	68.92	24.37	6.71
Violent Crime Stops	312,442	82.10	12.84	5.06
Property Crime Stops	413,276	75.11	20.33	4.56
Drug Stops	228,131	85.84	9.98	4.18
Weapon Stops	449,614	63.35	24.35	12.30
Trespass Stops	261,419	38.56	55.38	6.06
QOL Stops	25,764	59.77	32.98	7.25
Other Stops	542,381	69.18	24.81	6.00

stops and arrests as individual occurrences, each subject to Fourth Amendment review standards,[73] determining their legality based on the familiar *De Bour* standard for searches and seizures, rather than assessing the legality of the tactic itself.[74] This is because location alone does not provide the reasonable suspicion necessary for an investigatory stop.[75] Yet, by checking off "other" as a stop factor in the majority of trespass stops, the question of the circumstances of the stop become highly questionable and, in turn, constitutionally problematic.[76]

The highest rate of unjustified stops was for weapons offenses. Nine percent of the radio runs and 12.3 percent of the non-radio runs were classified as unjustified. This results in large part from the extensive use of *furtive movements* as a stop justification for weapons offenses: 60 percent of stops where a weapons offense was suspected were justified in whole or part by *furtive movement*. Another legally indeterminate stop factor, *suspicious bulge*,[77] was cited in 34.4 percent of weapons stops, and *high crime area* in nearly half the weapons stops. The use of these broad, highly discretionary and ill-defined indicia of suspicion, which on their

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73 *See, e.g., People v. Crawford*, 719 N.Y.S.2d 18, 19 (N.Y. App. Div. 2001) (failing to question the legality of TAP and finding officer had "an objective credible reason" to approach suspect); *People v. Thompson*, 686 A.D.2d 242, 243 (N.Y. App. Div. 1999) (failing to assess legality of vertical patrols when upholding a conviction for drug possession); *People v. Plower*, 574 N.Y.S.2d 337, 338 (N.Y. App. Div. 1991) (same).

74 *See generally People v. De Bour*, 352 N.E.2d 562 (1976) (articulating the standard for search and seizure under New York common law).

75 See, e.g., *United States v. See*, 574 F.3d 309, 313--14 (6th Cir. 2009) (finding unconstitutional stop that took place in high crime area because police lacked sufficient additional factors to create reasonable suspicion).

76 Similarly, if stops that take place during vertical patrols turn out to be systematic seizures, then the practice may violate the Supreme Court's ruling in *City of Indianapolis v. Edmond*, which struck down a narcotics roadblock because it constituted systematic, suspicionless seizures for the purpose of general crime control. *City of Indianapolis v. Edmond*, 531 U.S. 32, 34, 36 (2000)

77 Without more evidence or information available to the officer, the observation of a bulge in a suspect's clothes, even a suspect's waistband, cannot lead to reasonable suspicion and justify a stop or a frisk. *See People v. Barreto*, 555 N.Y.S.2d 303, 304 (1st Dep't 1990) (holding that an officer who saw a suspect run holding his waste and saw bulge in the suspects waistband lacked reasonable suspicion); *People v. Williams*, 554 N.Y.S.2d 23, 24 (1st Dep't 1990) (noting that case law consistently holds that "mere observation of an unidentifiable bulge in a person's pocket is insufficient" as basis for handgun frisk). Nevertheless, an officer may frisk an individual if he observes a bulge that is plainly shaped like a firearm. *People v. Prochilo*, 41 N.Y.2d 759, 762 (N.Y. 1977).

own are constitutionally problematic, may be contributing to the elevated rate of unjustified weapons stops. This is a weighty issue in thinking about the accuracy of the current regime for ascertaining RAS, since weapons offenses comprise 19.0 percent of all stops and ranks second in stop frequency behind only felony property crimes.

4. Stop Factors and Stop Patterns

a. Analytic Strategy

The previous analyses examine the derivation and application of stop factors in the conduct of stop and frisk activity. Conclusions regarding the legality of stop patterns – that is, on their legal sufficiency to meet constitutional standards for reasonable and articulable suspicion – were based both on a benchmark of constitutional standards and on the validity of their application to various contexts. These two dimensions of RAS have challenged Fourth Amendment jurisprudence both before and after *Wardlow*.[78]

The next analysis approaches this question in a different way. If RAS is functioning well as a set of standards that guide the discretion of officers making stops under the SQF guidelines articulated in the NYPD Patrol Guide,[79] the inclusion of these standards in a regression analysis predicting stop patterns should result in an overall improvement in the explanation of patterns of stops. That is, if the stop factors as implemented reflect a consistent and accurate pattern of the application of Fourth Amendment RAS standards, model fit – in other words, the capacity of a statistical model to capture the variance of a phenomenon across sampling units – should improve.[80] Also, the regression coefficients for non-legal factors should

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[78] *Illinois v. Wardlow*, 120 S. Ct. 673 (2000). See, e.g., Bernard E. Harcourt and Tracey L. Meares, "Randomization and the Fourth Amendment", supra note 71. See, also, Bernard E. Harcourt, "Rethinking Racial Profiling: A Critique of the Economics, Civil Liberties, and Constitutional Literature, and of Criminal Profiling More Generally," 71 *U. Chi. L. Rev.* 1275, 1292 (2004); Sherry F. Colb, "Innocence, Privacy, and Targeting in Fourth Amendment Jurisprudence," 96 *Colum. L. Rev.* 1456 (1996); William Stuntz, "Terry's Impossibility," supra note 71; Debra Livingston, "Police Discretion and the Quality of Life in Public Places: Courts, Communities and the New Policing, 97 *Colum. L. Rev.* 551 (1997).

[79] New York City Police Department, Patrol Guide Manual (2006 ed.), § 211-11, 696-7.

[80] The goodness of fit of a statistical model describes how well it fits a set of observations. Measures of goodness of fit typically summarize the discrepancy between observed values and the values expected under the model in question. Such measures can be used in statistical

diminish in magnitude and the variables representing the legal standards should become the strongest predictors of patterns of stops for each of the several types of crimes.

This test was conducted by re-estimating the regression models discussed in Sections IV.B. *supra* and in Table 5 *supra*. For each model in Table 5, the same model was completed again, this time including a variable for the percent of all stops in the precinct where each factor was checked. So, each model for this analysis included variables for (1) precinct racial composition, (2) precinct socio-economic status, (3) local crime conditions,[81] the percentage crime complaints that corresponds to the suspected crime for the model, (5) patrol strength, (6) a dummy variable indicating that the precinct was (or was not) one of the four business precincts, and (7) the average number of stops in the precinct and calendar quarter where each stop factor and additional circumstance was reported. Also, since multiple factors were checked for each stop, a variable for the average number of factors for each stop was included. All models controlled for the residential population of the precinct.

Table 13 summarizes four features of these analyses for each crime-specific model. First, it shows which of the stop factors or additional circumstances were significant positive predictors of the number of stops. Next, the table shows the negative predictors. These are stop factors or additional circumstances that were significantly less likely to be checked off on the UF-250 for each type of crime. Then, the table shows the marginal R^2, or explained variance, of the new models that include the stop factors. Fourth, it shows the change in R^2 – that is, the improvement over the model without stop factors or its weakening – when the stop factors and additional circumstances are included. Finally, the table expresses the change in R^2 as a percent change.

b. Results

The significant positive factors for Total Stops were *lookout* and *high crime area*. Both seem odd as predictors in a general model of stops that is nonspecific with respect to type of crime. *Lookout* reflects, perhaps, the high number of felony property crime stops, which is the most frequent stop category. *High crime area* is cited as a frequent factor in all types of crimes, including the two most common crime categories – property and weapons. The frequent and promiscuous use of

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hypothesis testing. See, e.g., David W. Hosmer and Stanley Lemeshow, "Goodness of Fit Statistics for the Logistic Regression Model," 9 *Communications in Statistics* 1043 (1980).

[81] Local crime conditions included the total number of crime complaints in the previous calendar quarter, and, for the crime-specific models, the percentage of complaints that are specific to that model.

high crime area suggests that officers may rely on this factor as a rationalization under conditions of uncertainty" as to the other constitutional bases for the stop.[82] The negative factors do not suggest any particular pattern or logic for this model. Overall improvement in model fit is .07 (seven percent), a negligible improvement over an already robust R^2 of .74. Here, then, the stop factors and additional circumstances do little to improve the model, and raise questions as to the validity of the selection and application of which among the stop factors are actually invoked. In other words, it is hard for an observer to draw a picture of RAS based on which stop factors or additional circumstances are invoked.

The results of the crime-specific models vary along the five criteria for assessing the value-added of the stop factors and additional circumstances. In general, the positive predictors fit the specific crime category. In other cases, the significant positive predictors seem meaningless with respect to the type of crime: Quality of Life/Disorder crimes are predicted by *lookout* and *associating with criminals*. Neither of these factors are suggestive of the types of suspected crimes in this category, and hint that stops for this type of suspected offense are based on vague criteria with respect to that particular set of offenses. The negative predictors suggest no particular pattern or meaning with respect to the suspected crimes of which they are putative predictors.

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[82] See, Ferguson and Bernache, High Crime Area Doctrine, supra note 67, for a review of the elasticity of the concept of "high crime area" and its challenges to reviewability, both in doctrinal caselaw and in practice.

Table 13. Factors Predicting Stop Rates by Suspected Crime and Change in Model Fit, Stops Excluding Radio Runs

Suspected Crime	*Positive Predictors*	*Negative Predictors*	*Model Fit*	*Overall Model Improvement*	*% Model Improvement*
Total Stops	Lookout High Crime Area	Suspicious Object Fits Description Casing Furtive Movements Report by Witness Evasive Response Associating with Criminals	.74	.07	10.4
Violent Stops	Actions of Violent Crime Ongoing Investigation	Suspicious Object Drug Transaction Suspicious Bulge CS - Other Report by Witness Evasive Response Assocation with Criminals	.49	.06	12.5
Property Stops	Casing Lookout	Fits Description Drug Transaction Furtive Movements Suspicious Bulge Evasive Response Associating with Criminals	.42	.06	17.5
Weapons Stops	Furtive Movements Actions of Violent Crime Suspicious Bulge	Fits Description Casing AC - Other Report by Witness Sights and Sounds of Crime	.29	-.20	-41.1
Trespass Stops		MODEL FAILS TO CONVERGE			
Drug Stops	Lookout Drug Transaction	Suspicious Object Fits Description Casing Furtive Movements Actions of Violent Crime Report by Witness Associating with Criminals	.49	.12	31.3
QOL Stops	Lookout Associating with Criminals	Casing Drug Transactions Suspicious Bulge Report by Witness	.22	.06	38.1

The more important basis for determining whether RAS as indicated is informing stops is whether model fit improves. That is, model fit should improve over chance when more potentially explanatory information is included in as predictors in the model to explain stops. In other words, more information should lead to less chance, and a more systematic understanding of how often, where and under what circumstances take place.

Table 13 shows that model fit improvement is modest, ranging from .06 to .12 in some cases. An improvement of .06, beyond a baseline R^2 of .49 in explained variance for violent crime, is a small and negligible improvement that conveys little new information. An improvement of .06 over a rate of .42 in explained variance for property crime also is a negligible improvement that offers no new information to better understand the distribution of stops. In one instance in Table 13, the model fit decreases, and by a relatively large amount: .20 (or -41.1% over the baseline model without stop factors). This suggests that the addition of RAS factors in the model actually introduces noise and uncertainty and weakens any interpretation of how and why stops take place, rather than reducing chance.

C. Stop Outcomes and the Accuracy of RAS Determinations

Another way to examine the accuracy of determinations of RAS determinations is to compute how often stops lead to either arrests or other legal sanctions. RAS determinations are predictions that crime is afoot or has recently occurred. An accurate determination of RAS could lead the apprehension of an offender who has just committed an offense, the apprehension of someone who is carrying contraband (including weapons), or the identification of a suspect in a prior crime who is still and large and sought by the police. This is commonly known as a "hit rate" analysis.[83] "Hit rates" are considered along two dimensions: whether a stop leads to an arrest of a suspect or a summons, and whether contraband is seized. Contraband includes guns, weapons (including guns), and contraband (e.g., stolen property, drugs, or perhaps weapons). In addition, the intersection of Plaintiffs' Fourth and Fourteenth Amendment claims can be assessed by

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[83] Steven N. Durlauf, "Assessing Racial Profiling," 116 *The Economic Journal* F402 (2006); John Knowles, Nicola G Persico, and Petra E. Todd, "Racial Bias in Motor Vehicle Searches: Theory and Evidence," 109 *Journal of Political Economy* 203 (2001); Jeff Dominiwitz and John Knowles, "Crime Minimization and Racial Bias: What Can We Learn from Police Data?" 116 *The Economic Journal* F368 (2006).

disaggregating "hit rates" by suspect race as well as by the racial composition of police precincts.

1. Descriptive Statistics

a. *Arrests, Summons, and Use of Force*

Table 14 shows the hit rates for four different stop outcomes. When probable cause is found for further legal sanctions by an officer, the suspect may be either taken into custody pursuant to an arrest, or the suspect may be issued a summons ordering her to appear either at a police precinct or in court. In addition, officers may use force in effecting the arrest.

Overall, the 5.37 percent of all stops result in an arrest; the range is from and 5.74 percent for Hispanic suspects to 4.61 percent for other race suspects. Summonses are issued at a slightly higher rate: 6.26 percent overall, with a range from 6.17 percent for other race suspects to 6.78 percent for Hispanic suspects. Force is used in nearly one stop in four, with force far more likely to be used against Black suspects (24.12 percent) and Hispanic suspects (24.75 percent) than White suspects (17.85 percent). When a more restrictive definition of force is used,[84] these disparities are narrow, yet still present. Hispanic suspects are more likely to be subject to this stronger use of force (8.45 percent) compared to White (7.65 percent) or Black suspects (7.51 percent).

b. *Seizure of Contraband*

Seizures of weapons or contraband are extremely rare. Overall, guns are seized in less than one percent of all stops: 0.15 percent. Weapons, including guns, knives, cutting instruments, or other weapons, are seized in less than one percent (0.94 percent) of all cases. Contraband, which may include weapons but also includes drugs or stolen property, is seized in 1.75 percent of all stops.

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[84] Putting suspect on the ground, pointing a firearm at the suspect, handcuffing the suspect, placing suspect against a wall or a car, drawing firearm, use of baton, use of pepper spray

Table 14. Stop Outcomes by Suspect Race (Percent of Stops)

	Stop Outcome				
Suspect Race	*Stops*	*Arrest*	*Summons*	*Force (Any)*	Force 2
White	286,753	5.63	6.33	17.85	7.65
Black	1,445,472	5.39	6.68	24.12	7.51
Hispanic	841,755	5.74	6.78	24.75	8.45
Other Race	224,447	4.61	6.17	21.49	7.94
Race Unknown	7,294	5.06	5.21	18.17	5.26
Total	2,805,721	5.37	6.26	23.51	8.02

Force 2 is the use of any force other than "hand on suspect"

Table 15. Seizures of Weapons or Other Contraband by Suspect Race (Percent of Stops Resulting in Seizures)

Suspect Race	*Stops*	*% Gun Seizure*	*% Weapon Seizure*	*% Contraband Seizure*
White	286,753	.08	1.07	2.22
Black	1,445,472	.20	.90	1.74
Hispanic	841,755	.12	1.04	1.70
Other Race	224,447	.10	.74	1.31
Race Unknown	7,294	.05	.69	1.52
Total	2,805,721	.15	.94	1.75

To put these performance indicators in perspective, "hit rates" in random checkpoint cases, where persons are stopped randomly in a search for drugs, often are far more successful. In *City of Indianapolis v. Edmond*,[85] the City of Indianapolis operated vehicle checkpoints to find unlawful drugs. Each stop was conducted without reasonable suspicion or probable cause. The 1,161 vehicle stops produced 55 drug related arrests and 49 non-drug related arrests, resulting in a 4.74 percent drug-arrest hit rate and an overall 8.96 percent hit-rate.[86] Other examples of checkpoint cases suggest comparable "hit rates". In *Martinez-Fuerte*[87] – a border immigration case - and *Sitz*[88] – a sobriety checkpoint case – "hit" rates were 0.12 and 1.6 percent respectively.[89] Accordingly, the NYPD stop and frisk tactics produce rates of seizures of guns or other contraband that are no greater than would be produced simply by chance.

2. Predicting Stop Outcomes

Identification of stop outcomes raises issues that address the intersection of Fourth and Fourteenth Amendment claims. The analytic method is a multilevel logistic regression, where suspect race, age and the suspected crime are the predictors, and precinct crime and social conditions are the conditioning variables. The regression coefficients are reported as odds ratios. An odds ratio of 1.0 implies that there is no difference in the odds of a member of a group having the outcome of interest. An odds ratio of greater than 1.0 means that the person is more likely to receive that outcome; an odds ratio of less than 1.0 means that the person is less likely to receive that outcome. For example, an odds ratio of 1.27 means that the person is 27 percent more likely to receive that outcome. An odds ratio of .73 means that the person is 27 percent (1.0 - .73) less likely to receive that outcome.[90] In these analyses, White suspects are the omitted or reference group, so that the odds ratio is a

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[85] 531 U.S. 32 (2000). During the random vehicle stop, an officer would conduct an open-view examination of the vehicle while another officer would walk a narcotics-detection dog around the vehicle.

[86] *Id.* at 35.

[87] See *United States v. Martinez-Fuerte*, 428 U.S. 543, 96 S.Ct. 3074 (1976)

[88] *Michigan Dept. of State Police v. Sitz*, 496 U.S. 444, 110 S.Ct. 2481 (1990)

[89] Sitz, id. The searches in both these cases were upheld, but primarily because the Court agreed that there was a grave and legitimate public interest involved in these checkpoint-type cases that was distinct from "normal law-enforcement needs." No such claim is made by Plaintiffs in their public discourse on the stop and frisk tactics of the NYPD. See, e.g., the letter from Police Commissioner Raymond Kelly to City Council Speaker Christine Quinn, April 29, 2009, supra note 1.

[90] See, Akiva Liberman, "How Much More Likely? The Implications of Odds Ratios for Public Policy," 26 *The American Journal of Evaluation* 253 (2005).

comparison of odds for the named group (Black, Hispanic or Other Race suspects) with Whites.

Models were estimated for two sets of outcomes. The first analysis examined whether an arrest or summons was issued, as well as whether force was used. Sanction first was examined as the likelihood of any sanction, whether arrest or summons. Then, the odds of an arrest was estimated, but only for those who received any summons. In other words, the table reports the odds of an arrest versus a summons, conditional on any sanction.[91] The second set of models examined seizures of weapons, contraband or guns.

a. Sanctions

Table 16 shows the regression results, and Figure 14 shows these results graphically. Black suspects are significantly less likely to receive any sanction. The odds ratio is .917, which means that they are 8.3 percent less likely than Whites to receive any sanction. The odds ratio for Hispanics was not significant. Other Race suspects were 11.7 percent less likely than White suspects to receive any sanction.

Among those receiving any sanction, Blacks were 31.4 percent more likely than White suspects to be arrested versus summonsed, and the result was statistically significant. There was no significant difference for Hispanics or Other Race suspects compared to Whites. It is important to remember that these differences in arrest likelihood control for the suspected crime, and here the results show some important differences. Stops for weapons offenses were significantly more likely to result in any sanction (71.1 percent, compared to a reference of property stops), but less likely to result in arrests (26.4 percent). Since arrest or summons charges were not systematically recorded, it is not possible to say what the sanction offense was. But if a summons was more likely, then this in all probability was not a felony offense.

Force was 14 percent more likely to be used in stops of Blacks compared to White suspects, and 9.3 percent more likely for Hispanics.

Additional analyses were conducted to determine whether the RAS factors improved the predictions and explanations of these various "hit rates." A set of regressions were produced that compared the explained variance – R2 – for models of arrest, sanction

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[91] This requires a control for the potential bias in determining which among the persons – the 11 percent - who are given any sanction. To do this, a propensity score was estimated an included in the models as a control for that selection bias. See, e.g., Heejung, Bang & James M. Robins "Doubly Robust Estimation in Missing Data and Causal Inference Models," 61 *Biometrics* 962 (2005); Alka Indurkhya, Nandita Mitra, & Deborah Schrag, "Using Propensity Scores to Estimate the Cost-Effectiveness of Medical Therapies," 25 *Statistics in Medicine* 1561 (2006).

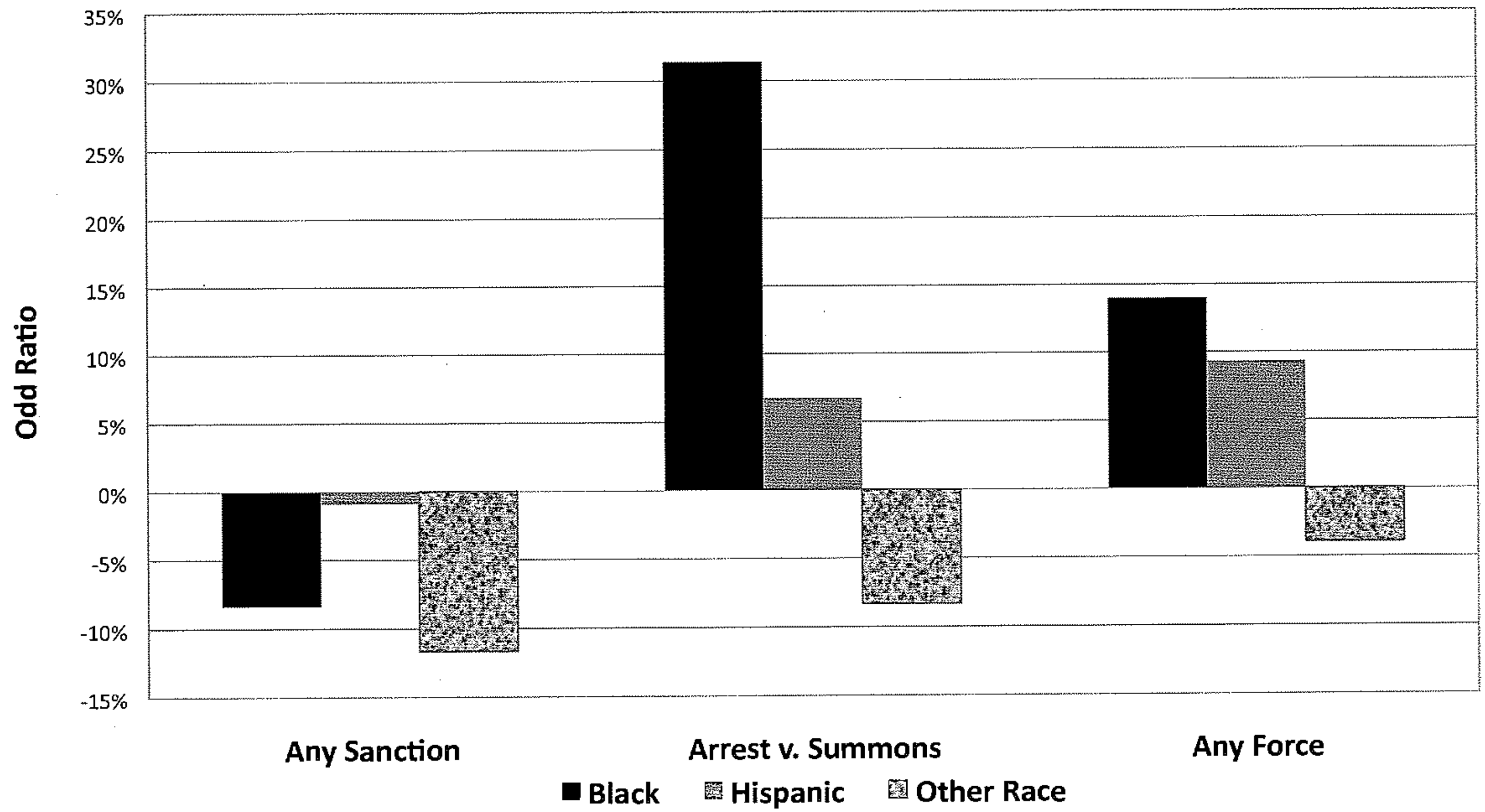
Table 16. Multilevel Logistic Regression of Three Stop Outcomes by Precinct Social and Crime Conditions and Suspect Characteristics (Exponentiated b,SE)

	Stop Outcome		
	Any Sanction	*Arrest Given Sanction*	*Any Force*
Intercept	.102 ***	1.117	.041 ***
	[.314]	[.539]	[.409]
Suspect Characteristics			
Suspect Black	.917 ***	1.314 ***	1.140 ***
	[.017]	[.035]	[.014]
Suspect Hispanic	.991	1.067	1.093 ***
	[.017]	[.035]	[.015]
Suspect Other Race	.883 ***	.917	.961 *
	[.023]	[.047]	[.019]
Suspect aged 16-20	.741 ***	1.073 *	1.207 ***
	[.011]	[.030]	[.008]
Suspect aged 21-25	.785 ***	1.019	1.149 ***
	[.012]	[.029]	[.009]
L1 - Violent Crime Stop	1.106 ***	1.815 ***	1.852 ***
	[.018]	[.037]	[.013]
L1 - Drug Stop	1.891 ***	1.714 ***	.969 *
	[.018]	[.055]	[.016]
L1 - Weapon Stop	1.711 ***	.734 ***	2.835 ***
	[.016]	[.048]	[.012]
L1 - Trespass Stop	1.455 ***	2.583 ***	.518 ***
	[.018]	[.044]	[.018]
L1 - QOL Stop	2.573 ***	1.346 **	1.079 *
	[.037]	[.100]	[.037]
L1 - Other crime Stop	1.570 ***	1.968 ***	1.495 ***
	[.016]	[.043]	[.013]
Sanction Propensity		.471	
		[.613]	
Precinct Conditions			
Complaints (lagged, logged)	1.166 **	1.267 **	1.120
	[.047]	[.080]	[.062]
Precinct % black	.485 ***	.174 ***	1.328
	[.147]	[.259]	[.189]
Low SES factor	.999 ***	.998 ***	1.000
	[.000]	[.000]	[.000]
Patrol Strength	2.373	.008 ***	.347
	[.512]	[.874]	[.673]
Business Precinct (1, 6, 14, 18	1.000 ***	1.000 ***	1.000
	[.000]	[.000]	[.000]

Significance: * p<.05, **p<.01, *** p < .001

Regression results for Precinct Socio-economic characteristics not shown

Figure 14. Odds Ratios of Stop Outcomes for Minority Suspects Compared to White Suspects



Odds Ratio Adjusted for Precinct Social and Crime Condtions and Suspected Crime. Arrest or Summons contingent on any sanction and force both with and without the inclusion of the stop factors.[92] If RAS is applied well, there should be improvement in model fit for stop outcomes – in other words, "hit rates" – when these factors are considered.

The results show that, as with the previous analysis of improvement in model fit (as measured by explained variance), there are improvements in model fit, but the overall model fit remains very poor. The explained variance in models predicting either arrest or summons increases from .02 with no RAS factors to .04 with RAS factors. This model provides no evidence that RAS factors are invoked in a manner to efficiently detect that crime is afoot.

b. Seizures of Weapons, Guns and Contraband

A parallel analysis examined seizures of guns, other weapons, and contraband.[93] The specific odds ratios here should be viewed in the context of the overall very low rates of seizures resulting from the stops. Recall that seizure rates reported in Table 15 were less than one percent for weapons and guns, and less than two percent for contraband of any sort. Accordingly, whatever differences there were by suspect race or any other parameter are small and unimportant differences when considered in the context of overall low seizure rates.

With that in mind, Table 17 shows that contraband seizures were significantly lower among Black suspects (14.8 percent) and Hispanic suspects (22.7 percent) compared to White suspects. There were no significant differences in weapons seizures by suspect race. Gun seizures were significantly higher among Black suspects (61.6 percent), but significantly lower among Hispanic suspects (2.8 percent less likely). Recall, though, that the overall seizure rate was less than two tenths of one percent (.15 percent), or a seizure rate of 1.5 guns for every 1,000 stops. While the reduction of even this small number of

[92] These models were estimated using a simpler regression form, where precinct characteristics were controlled using "fixed effects" instead of the actual variables to characterize precincts. The reason is that the data are heavily structured with binary (0,1) variables that place computational burdens on the mathematics of the MLM models that were used in the other analyses. In addition to suspect race and suspected offense, the stop factors and additional circumstances also are binaries. The covariance matrices with this number of binaries became unstable, and the MLM models would not converge. The fixed effects strategy is a widely used and well-accepted strategy for multivariate modeling. See, Andrew Gelman and Jennifer Hill, MULTILEVEL MODELING, supra note 35.

[93] The set of suspected crimes was reduced here to a small subset where the search for weapons was relevant to the suspected crime. These included stops where the suspected crime was a violent crime or a weapons offense. For the regressions for any contraband, the entire set of suspected crimes was considered.

Table 17. Multilevel Logistic Regression of Seizures by Precinct Social and Crime Conditions and Suspect Characteristics (Exponentiated b,SE)

	Stop Outcome		
	Weapons Seizure	*Any Contraband*	*Gun Seizure*
Intercept	.102	.036 ***	.000 ***
	[.627]	[.477]	[1.299]
Suspect Characteristics			
Suspect Black	1.018	.852 ***	1.616 **
	[.035]	[.038]	[.172]
Suspect Hispanic	1.012	.773 ***	.972 **
	[.037]	[.039]	[.181]
Suspect Other Race	.651 ***	.615 ***	.957
	[.055]	[.055]	[.223]
Suspect aged 16-20	.883 *	.803 ***	1.732
	[.055]	[.026]	[.087]
Suspect aged 21-25	.632 ***	.866 ***	1.672 ***
	[.076]	[.028]	[.094]
L1 - Violent Crime Stop	1.166 **	.803 ***	1.078 ***
	[.055]	[.056]	[.132]
L1 - Drug Stop		6.147 ***	
		[.040]	
L1 - Weapon Stop	5.490 ***	1.709 ***	4.280
	[.036]	[.044]	[.086]
L1 - Trespass Stop		2.291 ***	***
		[.047]	
L1 - QOL Stop		2.748 ***	
		[.093]	
L1 - Other crime Stop		2.270 ***	
		[.041]	
Precinct Conditions			
Precinct % black	.741 **	.334 ***	.446
	[.294]	[.226]	[.662]
Complaints (lagged, logged)	1.166	1.080	1.464 *
	[.092]	[.072]	[.187]
Patrol Strength	1.000 ***	.075 ***	.050
	[.969]	[.772]	[1.969]
Business Precinct (1, 6, 14, 18	1.000 ***	1.000	1.000
	[.000]	[.000]	[.000]
Stop for Property Crime	1.000 ***		.497 ***
	[.064]		[.166]

Significance: * = p<0.05, ** = p<0.01, *** -= p < .001

Regression Results for Precinct Socio-economic characteristics not shown guns is a social good, the extraordinary burden to produce this good falls mainly on Black citizens.

VI. Review and Re-Analysis of the RAND Report and Benchmarking Procedure

A. Overview

The City has cited the evidence presented in the RAND Report[94] to support legal, evidentiary and policy claims that the NYPD engages neither in "racial profiling" nor in racially disparate treatment of suspects once stopped.[95] For these reasons, I review the results of the RAND Report, and analyze its underlying assumptions and methods to provide information that bears on its accuracy and reliability as social science evidence on the role of race in policing. The methods and main findings of the RAND Report are presented in three chapters. Each analysis adopts a different approach to estimating the extent and nature of racial disparities in the conduct of pedestrian stops by NYPD officers. The review that follows assesses each chapter in turn.

B. Chapter 3 - External Benchmarks

1. Overview

Chapter 3 of the RAND Report shows the results of analyses that attempt to replicate, using 2006 data on stops and frisks, the results reported in December 1999 by the New York State Attorney General in his investigation of the "Stop and Frisk" practices of the NYPD from

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[94] Greg Ridgeway, Analysis of Racial Disparities in the New York Police Department's Stop, Question and Frisk Practices, RAND TR534 (2007), supra note _.

[95] See, e.g., Letter from Police Commissioner Raymond W. Kelly to Speaker Christine C. Quinn, April 29, 2009 (stating that "RAND researchers analyzed data on all street encounters between New York City Police Department officers and pedestrians that occurred during 2006, and determined that no pattern of racial profiling existed"). See, e.g., Christina Boyle and Tina Moore, *Blacks and Latinos Make Up About 80% Stopped and Questioned by NYPD, Study Finds*, N. Y. Daily News, January 16, 2009 (quoting Deputy Commissioner Paul Browne referring to the RAND study as showing that there is no evidence of racial profiling by the NYPD).

January 1998 – April 1999.[96] The 1999 results were subsequently re-analyzed and reported in an article published in the *Journal of the American Statistical Association* in 2007.[97] The results in the RAND Report include both replications of the methods that were used by Gelman et al. with 2006 data, and extensions of those analyses that include a series of alternate "external benchmarks." "External benchmarks" are the metrics used to compare and assess the stop rates for different racial groups.[98] There are several options for external benchmarks, and some differences of opinion as to which external benchmark offers the most accurate basis and metric for estimating the fairness or racial proportionality of stops.[99] The external benchmarks used by RAND reflect both methodological choices and also the translation of policy statements and preferences into statistical models.[100] Accordingly, the accuracy of these results depends on the assumptions about stop patterns and the accuracy of underlying data used in compiling the extensions.

Based on this analysis, the RAND Report concludes that:

- "Benchmarks based on crime-suspect descriptions may provide a good measure of the rates of participation in certain types of crimes by race, but being a valid benchmark requires that suspects, regardless of race, are equally exposed to police officers.
- We found that black pedestrians were stopped at a rate that is 20 to 30 percent lower than their representation in crime-suspect descriptions. Hispanic pedestrians were stopped disproportionately more, by 5 to 10 percent, than their representation among crime-suspect descriptions would predict.
- Black pedestrians were stopped at nearly the same rate as their representation among

96 Eliot Spitzer, The New York City Police Department's Stop and Frisk Practices: A Report to the People of the State of New York from the Office of the Attorney General, New York: Civil Rights Bureau, December 1, 1999, available at: http://www.ag.ny.gov/media_center/1999/dec/stp_frsk.pdf

97 Andrew Gelman, Jeffrey Fagan, and Alex Kiss, "An Analysis of the New York City Police Department's 'Stop-and-Frisk' Policy in the Context of Claims of Racial Bias," 102 *Journal of the American Statistical Association*, 813–823 (2007)

98 Lori A. Fridell, BY THE NUMBERS: A GUIDE FOR ANALYZING DATA FROM VEHICLE STOPS, 7 (2004); Jeffrey Fagan, "Law, Social Science and Racial Profiling," 4 *Justice Research and Policy* 104 (2002); Ian Ayres, "Outcome Tests of Racial Disparities in Police Practices," 4 *Justice Research and Policy* 133 (2002); Greg Ridgeway and John MacDonald, Methods for Assessing Racially Biased Policing, in RACE, ETHNICITY AND POLICING: ESSENTIAL READINGS (S.K. Rice and M.D. White, eds.) 180 (2010).

99 Ridgeway and MacDonald, id. See, also, Samuel Walker, "Searching for the Denominator: Problems With Police Traffic Stop Data And an Early Warning System Solution," 4 *Justice Research and Policy* 63 (2002).

100 See, for example, the quote from former NYPD Commissioner Howard Safir discussing the importance of examining stop patterns compared to known violent crime suspects, cited in RAND at 16.

arrestees would suggest. Hispanic suspects appear to be stopped at a rate slightly higher (6 percent higher) than their representation among arrestees.

- The most widely used, but least reliable, benchmark is the residential census. Census benchmarks do not account for differential rates of crime participation by race or for differential exposure to the police. Comparisons to the residential census are not suitable for assessing racial bias.
- Black pedestrians were stopped at a rate that is 50 percent greater than their representation in the residential census. The stop rate for Hispanic pedestrians equaled their residential census representation."[101]

2. The Data Infrastructure for the Analyses

Benchmarking is necessary to identify the pool of eligible citizens from which some are selected for stops, and potentially for frisks and searches. Consider three alternatives. Police may choose suspects from the entire population of persons who are available for stops. The benchmark for this analysis would be either the residential population of an area, or the population that inhabits an area during specific hours. For example, we may want to know the characteristics of the population in a commercial area during the daytime hours, since that area may have a low residential population in the evenings when businesses are closed. Whether using residential or other population estimates, population provides an estimate of the number of persons exposed to the police and who are available for stops should the police decide first that the behavior is suspicions and second, to act on that suspicion by affecting a stop.

In the second option, police may choose from among the persons who are visible to their patrol who fit the criteria of "reasonable suspicion" that are dictated by federal and state caselaw.[102] Researchers seeking to measure the racial and ethnic distribution of police stops of citizens would require an estimate of the prevalence of such "suspicious" behavior by population group that is independent of the police officer's perception. Few studies have attempted to construct this measure apart from efforts to gauge the reasons why police officers have identified a specific person as exhibiting "suspicious" behavior.[103] A third choice would require measures of criminal activity in an area, with sufficient detail

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101 RAND at 13

102 *Terry V. Ohio.* 392 U.S. 1 (1968), *People v. De Bour*, 40 N.Y. 2d 210 (1976)

103 See, for example, Geoffrey Alpert, John MacDonald and Roger Dunham, "Police Suspicion And Discretionary Decision Making During Citizen Stops," 43 *Criminology* 407–434 (2005). See, also, Joel Miller, *Profiling Populations Available for Stops and Searches* (Police Research Series paper 131. London: Home Office).

on the crimes and their racial distribution as to provide a reliable if not accurate measure of actual crimes. The choices here are simple: either voluntary reports by citizens to police of criminal activity, or observations by police of criminal activity that translate into arrests.

The RAND analysis strongly rejects the exclusive use of residential census information as a benchmark against which to assess racial bias in the decision to stop a citizen.[104] RAND states that the primary reason for using census data is that "it is inexpensive, quick, and easy,"[105] but that census data will produce biased estimates of racial disparity since officers are responding to indicia of suspicion of crime rather than the general population characteristics. RAND argues instead for an analysis of stops within local areas using a benchmark of local crime incidence to estimate the racial proportionality of stops, conditional on the racial and ethnic (and gender) characteristics of the population to which police officers are exposed. Crime is the metric by which the NYPD allocates officers to specific places, and by virtue of their training, shapes the cognitive frames of police officers patrolling specific neighborhoods on the lookout for criminal activity. So, crime patterns translate, in some unspecified cognitive process, into perceptions of the indicia of suspicion that are articulated in a set of non-overlapping "circumstances of the stop" that are checked off by NYPD officers in their documentation of stops. Officers can mark all the circumstances that apply to the incident.

The analysis in Chapter 3 of the RAND report replicates the analysis of 1998-9 stop and frisk data by Gelman, Fagan and Kiss (2007) in two ways. First, RAND adopts the functional form of the multilevel model used in that study. Second, RAND replicates the benchmarks that Gelman et al used: criminal arrest activity in the local area (the precinct) in the previous year.[106] The results are shown graphically in Figure 3.1 (p. 18) and discussed in the accompanying text.[107] RAND estimated these models using Equation 4 in Gelman et al. However, the results reported in Chapter 3 are an incomplete replication of Gelman et al: RAND states in its Appendix A that they rejected the Gelman et al. (and Spitzer Report) specification that included parameters for racial population composition and precinct effects, but they give no reason other than stating that it is "not necessary to

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104 RAND at 14-15

105 RAND at 16

106 Gelman et al. used arrest data provided by the State of New York, disaggregated by suspect race and the most serious criminal charge. RAND used arrest data culled from the City's online booking system. There are no studies to confirm the consistency of how charges are recorded in the respective databases. The state receives arrest data from the City to post to its archive, but it is not known if the same data in the City's online system are reported to the state, or if there is some processing of the information before reporting to the State.

107 RAND at 17-19

estimate the race effect."[108] No reason is given for this conclusion. Accordingly, the specification producing the results in Figure 3.1 is only a partial replication that cannot be compared to the original results reported by Gelman et al.

Even with this uncertainty as to the fealty of the replication, Figure 3.1 shows that stops of Blacks and Hispanics were disproportionately high when using a benchmark of weapons arrests in the prior year.

Three additional models were estimated using benchmarks that were based in whole or part on the incidence of violent crimes where there was a description of a suspect. The rationale for this benchmark is an oft-cited quote from former NYPD Commissioner Howard Safir mentioned earlier, that stops are proportionate to "the demographics of *known* violent crime suspects as reported by crime victims"[109] One model used a benchmark solely with this parameter, and two others combined this parameter with other parameters (e.g., the number of stops based on a prior suspect description). These results showed that stops of Blacks were disproportionately low relative to this benchmark, by a large margin. Stops of Hispanics and Whites were disproportionately high relative to these three benchmarks.

The relevance of violent crime complaints for evaluating stop activity is limited by the relative infrequency of violent crime across the city. Between 2004 and 2009, violent felonies (murder, negligent and non-negligent homicide, rape, robbery, assault, and kidnapping) comprised fewer than 10% of all crime complaints. Moreover, very little of the stop activity (14%) recorded is related to felony violent crime. Even when considering weapons stops (20% of all stops) as related to the prevention of violent crime, the vast majority of documented stops are not related to violent crime. The probative value of known crime suspects as a basis for comparison is therefore limited.

The probative value of the results using violent crime suspect descriptions further depends on a key word in former Commissioner Safir's quote: *known*. If a significant number of violent crimes are reported where the suspect race is unknown, there will be a potentially serious bias in estimates of racial proportionality in stops when these cases are either excluded or assumed to be persons of another race. The RAND report doesn't provide information on the racial composition of the cases that were used in the three benchmarks, other than to say that 30 percent of all stops were based either on a suspect description or a call-for-service.

Table 18 shows the racial composition of suspects in complaints for violent crimes and other crimes in 2005 and 2006. In violent crime complaints in 2005 where the suspect

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[108] RAND at 47

[109] RAND at 16, quoting Spitzer, supra note 39 and Gelman-Fagan, supra note 39. Emphasis added.

Table 18. Suspect Race in Violent Crime Complaints, Number and % of Total, 2005-6

Suspect Race	*2005* Crime Type Other	*2005* Crime Type Violent	*2005* Crime Type Total	*2006* Crime Type Other	*2006* Crime Type Violent	*2006* Crime Type Total
White	27,043	1,681	28,724	26,594	1,523	28,117
	5.30	3.37	5.13	5.27	3.13	5.08
Black	81,407	19,206	100,613	77,254	18,843	96,097
	15.96	38.50	17.96	15.30	38.77	17.36
Hispanic	34,514	5,562	40,076	33,031	5,107	38,138
	6.77	11.15	7.16	6.54	10.51	6.89
Other Race	5,984	564	6,548	5,811	502	6,313
	1.17	1.13	1.17	1.15	1.03	1.14
Race Unknown	42,621	7,874	50,495	48,987	8,476	57,463
	8.35	15.78	9.02	9.70	17.44	10.38
Race Missing	318,602	14,997	333,599	313,408	14,152	327,560
	62.45	30.06	59.57	62.05	29.12	59.16
Total	510,171	49,884	560,055	505,085	48,603	553,688
	100.00	100.00	100.00	100.00	100.00	100.00
Total Race Unknown	361,223	22,871	384,094	362,395	22,628	385,023
or Missing	70.80	45.85	68.58	71.75	46.56	69.54

Source: NYPD Crime Complaint Files, 2004-9

* Violent crime includes murder, manslaughter, robbery, rape, aggravated assault, kidnap. Black includes Non-Hispanic Black and Hispanic Black

race was known, 71.10% of suspects were Black. In such cases in 2006, 72.54% of suspects were Black. However, these statistics fail to consider the 45.85% of violent crime complaints in 2005, and 46.56% in 2006, where the race of suspect was missing or unknown. Some simple arithmetic shows that Blacks were, in fact, identified as the suspect's race in only 38.50% of all violent crime complaints (.7110 x .5415) in 2005, the benchmark year for the analyses in Figure 3.1.[110] Information about the 45% of cases where the suspect race was unknown in violent crimes was not incorporated into the analysis, and the analysis proceeds without accounting for the selection bias of racial identification in violent crime complaints. Information about the specific type of violent crime is not helpful either, since the racial composition of these groups varies: 49.3% of robbery suspects in 2006 were Black and 35.2% were unknown race, while 23.0% of felony assault suspects were Black and 64.2% were unknown race.

In effect, the included cases are selected based on the response variable: suspect race.[111] We cannot know the data-generating process by which the large set of non-observed cases of the missing suspect race were created, and thus are challenged to make reasonable and testable assumptions about their distribution. Yet the analysis proceeds simply by excluding these cases without accommodation for the potential biasing effects of the characteristics of other violent crime cases. The analysis proceeds assuming that the distribution of suspects by race in the totality of stops assume (where it is known), or even in this subset of crime complaints, is similar to the distribution of the race-known cases. There is no basis to make that inference, and conclusions based on analyses that ignore this selection process are unreliable.[112]

3. Conclusion

It is true that the conclusions in RAND's external benchmark analysis are sensitive to more than just the choice of benchmark. As RAND acknowledges, "[external benchmarking] can either detect or hide racial bias *due to unobserved or unmeasured factors that affect both the racial distribution that the benchmark establishes* and the racial distribution of the stops."[113] That seems to be the case here, given the fact that suspect race is unknown and

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110 The fraction of cases where a suspect race was known in 2006 is 1.000-.4585=.5415. Blacks comprised .7110 of the known violent crime suspects, but only 38.5% of all violent crime suspects.

111 Richard Berk, Azusa Li and Laura J. Hickman, "Statistical Difficulties in Determining the Role of Race in Capital Cases: A Re-analysis of Data from the State of Maryland," 21 *J. Quant. Crim'gy* 365 (2005).

112 Richard A. Berk "An Introduction to Sample Selection Bias in Sociological Data," 49 *American Sociological Review* 386-398 (1983). James J. Heckman, "Sample Selection Bias as a Specification Error," 47 *Econometrica* 153-161 (1979)

113 RAND at 19

unknowable in nearly half the crime complaints in 2005-6. The large proportion of crime complaints where suspect race is not observed casts strong doubt on the conclusions based solely on the half of the cases where suspect race is known.

C. Chapter 4 - Internal Benchmarks and the Prevalence of Racial Disparities in the Decision to Stop Suspects

Chapter 4 is designed to inform the NYPD whether there is racial bias among its officers as indicated by officers whose patterns of stops differ significantly from their matched "peers," and therefore estimate the prevalence of racial bias among its officers who are most active in making stops. The chapter describes the procedure to identify "outliers" among police officers who made 50 or more stops in 2006.[114]

In contrast to most research on racially selective enforcement, where the unit of analysis is the stop, the RAND Report approaches this question with an analysis of the behaviors of individual officers. The program compares the racial distribution of citizens stopped by each officer with the racial distribution of a set of stops whose characteristics are similarly situated to the stops made by the target officer: the stops were made by officers patrolling in the same areas, having the same role (command assignment), and whose stops take place at similar times and places.[115] The goal is to ensure that each officer is compared to other officers who are exposed to a matched set of offenses and offenders. RAND refers to this as an "internal benchmarking procedure" and applies this method to identify outliers, or "potential problem officers."[116] Outliers are identified along two dimensions: stops of Black or Hispanic suspects, and stops that are either significantly greater in number than or significantly fewer in number than stops by other officers. The statistical procedure is described in detail in Appendix A of the RAND report.

Based on this analysis, RAND reports in Chapter 4 that:

- "Five officers appear to have stopped substantially more black suspects than other officers made when patrolling the same areas, at the same times, and with the same assignment. Nine officers stopped substantially fewer black suspects than expected.
- Ten officers appear to have stopped substantially more Hispanic suspects than other officers made when patrolling the same areas, at the same times, and with the same assignment. Four officers stopped substantially fewer Hispanic suspects than

114 RAND at 21

115 Other matching categories include time of day, day of week, geographic location of the stop, whether it was made in a transit or public housing location, whether the officer was in uniform, and whether the stop was discretionary or the result of a 'radio run'. RAND, at 22

116 Id.

expected.

- Six of the 15 flagged officers are from the Queens South borough."[117]

To assess the accuracy, reliability and sensitivity of these conclusions, the following review of Chapter 4 addresses the conceptual and technical foundations of the program with respect to its sensitivity to variations in the distribution by suspect race of NYPD officers' stop activities.

1. What the Program Does

For each officer making 50 or more stops during a year, the program finds a weighted set of other stops most like this "focal officer's" stops. It does this by identifying stops that resemble the focal officer's stops in terms of several observable variables.[118]. This set of stops is referred to in the RAND analysis as the officer's *benchmark stops*. Each officer's patterns of stops is compared to his or her benchmark in terms of the percent of stops that are of Black suspects, and the percent of stops that are of Hispanic suspects.

The program then calculates a Z-score that describes how much the focal officer's racial fraction – Black or Hispanic – differs from the weighted racial composition of his or her benchmark stops, and uses this Z-score to assess the statistical and substantive significance of this difference. These calculations are done separately for stops of Black and Hispanic citizens, and an officer whose observed stop composition is significantly different than that of his benchmark stops (for stops of either Blacks or Hispanics), is termed an outlier.

The essential step in this procedure is the identification of the set of comparison stops for each officer. The first step in finding comparison stops is to rule out consideration of any stops with discrete variable values that don't occur in the focal officer's stops. For example, if an officer made stops only in precincts 77 and 79 and was always in uniform, then all stops made in other precincts and all stops made out of uniform would be dropped from consideration as comparison stops.

Remaining stops are then assessed to determine their suitability as comparison stops for the focal officer. This is done using a *propensity score weighting* approach, in which each stop made by officers other than the focal officer is evaluated for its resemblance to the focal officer's stops. Stops that closely resemble the focal officer's are heavily weighted in the comparison sample; stops that do not resemble the officer's stops (e.g., are made at night while the focal

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117 Id.

118 Time of day, day of week and month of each stop, the local area of each stop (which is defined based on the precise geographical location of each stop), her command assignment, whether the stop occurred indoors, whether the stop was done by an officer assigned to housing or transit units, whether the stop was due to a radio call, and whether the officer was in uniform.

officer predominantly works days, or result from a "radio run" when the focal officer makes few such stops) are downweighted[119].

Once an officer's comparison stops have been weighted, the program estimates how the probability that each stop of a black suspect, for example, is related to observable stop characteristics. This is done via a logistic regression model,[120] using the computed weights, and controlling not only for whether the stop is a "focal officer stop" or a "comparison group stop", but also for any observed stop characteristics that were not closely balanced in the propensity score weighting process. [121] Similar models estimate the probability that each stop is of a Hispanic suspect.

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[119] The propensity score weights could be estimated using a variety of strategies, each designed to minimize the observable differences between the focal officer's stops and his comparison stops. While the most common method of propensity score estimation is a parametric logistic regression model, the RAND model uses *generalized boosted modeling* and a series of *regression trees*, a non-parametric, data-driven approach intended to improve model fit. Each branch of a "regression tree" refers to a division of the comparison sample: e.g., stops made in uniform vs. stops not made in uniform, or stops made on weekdays vs. stops made on weekends. Splits can occur between any pair of observed values of any of the covariates, and model fit is considered good when the split of observable covariates can predict whether stops were made by the focal officer or a comparison officer. Sample splits begin with some crude decision rules, and are refined iteratively to improve model fit at each split. At each iteration, the split is chosen to increase the value of the Bernoulli log-likelihood function for the estimated probability that the stop is the focal officer's. The program continues iterating until the ASAM (the average standardized absolute mean) difference of the covariates is minimized.

The RAND analysis uses a random subsample of data in the iterative process, as has been shown to improve model fit. See, Daniel F. McCaffrey, Greg Ridgeway, and Andrew R. Morral, Propensity Score Estimation With Boosted Regression for Evaluating Causal Effects in Observational Studies, 9 *Psychological Methods* 403, 410 (2004). However, by introducing randomness, without setting a random seed, the analysis sacrifices a degree of reproducibility. The re-analysis of the 2007 data presented in this report thus differs from the analysis generated by the City.

[120] Logistic regressions are regression models for identifying which factors among a set of candidate factors are predictive of a binary outcome (in this case, whether the stop was made of a Black suspect or a suspect of a different race). See, William Greene, Econometric Analysis (6th ed.) (2008).

[121] Given a weighted set of comparison stops, one could simply calculate the weighted mean of a variable for the race of the person stopped (y) in all the comparison stops, and compare that to the race fraction for each officer. However, this would ignore the fact that while the differences between the officer's and the comparison stops' averages may be minimized, they still are likely to be greater than zero and in fact may be relatively sizable. The regression adjustment compensates to some extent for an imperfect set of weighted comparison stops, by controlling for all predictor variables whose means differ by more than 2% between the focal officer's stops and the comparison group stops.

The regression coefficient associated with whether or not stops were conducted by the focal officer (i.e., the "officer regression coefficient") gives a measure of how much the officer's race fraction differs from that of his comparison stops. A Z-score[122] is calculated from the point estimate and standard error of the officer regression coefficient, an adjusted measure of the deviance between officers and their benchmarks. This is the essential statistic from which the program identifies "outliers."

The program examines the distribution of Z-scores to identify the individual officers who deviate most sharply from their benchmarks; however, testing for outliers is complicated by the multiple comparisons (of officers and stops) inherent in the examination of Z-scores. Each officer's Z-score is related to others' in the distribution, since, for example, the comparison stops for an Officer A may include stops made by an Officer B, and the Z-score of Officer A's stops in turn are considered as potential matches for Officer B. As a result, the Z-scores of Officers A and B are not independent. To adjust for this dependence, the program computes each officer's probability of exceeding their benchmark using a statistic known as the "local false discovery rate", or, in this case, the probability that the officer is not problematic, given his or her Z-score[123]. The probability that the officer is, in fact, problematic, is assumed to be the inverse of the false discovery rate, and officers are identified as "outliers" if their probability is greater than or equal to 50%.

2. Limitations of the Matching Logic

The officer-based analysis seeks to identify a closely matched set of stops for each officer who made at least 50 stops in 2006. The matches are used to create a pool of similarly-situated

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[122] A Z-score for a particular observation of a variable is the value of the individual observation, minus the mean value of the variable, divided by the variable's standard deviation. This is a way of standardizing how much a particular observation differs from the norm, and can be visualized as locating an individual officer on the familiar bell-shaped curve, determining whether he is in the middle of the distribution or either the upper or lower tail. A Z-score of 1 means that its value is one standard deviation above the mean, while a Z-score of -1 means that its value is one standard deviation below the mean. This distribution translates to the determination that an officer is an "overstopper" or an "understopper." A Z-score of zero indicates that the observation in question takes on the variable's mean value.

[123] The purpose of a "Local False Discovery Rate" analysis is to identify a small set of interesting cases that defy the problem of high rates of statistical significance that may not be substantively meaningful when there are thousands of interdependent comparisons in the analysis., LFDR analysis is an empirical Bayesian method that addresses the problem of high rates of false positives, or Type I errors, in analyses that require multiple comparisons and where simultaneous inference results from the large volume of comparisons. The local false discovery rate for an individual case is defined as: $fdr(z) = f0+(z) / f(z)$, which is the Bayesian a posteriori, using $f0+(z) = p0f0(z)$. See, e.g., Bradley Efron, Size, "Power and False Discovery," 35 *The Annals of Statistics*, 1351 (2007).

stops that comprise the sample of cases to be examined for the presence of seeing which officers deviate from the observed patterns. Using the methods described above, each officer's stops are assessed, along with his comparison stops, to estimate whether the officer is disproportionately likely to stop Black and Hispanics – or whether the racial composition of his or her stops is statistically significantly different from that of a matched set of stops. The validity of this procedure is questionable due to several concerns.

a. Insufficient Matching Information

The benchmarking program assumes that all necessary information to match those stops is incorporated into the pool of stops. The matches are based on a limited set of structural features of the stops, really not much more than an actuarial match. Every factor is matched if not balanced, including the race of the suspect.[124] Matching assumes that the selection of matching components is sufficiently rich conceptually to give practical meaning to the matches. If the goal of the benchmarking exercise is to determine whether some officers are biased in their pattern of stops, as evidenced by whether they are "overstoppers" relative to their peers, then we would expect that the matching variables would be connected conceptually to that bias. In other words, there should be a theory of bias in stops that should inform the matching process, rather than just employing an actuarial method.

Whether the actuarial matches on time of day, command assignment, etc., are reasonable proxies for the social and psychological processes that lead to a stop is questionable. Ideally, the controls should specify a set of pre-stop characteristics that make the decision to stop, and the comparison to other decision patterns, to establish the comparison about race, and not about factors that are only structurally or logistically correlated with race.[125] A simple example would be the role of "circumstances of the stop" in the pattern of stops. Officers make stops based not on just the time of day or whether they are in a housing or transit unit, but instead on the basis of reasonable and articulable suspicion, as required by federal and state caselaw.[126] Those

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124 Matching itself raises issues with respect to those events (stops) that either are excluded or cannot be matched, a topic that is visited below in § V.C.2.d *infra*, in the discussion of the characteristics of excluded stops and also in the discussion of the analysis of post-stop outcomes.

125 See, for example, Donald Rubin, Estimating Causal Effects from Large Datasets using Propensity Scores, 127 *Annals of Internal Medicine* 757 (1997). Rubin states the probability of being in a "treatment" group, in this case race, should be based on confounding covariates, such as place, and that outcomes (in this case, stops) play no role. Those assumptions are violated in the benchmarking routines used here. For an example from studies of the effects of labor market training, see James Heckman, et al., "Characterizing Selection Bias Using Experimental Data," 66 *Econometrica* 1017 (1998). See, *generally*, Paul Rosenbaum and Donald Rubin, "The Central Role of the Propensity Score in Observational Studies for Causal Effects," 70 *Biometrika*, 41-55 (1983).

126 *Terry* v Ohio, *392 U.S. 1 (1968)*; *De Bour*, supra note 63. Even here, though, there is a risk that the subjective assessment of "suspicion" may itself be conflated with race. See, William J. Stuntz, "*Terry*

rationales – in the form of the "circumstance of the stop" or "additional circumstances" on which officers are trained are not included in the matching process. This analytic choice creates an omitted variable bias that makes the propensity scores themselves suspect.

b. Overcontrolling and the Neutralization of Variance: The Example of Place

The inclusion criteria may lead both to selection concerns and specification errors by narrowing of the comparison pools for the high-stop officers to a specific set of places where stops of Blacks are more likely. Since the majority of persons stopped in 2006 were Black citizens, and also because stops of Blacks were concentrated in police precincts where the Black (percentage of the residential) population is likely to be higher,[127] the stops in the pool for these analyses are heavily concentrated in specific areas that are distinctly different from other places where other, unmatched stops are just as likely to take place. This strategy treats places as markers in the conduct of stops that are no different than, say, the time of day or the officer's command assignment. In other words, the design leads to oversampling of stops of Blacks and may minimize the necessary conditions in which to accurately gauge the role of race in the decision to make a stop.

As a result, the pool of examined officers and their stops are composed of a set of events that represents a very limited set of *local conditions and circumstances*. So, we are uncertain whether these locales are representative of the totality of areas where stops take place, or if they simply are representative of the places where officers were more likely to make 50 or more stops in 2006. More information on that question is presented below, in § 3 *infra*. Put simply, there are doubts about the comparability of the locations where benchmarked officers made stops with other locations in the City that were not considered, and whether this narrowing process artifactually constrains the comparisons.

Both the conceptual and analytic logic is based in part (and perhaps in large part) on the decision to match on "place" (the x-y geographic coordinates) rather than explicitly model place as a component of a stop.[128] The decision to stop a citizen is a decision that is embedded or nested in a particular social context, and the influence of that context is critical to understanding

and Legal Theory: *Terry's* Impossibility," 72 *St. John's Law. Review* 1213 (1998); Anthony C. Thompson, "Stopping the Usual Suspects: Race and the Fourth Amendment", 74 *N.Y.U. L. Rev*. 956 (1999); R. Richard Banks, "Beyond Profiling: Race, Policing, and the Drug War," *56 Stanford Law Review 571* (2003).

127 Fagan et al., "Street Stops and Broken Windows Revisited," supra note 39.

128 See, Robert J. Sampson, "Gold Standard Myths: Observations on the Experimental Turn in Quantitative Criminology," *J. Quant. Crim'gy* (2010, forthcoming). (noting that many criminal justice experiments and quasi-experiments consciously and purposefully reject place as a causal mechanism and chose instead to treat it as a factor to be controlled out of the causal chain).

the decision itself.[129] If officers' practices and directives vary by command, then limiting officer comparisons to those making stops in the same geographic areas will ignore potentially important disparities in the way that different precincts are policed. In particular, if officers in predominantly Black precincts police more aggressively than in other parts of the city, both Blacks and Whites in these areas might be subjected to more intense stop activity. Even if the within-place differences in the treatment of Blacks and Whites are negligible, variation in police practices across the city's precincts could lead to disparate treatment that goes undetected in the internal benchmark.

The concentration of stops, or even of the deployment of officers concentrated in particular locations, may also bias the decision to stop through an *availability heuristic*, where the concentration of similarly-situated persons may easily lead to "attribute substitution" and make inferences when a decision-maker uses the characteristics of known cases when confronted with unknown but similar ones.[130] These heuristics, in other words, can lead to behavioral shortcuts that can lead to conclusions quickly and with little effort, but perhaps leaving off important information and thus producing inaccuracies.[131] So, if officers are clustered in particular social and spatial contexts where they encounter similar persons, those substitutions are easy and convenient.

The emphasis on the past decade on the role of "context" in decisions by criminal justice actors has led to significant debate among researchers.[132] In turn, this has led both to theories of the exercise of discretion and to analytic models to identify the factors that shape that discretion. The attention to context derives from a simple claim: a marker for place, whether county, city,

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129 Alpert et al., "Police Suspicion And Discretionary Decision Making During Citizen Stops," supra note 9.

130 *See* Amos Tversky & Daniel Kahneman, "Availability: A Heuristic for Judging Frequency and Probability," 5 *Cognitive Psychol.* 207,208 (1973). Amos Tversky & Daniel Kahneman, "Availability: A Heuristic for Judging Frequency and Probability", 5 *Cognitive Psychol.* 207 (1973).

131 Daniel Kahneman, and Amos Tversky, "Prospect Theory: An Analysis of Decision under Risk," XLVII *Econometrica* 263-291 (1979). People use the availability heuristic to determine the likelihood or frequency of an event based on how quickly instances or associations come to mind. The problem is that "[t]here are many factors uncorrelated with frequency . . . [that] can influence an event's immediate perceptual salience, the vividness or completeness with which it is recalled, or the ease with which it is imagined." See, Jon Hanson & David Yosifon, "The Situational Character: A Critical Realist Perspective on the Human Animal," 93 *Georgetown L. J.* 1 (2004).

132 See, e.g., Wesley Skogan and Kathleen Frydl, FAIRNESS AND EFFECTIVENESS IN POLICING: THE EVIDENCE (2004); David Weisburd et al., *The Effects of Problem-Oriented Policing on Crime and Disorder*, Final Report, Grant 2007-IJ-CX-0045 (2005);. Robert J. Sampson, "Moving to Inequality: Neighborhood Effects and Experiments Meet Social Structure," 114 *American Journal of Sociology* 189 (2008).

neighborhood or even a microarea (such as a census block group) is a proxy for other processes that go on in that place that generate the event of interest and that may shape its outcome. Including the marker doesn't qualify as an analysis of those processes.[133] Matching on place, as is the case in the internal benchmarking exercise, ignores the effects of place rather than incorporating it into the explanation of the occurrence of events and their outcomes. (This concern extends to the analysis of post-stop outcomes, *infra* § D).

These exclusions matter, and come into play both in terms of the matching logic and, as is discussed below, in the inclusion criteria. The distribution of persons available for stops, the mix of suspects of different races and ethnic groups, and the contexts of that exposure, are all factors that are characteristic of places. If, as RAND reports, there are few "outliers" in the pool of officers making 50 stops or more, we cannot rule out whether there may be other unmatched or discarded stops that took place in areas with different social and crime conditions. Place matters, because the formation of suspicion and the decision to stop often are conditional on the characteristics of the locale where the officer observes the suspect.[134] Indeed, in 2009, police marked "additional circumstance – area has high incidence of reported crime" in nearly 60% of all stops of Black suspects.

The conflation of race and locale in the matching procedure suggests that the model is strained to statistically identify a unique race component in the stops. In fact, by matching on race and place simultaneously, the matching routine introduces spuriousness or causal confusion to the interpretation of the race variable.

An analytic strategy to address this is the use of multi-level models that simultaneously examine the influence of the context in which the event is nested and individual characteristics of the event itself. The importance of using a multi-level model in making inferences about the factors that shape outcomes is "causal heterogeneity."[135] Put simply, the causal processes at the individual level that may produce an outcome are conditioned or moderated by factors at a higher level, in which the event is nested. Matching on these higher-level factors, even if just proxies for these higher-level processes, simply neutralizes them, rather than explicitly taking them into account. A complete understanding of these decisions would include a systematic

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133 See, e.g., Richard A. Berk "An Introduction to Sample Selection Bias in Sociological Data," 49 *American Sociological Review* 386-398 (1983).

134 Geoffrey Alpert et al., "Police Suspicion And Discretionary Decision Making During Citizen Stops," *supra* note 9.

135 Bruce Western, "Causal heterogeneity in comparative research: A Bayesian hierarchical modeling approach." 42 *American Journal of Political Science* 1233 (1998). See, also, Robert J. Sampson, "Gold Standard Myths: Observations on the Experimental Turn in Quantitative Criminology," *J. Quant. Crim'gy* (2010, forthcoming).

effort to examine and perhaps model these cross-level effects.[136]

There are statistical and interpretational reasons why this is important, as well. Observations that are clustered in specific places are not independent due to their clustering in specific places. Matching on place doesn't avoid this problem, it instead instantiates it in the clusters of events that take place in the limited number of places included in the RAND internal benchmarking analysis for 2006. There is no accounting for parameter differences across (in this case) spatial clusters of stops such as the one illustrated in the RAND report in Figure 4.1,[137] nor for unobserved factors (heterogeneity) in the effects of the characteristics of the places themselves on the decision to stop a citizen. If events in the same cluster share the same cluster-specific influences, their non-independence biases the estimators of the response variable, and the errors in these estimates (in this case, of their similarity to other stops) would be biased toward zero.

Controlling away (via matching) on a narrow set of spatial clusters leads to one final and nontrivial concern: these places are a subset of all the places where stops take place. The RAND analysis in Chapter 4 includes stops made by 2,756 of its most active officers, whose stops were concentrated in a limited number of areas.[138] The excluded 15,855 officers made more than 232,000 stops in 2006, 46% of all stops made that year.[139] If one of the goals of the internal benchmarking exercise is to generalize to the larger population of officers who are most active and to the stops that they make, and even those less active, then incorporating information about other locales is essential to an accurate inference to other clusters, especially spatially dependent

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136 See, e.g., Thomas A. DiPrete, and Jerry D. Forristal, "Multilevel Models: Methods and Substance." 20 *Annual Review of Sociology* 20:331–357 (1994). Andrew Gelman and Jennifer Hill, DATA ANALYSIS USING REGRESSION AND MULTILEVEL/HIERARCHICAL MODELS (2007); Anthony Bryk and Stephen Raudenbush, HIERARCHICAL LINEAR MODELS FOR SOCIAL AND BEHAVIORAL RESEARCH: APPLICATIONS AND DATA ANALYSIS METHODS (1992); Sophia Rabe-Hesketh and Anders Skrondal, MULTI-LEVEL MODELING, 2008; Judith D. Singer and John B. Willett, APPLIED LONGITUDINAL DATA ANALYSIS: MODELING CHANGE AND EVENT OCCURRENCE (2003); Ralph B. Taylor, "Communities, Crime, and Reactions to Crime Multilevel Models: Accomplishments and Meta-Challenges," *Journal of Quantitative Criminology* (forthcoming, 2010, available at http://www.springerlink.com/content/53l6295t7w628088/

137 RAND at 23.

138 While 3,034 officers made 50 stops or more over the year, 278 of these officers were excluded because of the inability to find a "suitable" set of comparison-group stops. RAND at 25. These officers made fewer stops, scattered across "numerous" precincts and multiple boroughs, and in a variety of roles (e.g., transit, housing, or in uniform). RAND at 26.

139 RAND at 30

data.[140]

c. Stability

One way to assess the validity of the RAND benchmarking program is to examine its stability over time. On the one hand, we may expect some variation over time in both the aggregate patterns of stops and the patterns of individual officers, since personnel often are deployed in specific locations as crime conditions change. On the other hand, given the stability over time in the racial makeup of citizens who are stopped and the concentrations of stops in particular precincts, it is reasonable to expect stability in the year-to-year identification of outliers.

The internal benchmarking analysis for 2006 is based on analyses of stops made by 2,756 officers who completed 50 or more UF-250 forms in that year.[141] The included officers made 54% of all stops during 2006. Each officer's Z-score was used to determine the probability that she or he was an outlier. A 50% probability was used as the cutoff, a suggested cutoff that is lower than the industry standard of 80%, as cited in the report.[142] Applying these methods, RAND identified five officers who "overstopped" Blacks in 2006, and nine others who "understopped" Blacks relative to their internal benchmarks. For Hispanics, RAND identified 10 officers who "overstopped" Hispanics and four who "understopped" Hispanics.[143]

To get a sense of the stability of the internal benchmarking program, Plaintiffs obtained the software from the City for use in a series of analyses to replicate and extend the RAND analysis over time. If the benchmarking software is a reliable method to identify officers with a tendency to over/understop blacks and Hispanics, the patterns should be consistent across runs. The first step was to determine first if the results for 2006 in the RAND report could be replicated. The program was run on 2006 stop-and-frisk data, with officer identifiers encrypted by the City to preserve their anonymity. Plaintiffs ran the software using the specifications in the program documentation for preparing the dataset and executing the program.

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140 Hao Zhang, "On Estimation and Prediction For Spatial Generalized Linear Mixed Models." 58 *Biometrics* 129–136 (2002).

141 RAND at 25. The 278 excluded officers varied by more than 10 percent on some of the matching factors. RAND at 26.

142 Id., citing, Bradley Efron, "Large-Scale Simultaneous Hypothesis Testing: The Choice of a Null Hypothesis," 99 *Journal of the American Statistical Association*, 96–104 (2004).

143 RAND at 27-28. When applying more restrictive criteria for eligible stops, criteria that eliminated low discretion stops such as those pursuant to radio runs or stops where the person stopped was judged to "fit a suspect description", the pool of officers for whom good benchmarks could be constructed was reduced to 1,910; two officers were identified as "overstoppers" in this reduced pool. *Id.*

The second step was a replication of the program using 2007 data. An analysis of outliers for that year was done by the City, using the internal benchmarking program that was provided to the City by RAND. Results were provided to Plaintiffs, and in turn, an attempt was made to replicate the results. Both sets of analyses examine the 2,670 officers who conducted 50 or more stops in 2007. These 2,670 officers represent 15% of the 17,861 officers making one or more stops in the year; they made approximately 57% of all stops in 2007.

As anticipated, both runs of the benchmarking program compute "percent black" totals that match those provided by the City, as these numbers are directly calculated from each officer's stop-level data. However, Plaintiffs were unable to replicate the City's exact results for the "benchmark percent black": the replication produced a "benchmark percent black" of .534939 (standard deviation =.2516027). The NYPD run of the 2007 data resulted in benchmark percent black of .5349202 (standard deviation = .2515774). As noted earlier[144], the weighting of comparison stops to construct each officer's benchmark is based on a propensity score model using regression trees with a random component. The stochastic nature of this estimation, in absence of a designated "random seed" to generate the random samples, means that the exact results produced by RAND and the City could not be replicated.

The differences in the results across runs are slight, but non-negligible. The officers identified as "overstoppers of Blacks" do not change between the City's runs and the replication runs: each run identifies a single overstopper of Blacks who stopped blacks 90.7% of the time, while his comparison stops were only of Blacks 60.8% of the time. However, the two analyses reported dissimilar results for overstoppers of Hispanics. The replication runs identified 19 officers as overstoppers of Hispanics, while the City's runs identified 22: the same 19 identified in the replication runs, as well as three additional officers. While these differences are an understandable consequence of the stochastic nature of the analysis, they pose a challenge for policymakers using the software to inform practical decisions. Officers identified as potentially problematic in one run of the model but not another may be at risk of unnecessary additional scrutiny, or of having inappropriate behaviors go undetected.

As an additional test of stability, the benchmarking program was run for the years 2006-2009. Given the relative stability in stop patterns by precinct over time, including both the volume of stops and their distribution by racial groups, one might expect to see consistency from one year to the next in the identification of all four types of outliers. Table 19 reports the number of "overstoppers" and "understoppers" of Blacks and Hispanics respectively for each year in this time series.

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[144] RAND at 22

Table 19. Replication of RAND Internal Benchmarking Programfor 2006-9 Stops

Stops of Blacks

	"Understoppers"			*"Overstoppers"*		
Year	N	Mean	Range	N	Mean	Range
2006	13	78	53-152	4	156	59-237
2007	14	94	51-162	1	97	97-97
2008	26	96	51-231	32	136	50-486
2009	33	107	43-245	9	116	55-304

Stops of Hispanics

	"Understoppers"			*"Overstoppers"*		
Year	N	Mean	Range	N	Mean	Range
2006	7	103	59-218	7	92	51-200
2007	13	95	50-164	23	124	51-372
2008	9	102	50-221	8	130	52-231
2009	18	111	50-304	24	105	50-254

The internal benchmarking program seems to be unstable in the identification of outliers over time. The instability in the number of both under- and overstoppers is a stark contrast with the overall stability in stop patterns. Overstoppers of Blacks range from four in 2006 to 32 in 2008, and the number then declines in 2009 to nine. For Hispanics, the range in overstoppers is seven to 24. Understoppers also vary within a broad range: from 14 for Blacks in 2007 to 26 in the following year. For Hispanics, the range is slightly narrower: seven in 2006 to 18 in 2009.

The instability over time raises questions about exactly what it is that the program is identifying. For example, the replication analyses identified one officer whose stops of Blacks were 24% of his overall stops in 2008, a year when he was considered an overstopper. In the preceding year, he made more stops, and Blacks were nearly 40% of his overall stops, yet he was considered neither an overstopper nor an understopper. Apart from the logical flaws in the design of the matching program, these results suggest that the exercise is measuring something other than bias or egregious behavior. Whether stops of blacks or Hispanics are outside the range of what is considered acceptable behavior depends inextricably on the behavior of other officers making similarly situated stops, and the results therefore do little to identify which officer actions are inappropriate when in fact all may be biased.

d. Selectivity and Sensitivity

The 2,756 officers examined in the 2006 analysis were selected based on a cutpoint of 50 stops per year. The rationale for selecting a threshold of 50 stops for inclusion of an officer in the internal benchmarking analysis is discussed briefly by RAND: 50 stops is "the minimum number of stops for which we could accurately establish an internal benchmark."[145] There was no discussion of the reasons for this claim, nor any sensitivity tests to show whether the results might have changed with different cutoffs.

Table 20 shows that the included officers (before dropping the 278 that could not be matched) made 58.1% of the 506,489 stops made by all officers in 2006. These officers were slightly more likely than excluded officers to stop black citizens: Black citizens were 55.4% of the included stops in that year, and 52.8% of all stops, a small difference. Looking over time, however, reveals some variation in the rate of inclusion at the 50-stop threshold. For example, changing the threshold to fewer stops would have resulted in a higher inclusion rate in 2006, as well as in other years. The 50-stop cutoff, for example, would have excluded more than half the stops in 2004 and 2005, but less than half in 2007-9. A 40-stop cutoff in 2006 would increase the inclusion rate to nearly two in three stops in 2006; a 30-stop cutoff would expand the sample of stops to nearly three in four. Again, while 50 stops might be necessary for the statistical power to detect patterns in stop

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145 RAND at 25

Table 20. Number of Included Stops for Alternate Minimum Stops and Percent of All Stops, 2004-9

Minimum Stops per Officer		*Year*					
		2004	*2005*	*2006*	*2007*	*2008*	*2009*
50	N	153,243	196,280	294,370	267,901	319,898	372,033
	%	48.9	49.3	58.1	56.7	59.2	64.5
40	N	177,785	227,489	331,862	302,436	361,987	413,237
	%	56.7	57.1	65.5	64.1	67	71.7
30	N	205,987	267,169	376,463	343,556	411,408	457,366
	%	65.7	67.1	74.3	72.8	76.1	79.3
20	N	237,987	310,234	427,841	391,115	463,791	504,380
	%	75.9	77.9	84.5	82.8	85.8	87.5
10	N	276,451	356,889	476,479	442,246	512,761	549,748
	%	88.2	89.6	94.1	93.7	94.9	95.4
All Stops		313,523	398,191	506,489	472,096	540,302	576,394

activity, extrapolation from the highest-stop officers to lower-stop officers presents obvious challenges.

e. Accuracy and Validity

One additional question that can be posed to evaluate the veridicality of the internal benchmarking program is to examine the circumstances and patterns of those officers who were flagged as "outliers." Equation C.2 of the RAND report defines the probability of an officer being an outlier, given his or her Z-score, based on his or her "false discovery rate" (*infra.* §C.1). Specifically, the report concludes:

$$P(outlier \mid z) \geq 1 - \frac{f_o(z)}{f(z)}$$

> "...or that the probability of an officer with Z-score *z* being an outlier is greater than or equal to one minus the false discovery rate."[146]

However, the probabilities presented in the software are based on the following assumption: "If the fraction of problem officers is small (less than 10 percent), the bound in the last line of Equation C.2 is near equality."[147] In other words, the likelihood that the software returns only a small number of outliers is built into the program's modeling assumptions.

Closer observation of the model's results, and the officers identified as outliers, suggests that these assumptions may not be well-grounded. One might reasonably expect that a procedure designed to identify persons stopping an inappropriate number of blacks (or Hispanics) would be operating primarily in areas where black (or Hispanic) residents were concentrated. However, this is not the case. For example, the lone overstopper of Blacks made 97 stops in 2007, most (88) of which were stops of Black citizens. The precinct breakdown of these 88 stops suggests that they took place in areas of the City that are, for the most part, places without a dense concentration of Black population:

- 1 in the 13th
- 66 in the 23rd
- 10 in the 25th
- 20 in the 28th

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146 RAND, at 51-2

147 Id.

Only the 28th precinct (Central Harlem) is located in an area with a high percent Black population. The 23rd and 25th precincts are located on the periphery of the largely Hispanic precincts in East Harlem. None of the officers who made 50 or more stops were flagged as outliers ("overstoppers" of Blacks) in places with the highest concentrations of stops of Blacks and Black population, places such as 73rd, 75th, or 81st precincts in Brooklyn.[148]

Both the City's benchmarking analysis and the replication analysis show a similar heterogeneity among the "overstoppers" of Hispanics. First, less than half the stops (44% of the 2,719 stops) made by these 22 officers are of Hispanic citizens. Second, these stops are spread across the City's police precincts, and a significant portion (20%) were made in precincts with more than 75% Black population (73rd, 75th, and 81st). Another 13% were made in precincts 75% White or more (6th, 19th, 122nd, 123rd). These patterns suggest a severe mismatch between the program's internal logic and the actual implementation of stop and frisk tactics.

3. Conclusions

The RAND internal benchmarking program has several limitations that call its conclusions into question. In addition to analyzing only a small fraction of the NYPD's officers in a given year, and excluding a large portion of stops from consideration, the program both omits controls for important and unobservable variables such as suspect demeanor or suspicious behavior, and over-controls for factors closely tied to officer decision-making, such as precinct assignment and geographic location. In so doing, the program defines a narrow space for comparison, which provides few meaningful implications for policy or practice.

Moreover, the program is internally self-referencing, defining officer behavior as appropriate or problematic based not on the behavior itself, but solely on how each officer compares to those around him. The identification of outliers is based on an untested assumption that few officers display racially biased behavior; if problem behavior is more common than anticipated, then the results are meaningless.

Finally, the instability of the model's results, both between runs and over time, suggest that the model does little to address the practical concerns related to stop and frisk behavior. The extent to which each officer displays problem behavior (as defined by the model) varies considerably, and the model is unable to identify which specific stop activity

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148 See, e.g, Ray Rivera, Al Baker and Janet Roberts, "A Few Blocks, 4 Years, 52,000 Police Stops, *New York Times*, July 12, 2010 at A1 (documenting frequent stops in a neighborhood with a very high percent Black population).

is inappropriate. Moreover, the failure to identify officers stopping "too many blacks" in largely black precincts, or "too many Hispanics" in largely Hispanic precincts, raises serious concerns that the model's logic fails to capture important determinants of inappropriate police behavior.

The author of the RAND report raises similar concerns about the model's severe limitations in an article in an academic journal published two years after the release of the RAND report. In a 2009 article published in the *Journal of the American Statistical Association,*[149] the authors describe the internal benchmarking analysis, but openly discuss several limitations that echo the concerns raised in this report:

> "Omitted variable bias is possible in all studies using observational data. If there is a confounding variable (besides racial bias) that is associated with both the officer and the likelihood of stopping a nonwhite pedestrian, then the estimated race effect will be biased. The analysis uses all observable features of time, place, and assignment that are clearly confounding variables, but an unmeasured variable may explain the observed differences." (p. 666)
>
> "Implicit in the proposed framework, which draws on a multiple-comparison idea relevant to hypothesis testing, is an assumption that numerous officers have the same level of bias, which is either near zero or identically equal to zero. Although the method compares officers to their peers, it is not necessarily the case that their peers are unbiased. If, for example, all of the officers in a precinct act in a racially biased manner then when each is compared with the others, none of the officers in this precinct will be flagged as problematic. Only in the case that most officers are unbiased and only a few are problematic, the setting several police executives have suggested, will the method actually measure race bias among officers." (p. 666).
>
> "Our analysis computed benchmark comparisons for only those officers making more than 50 stops. Whereas these officers cover the majority of pedestrian stops, this cutoff prevents the analysis from detecting biases in those officers making fewer than 50 stops." (p.666)
>
> "Our analysis also dropped 278 officers for whom we could not construct an adequate benchmark. The problem occurs when some officers had very unique assignments." (p.666)

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149 Greg Ridgeway and John Macdonald, "Doubly Robust Internal Benchmarking and False Discovery Rates for Detecting Racial Bias in Police Stops." 104 *Journal of the American Statistical Association* 661 (2009)

Given these and the other limitations of the RAND internal benchmarking analysis, I conclude that this analysis cannot be reliably used as evidence of the absence of racial bias in NYPD stop and frisk activity.

D. Racial Disparities in Post-Stop Outcomes

1. Overview

Chapter 5 in the RAND Report analyzes whether there are differences in the post-stop treatment of suspects and the outcomes of stops of white and non-white citizens. Differences by race in either of these dimensions would indicate preferential or disparate treatment by suspect race. The procedure used here to approximate experimental conditions is propensity-score weighting, similar to the method in Chapter 4, but with a different set of characteristics. The analysis in this chapter relies on stops of similarly-situated White, Black and Hispanic citizens and then compares their outcomes, with race or ethnicity as the "experimental" treatment.[150] The weighting procedure adjusts for the fact that the circumstances and locations of typical stops of nonwhite citizens are different from the stops of white citizens, and vice versa.[151] By doing so, the characteristics of the location of the stop are statistically equalized, a point to which I return to below.

Based on the analyses reported in Chapter 5, RAND concludes that:

- "Officers frisked white suspects slightly less frequently than they did *similarly situated* nonwhites (29 percent of stops versus 33 percent of stops). Black suspects were slightly likelier to have been frisked than white suspects stopped in circumstances similar to the black suspects (46 percent versus 42 percent). While there is a gap, this difference is much smaller than what the aggregate statistics indicated.

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150 Stops were matched by race on month of the year, gender (male), day of the week, the type of identification (physical or verbal), whether the stop was based on a radio run, the x-y coordinates of the stop location, being reported by witness, being part of an ongoing investigation, being in an high-crime area, being at a high-crime time of day, being close to the scene of an incident, detecting sights and sounds of criminal activity, evasiveness, association with known criminals, changing direction at the sight of an officer, carrying a suspicious object, fitting a suspect description, appearing to be casing, acting as a lookout, wearing clothes consistent with those commonly used in crime, making furtive movements, acting in a manner consistent with a drug transaction or a violent crime, or having a suspicious bulge. RAND, at 34. The stop categories of "OTHER" stop factor or "OTHER ADDITIONAL CIRCUMSTANCE" were not in included in the matching procedure. See, *infra* at VI.C.2.a and accompanying notes.

151 RAND at 32

- The rates of searches were nearly equal across racial groups, between 6 and 7 percent. However, in Staten Island, the rate of searching nonwhite suspects was significantly greater than that of searching white suspects.
- White suspects were slightly likelier to be issued a summons than were similarly situated nonwhite suspects (5.7 percent versus 5.2 percent). On the other hand, arrest rates for white suspects were slightly lower than those for similarly situated nonwhites (4.8 percent versus 5.1 percent).
- Officers were slightly less likely to use force against white suspects than they were to use it against similarly situated nonwhites (15 percent versus 16 percent); however, in Queens, Brooklyn North, and the Bronx, there was no evidence that use-of-force rates varied across races.
- Officers recovered contraband (such as weapons, illegal drugs, or stolen property) in 6.4 percent of the stops of white suspects. The contraband recovery rate was 5.7 percent for similarly situated black suspects and 5.4 percent for similarly situated Hispanic suspects."[152]

This part of RAND's analysis is important because even if officers stop white and nonwhite pedestrians at the same rate, differences in treatment after being stopped can reveal residual and subsequent disparities—disparities that provide an alternate measure of racial preference and accordingly may bear on the constitutional claims in this case. If, for example, stops are made that are measurably and significantly less productive for one racial group in terms of identifying situations where "crime is afoot",[153] then the initial basis for suspicion that animates these stops may be distinctly different and suggestive of a separate and wider basis for stopping these suspects. These outcomes also carry meaningful potential impacts that, if racially unbalanced, place a disproportionate burden on nonwhites.[154]

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152 RAND at 31.

153 Terry, supra note 67.

154 William J. Stuntz, "*Terry* and Legal Theory: Terry's Impossibility," 72 *St. John's Law Review* 1213-1229 (1998). Street stops are hardly neutral with respect to the person stopped and found to be innocent of any wrongdoing. Stuntz notes four distinct harms that victims of unjustified and inaccurate stops might suffer. "The first is a harm to the victim's privacy - the injury suffered if some agent of the state rummages around in the victim's briefcase, or examines the contents of his jacket pockets. The second is … 'targeting harm,' The injury suffered by one who is singled out by the police and publicly treated like a criminal suspect. Third is the injury that flows from discrimination, the harm a black suspect feels when he believes he is treated the way he is treated because he is black. Fourth is the harm that flows from police violence, the physical injury and associated fear of physical injury that attends the improper police use of force."

2. Limitations in the Analysis

a. Matching and the Context of Stops

The RAND analysis constructs a quasi-experiment to determine if similarly-situated – that is, propensity-score matched– pedestrian stops of white and nonwhite citizens result in different treatment by officers. The matching procedure is designed to reduce or if possible eliminate any differences between citizens other than race/ethnicity. The results of the matching procedure are shown in their Table 5.1.

The validity of the conclusions in Chapter 5 depends on the extent to which the matching procedure can eliminate bias in the estimates due to unobserved components of the post-stop interactions and decisions. The analysis leans heavily on the assumption that matching on observed variables such as time of day or the indicia of suspicion can proportionately distribute or account for the racial distribution of unobserved factors – such as the presence of bystanders, or the demeanor of both officer and suspect. It cannot.[155]

In fact, demeanor does matter in police-citizen encounters.[156] It is one thing to be stopped and to have a mutually respectful exchange with an officer, it is quite another to be frisked, searched, thrown against the pavement or arrested. Mutuality is important here. Often, though not always, officers have no direct prior interaction with pedestrians they determine to stop. However, the decision to frisk, search, use force, or to arrest a suspect is highly contingent on actual interactions between officer and pedestrian. Subtleties in these interactions are largely lost in the data, rendering conclusions based on these data incomplete and highly speculative. "For

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155 Behaviors and exchanges within stop encounters are largely unobserved in the data. Yet the decision to frisk, search, use force, or to arrest a suspect is often highly contingent on actual interactions between officer and pedestrian. It also is contingent on the location of where the event takes place. See Douglas Smith, Christy Visher, and Laura Davidson, "Equity and Discretionary Justice: The Influence of Race on *Police* Arrest Decisions," 75 *Journal of Criminal Law and Criminology* 234 (1984). Subtleties in these interactions are largely lost in the data, rendering conclusions based on these data incomplete and highly speculative. "For example, a racial group might be disproportionately searched if members of that group were 'disproportionately antagonistic or disrespectful toward police." See, Ian Ayres and Jonathan Borowsky, a Study of Racially Disparate Outcomes in the Los Angeles Police Department, at 5 (October 2008), available at http://www.aclu-sc.org/documents/view/47." Yet it may be that members of that racial group are disproportionately antagonistic or disrespectful because the police treat them initially with greater suspicion and disregard. An officer's prior experiences with members of that racial group, however, may warrant greater suspicion from his perspective, leading to a speculative cycle cannot be resolved with these data.

156 Robin Shepard Engel et al., "Further Exploration of The Demeanor Hypothesis: The Interaction Effects of Suspects' Characteristics And Demeanor On Police Behavior," 17 *Justice Quarterly* 235 (2000); Roger G. Dunham and Geoffrey P. Alpert, "Officer and Suspect Demeanor: A Qualitative Analysis of Change, 12 *Police Quarterly* 6 (2009)

example, a racial group might be disproportionately searched if members of that group were 'disproportionately antagonistic or disrespectful toward police.'"[157] Yet it may be that members of that racial group are disproportionately antagonistic or disrespectful because the police treat them initially with greater suspicion and disregard. An officer's prior experiences with members of that racial group, however, may warrant greater suspicion from his perspective, and so on. The speculative cycle cannot be resolved with these data. Behaviors and exchanges within stop encounters are largely unobserved in the data.

Nonetheless we know some things about these encounters, in particular, that they take place within specific settings and contexts. Systemic differences across the contexts in which white and nonwhite suspects are stopped, frisked, searched and arrested may account for the "large racial disparities in the outcomes of stops" observed in "the raw statistics."[158] Hence, the essential purpose of this chapter in the RAND analysis is to control for context when assessing post-stop outcomes of pedestrians. The operational definition of the broad "context" of a stop (where, when and why the stop occurred) is expressed by the matching criteria, which RAND defines as the salient features of each stop.[159]

But this is a narrow and attenuated view of the components of a stop and the complex interdependence among the factors that launch the stop and influence what happens after. Consider the following thought experiment, which illustrates the intuition behind the RAND approach. Imagine a subset of the data—a sample of stops taken from the whole dataset—where the salient features of each stop in the sample are exactly the same, with the single exception of the suspect's reported race. Cases that are not matched are set aside. This subset of the data is known as a matched sample and if the match is done well then the suspect's reported race becomes the sole remaining source of variation that could account for any systemic disparities in post-stop treatment by the police. If no systemic disparities are observed, then there is little evidence that the suspect's reported race leads to differences in outcomes involving stops with features like those in the matched sample. On the other hand, if systemic disparities are observed in the matched sample then there is greater evidence that the suspect's reported race is the source of disparities in stops with those features.

Real experiments, regrettably, are never as convenient as thought experiments, and, compared to the thought experiment described above, the RAND analysis faces a number of practical challenges. It addresses these challenges with mixed success. First, the overlap in the "where, when and why" of stops between white and nonwhite suspects is limited. Because these suspects are not comparably distributed across stops—whites tend to be stops at places,

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157 Ian Ayres and Jonathan Borowsky, A Study of Racially Disparate Outcomes in the Los Angeles Police Department, at 5 (October 2008), available at http://www.aclu-sc.org/documents/view/47.

158 RAND at 31

159 Supra note 150

times and for reasons that are dissimilar to the context in which nonwhites are stopped—there is no natural convenient matched sample.

To address the problem of limited overlap in distribution of suspects, the RAND analysis again employs the statistical technique of propensity score matching. The procedure "reweight(s) the stops involving nonwhite pedestrians so that they have the same distribution of features as those involving white pedestrians."[160] As a result of matching, "[a]ny differences in search rates … cannot be due to differences in any of the features" that were used to match cases.[161]

To appreciate the utility of propensity scoring, recall that in the thought experiment, a subset of stops with matched features was constructed by eliminating mismatches. In the illustration in Chapter 5, 31,716 stops of non-whites in Manhattan South in 2006 were reduced to a sample of 9,781 comparable stops that were compared to 5,547 stops of whites.[162] For the entire city, a total of 77,383 stops of nonwhites were matched to 53,500 stops of whites, out of the more than 500,000 stops made in 2006. There is no information provided on the characteristics of included and non-included cases across the City.

Accordingly, with limited overlap of stop features across white and nonwhite suspects, however, most of the sample was eliminated to assess racial disparities in Chapter 5. Moreover, serious doubts about the representativeness of the actual matches would plague the analysis since if matches are uncommon, their characteristics may be atypical. Propensity score weighting responds to these concerns by abandoning the search for perfect matches and instead assigning probabilities to nonwhite suspects that the features of their stops are the same as that of their white counterparts, or vice versa.[163] More probably, matches are weighted more heavily in the analysis than those "matches" with lower probabilities.

A second challenge arises in the propensity scoring solution: namely, which background features should be used to assign propensity scores to suspects. Should the baseline context be that in which whites are stopped, or should it be the typical context where blacks are stopped, or should it be the Hispanic or some other context? Differences might result if, for instance, intensive enforcement in environments where Blacks are typically stopped swamps out otherwise observable differences in police treatment across race. The context where whites are stopped would in that case provide a more sensitive test for racial disparities. The RAND analysis

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160 RAND at 32

161 Id.

162 RAND at 34, Table 5.1

163 For details, see Greg Ridgeway, Assessing the Effect of Race Bias in Post-Traffic Stop Outcomes Using Propensity Scores, RAND Corporation RP-1252 (2006), http://www.rand.org/pubs/reprints/RP1252/

reports results using both the typical white context and the typical black context, and by matching, gives equal weight to the two contexts.

A third challenge arises from the use of a narrow set of conditions and features to control for context. Again, recall that in the thought experiment, everything except race or ethnicity was accounted for through matching. However, the report acknowledges, "[i]t is possible that bias causes some of the differences in when, where, and why these stops occurred."[164] Thus by controlling for certain aspects of the stop that are correlated with race, the analysis may be controlling for race and racial consideration also, which is the one thing that must be left unaccounted for in order to test for disparities. If for example, officers are more likely to interpret a style of dress on blacks (say baggy pants or bulky hooded sweatshirts) as more probative of criminal activity than the same style worn by whites, then controlling for clothing worn, which the RAND analysis does,[165] would understate the effect of race in stops. At the very least, interpretation of this factor by an officer *in situ* is sufficiently subjective as to introduce heterogeneity and inconsistency into its interpretation despite its uni-dimensional analytic application.

Carrying a suspicious object or having a suspicious bulge, two additional controls used in the RAND analysis, also run the risk of being simultaneously determined with race. This is not mere speculation. A number of visual processing studies conducted in the wake of the 1999 Amadou Diallo shooting, using both undergraduates and police officers as subjects, indicate that seeing black faces influences the interpretation of crime-relevant objects.[166] This appears to be a pervasive psychological phenomenon that operates at an implicit level, making it a difficult but not impossible problem to eradicate. As a separate matter, a statistical problem arises "when a variable that is not a legitimate control variable, but that is correlated with race or ethnicity, is included in the regression."[167] This problem, alternatively known as included variable bias or diverting variable bias, is comparatively easier to resolve.

b. Re-interpreting the Results

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164 RAND at 32

165 Supra note 150, quoting the list of factors considered in the stopping routine to include "wearing clothes consistent with those commonly used in crime"

166 See e.g., Jennifer L. Eberhardt, Valerie J. Purdie, Phillip Atiba Goff and Paul G. Davies, "Seeing Black: Race, Crime, and Visual Processing," 87 *Journal of Personality and Social Psychology*, 876 (2004); Joshua Correll, Bernd Wittenbrink, Bernadette Park and Charles M. Judd, Melody S. Sadler, and Tracie Keesee, "Across the Thin Blue Line: Police Officers and Racial Bias in the Decision to Shoot," 92 *Journal of Personality and Social Psychology* 1006 (2007)

167 John Yinger, "Evidence on Discrimination in Consumer Markets," 12 *J. Econ. Persp.* 23, 27 (1998). See, also, Ian Ayres and Jonathan Borowsky, A Study of Racially Disparate Outcomes in the Los Angeles Police Department (2008), available at http://www.aclu-sc.org/documents/view/47.

Another relatively easy-to-resolve challenge of the RAND analysis in Chapter 5 concerns the reported results and discussion. The RAND study's discussion repeatedly de-emphasizes the effect of its own findings. For example, Table 5.2 shows that overall blacks and whites have statistically significant differences for every outcome variable considered. Instead of highlighting this important fact along with the other results it discusses, the chapter focuses on white-nonwhite comparisons, which produce more muted differences (note that nonwhites include Hispanics, Asians and others) than the stark black-white results. Simple tests for bivariate comparisons are available in such circumstances, but if they were completed, they were not reported here.

Moreover, in many places, the study understates the magnitude of racial differences by conflating percentages and percentage points. For example, the Report observes, while referring to Table 5.2, that "stopped nonwhites have a frisk rate that is about 3 to 4 percent higher than that for white pedestrians."[168] It should have stated that the nonwhite-white frisk rate difference is 3 to 4 percentage points, which at the reported magnitudes represents a 10 to 12 higher rate of being frisked for nonwhites, or roughly three times as great as the study claimed.[169] Blacks are almost 15 percent more likely to be frisked than whites. The extent to which this statistic is practically meaningful is a judgment call, but at 4 to 5 times greater than that suggested by the RAND Report it is worth noting. This pattern is carried over to the discussion of Table 5.3 (which is based on the propensity weighting using the Black context).[170] Toward the end of this discussion, however, the Study does acknowledge differences in percentage points and nicely indicates the practical implications of small single digit percentage point differences given the number of stops. A careful reading of this section, then, suggests that there in fact is a consistent pattern of racial disparity in nearly all the post-stop outcomes.

Finally, the analysis of arrest or summons ignores the conditional relationship between

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[168] RAND at 35. Note also that footnote *a* in Table 5.2 should read "Figures that differ statistically from the rate for white pedestrians," not "black pedestrians.

[169] This is a form of the distortion that results when absolute disparities are used instead of comparative disparities. Imagine a jury pool where the minority percentage in the general population is 70 percent but is 60 percent in the jury pool. This absolute disparity of 10% is quite different from an absolute disparity of 10% when the general population is 20% minority but the jury pool is 10% minority. Comparative disparities would provide a more accurate metric of the difference in these two conditions. See, for example, David Kairys, Joseph B. Kadane and John P. Lehoczky, "Jury Representativeness: A Mandate for Multiple Source Lists," 65 *California Law Review*, 776-827 (1977); Richard Seltzer et al., "Fair Cross-Section Challenges in Maryland: An Analysis and Proposal," 25 *U. Balt. L. Rev*. 127 (1996). The same applies here.

[170] Clearly the authors know better. Indeed in the conclusion of the chapter, the Report notes appropriately that the contraband "recovery rate for white suspects is 12 percent greater than for black suspects (6.4 percent versus 5.7 percent)." RAND at 42.

these two outcomes. Tables 5.2 and 5.3 report separate tests to compare the rate of arrest or summons in the matched cases across racial groups. However, arrest and summons are not separate outcomes, but instead are conditional outcomes. That is, once a stop has been determined to provide probable cause evidence to issue a criminal sanction, the officer has the choice, dependent on the offense classification and the evaluation of several subjective characteristics, of issuing a "summons" or affecting an arrest where the suspect is taken into custody.[171] The RAND analysis approached these as independent outcomes and reports them separately. A more appropriate analysis would be a two-stage analysis to determine first, which citizens are subject to any criminal sanction, and then, within that group, which receive summons and which are arrested.

The bias in the RAND approach is well known in the social science literature as selection bias.[172] Since the characteristics of persons subject to any sanction may be correlated with the treatment, race, the appropriate comparison would first determine who is sanctioned. The next comparison, then, would be within that sanctioned group to determine which citizens are subject to arrest and which receive summonses, controlling for the probability of receiving any sanction. If Blacks, for example, are more often sanctioned following a stop, then the pool of sanctioned persons will be disproportionately Black and the measured outcome – arrest versus summons, in this case will be biased by overrepresentation of Blacks. The likelihood of a race effect on arrest is likely to be underestimated. As a result, the lower rates of arrests and summons for Blacks versus Hispanics or Whites is biased and likely to be uninterpretable.

171 See, NYPD Patrol Guide, § 212-11 (2006)

172 See, for example, James J. Heckman, "Sample Selection Bias as a Specification Error," 47 *Econometrica* 153-161 (1979); Richard A. Berk "An Introduction to Sample Selection Bias in Sociological Data," 49 *American Sociological Review* 386-398 (1983).

DECLARATION

I have been compensated for this work at the rate of $350 per hour.

10/15/2010

Jeffrey Fagan, Ph.D.

October 15, 2010

APPENDICES

A. Curriculum Vitae

B. Sample UF-250 Form

C. Crime Codes for Suspected Crimes and Crime Complaints

1. Sample of Raw Codes to Create Suspected Crime Codes from UF-250
2. Categories for Suspected Crimes Provided by NYPD with Supplemental Codes based on Actual Codes
3. Classification of Crime Suspected into Aggregate Crime Codes
4. Higher Order Classification of Aggregate Crime Codes into Meta-Categories
5. Histogram of Frequency of Aggregate Crime Codes
6. Histogram of Frequency of Meta-Categories

D. Analysis of Stop Factors and Memorandum on Case Law

E. Calculation of Patrol Strength

1. Command Codes
2. Allocation of Patrol Strength Data to Precincts

F. Transcript of March 9, 2010 Forum on Stop and Frisk at the Association of the Bar of the City of New York

G. Letter from Police Commissioner Raymond Kelly to City Council Speaker Christine Quinn

H. List of Sources and Materials Cited

Appendix A.

Curriculum Vitae

Jeffrey Fagan, Ph.D.

CURRICULUM VITAE

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PROFESSIONAL EXPERIENCE:

2010-11:	Fellow, Straus Institute for the Advanced Study of Law and Justice, New York University School of Law
2010-present:	Senior Research Scholar, Yale Law School
2009-10:	Visiting Professor, Yale Law School
2001-present:	Professor, Columbia Law School Director, Center for Crime, Community and Law, Columbia Law School
2001-2006	Director, Doctor of Juridical Science in Law (JSD) Program, Columbia Law School
1999-present	Faculty Fellow, Institute for Social and Economic Research and Policy, Columbia University
1998-2001:	Visiting Professor, Columbia Law School
1996-present:	Professor, Department of Epidemiology, Mailman School of Public Health, Columbia University
1995-2002:	Founding Director, Center for Violence Research and Prevention, Mailman School of Public Health, Columbia University
1989-1996:	Associate Professor to Professor, School of Criminal Justice, Rutgers-The State University of New Jersey
1988-1989:	Associate Professor, Department of Law and Police Science, John Jay College of Criminal Justice, City University of New York; Associate Professor, Doctoral Program in Criminal Justice, City University of New York Graduate Center; Associate Director for Research, Criminal Justice Center, John Jay College of Criminal Justice, City University of New York
1986-1988:	Senior Research Fellow, New York City Criminal Justice Agency.
1977-1986:	Director, Center for Law and Social Policy, URSA Institute, San Francisco.
1975-1976:	Research Director, Northern California Service League, San Francisco, California.
1974-1975:	Associate Research Analyst, Office of Criminal Justice Planning, Oakland, California.
1970-1974:	Director, College of Urban Studies, State University of New York at Buffalo.
1969-1971:	Teaching Assistant and Research Associate, Department of Psychology, State University of New York at Buffalo

EDUCATION:

PhD, 1975, Policy Science, Department of Civil Engineering, State University of New York at Buffalo. Dissertation: "A Predictive Model of Success in Criminal Justice Employment Programs."

MS, 1971, Human Factors Engineering, Department of Industrial Engineering, State University of New York at Buffalo.

BE, 1968, Industrial Engineering, New York University.

AWARDS AND HONORS:

Fellow, American Society of Criminology, elected April 2002
Senior Justice Fellow, Open Society Institute, 2005-6
Health Policy Scholar Award, Robert Wood Johnson Foundation, 2002-2004
Book Award, "Best Book on Adolescence and Social Policy" for *Changing Borders of Juvenile Justice* (with F. Zimring), Society for Research on Adolescence, 2002
Public Interest Achievement Award, Public Interest Law Foundation of Columbia University, Spring 2001
Bruce Smith Senior Award, Academy for Criminal Justice Sciences, March 2000.
Lecturer, Fortunoff Colloquium, *Social Contagion of Violence.* New York University School of Law, April 1999.
Fellow, Earl Warren Legal Institute, School of Law, University of California-Berkeley, 1999-present
University Faculty Merit Award, Rutgers University, 1990-94
Lecturer in Colloquium on Race, Ethnicity and Poverty Workshop, Center for the Study of Urban Inequality, University of Chicago, June 1992
External Examiner, Department of Sociology, University of Toronto, 1992
University Research Council Grantee, Rutgers University, 1989-90
Lecturer, Fortunoff Colloquium, *Preventive Detention and the Validity of Judicial Predictions of Dangerousness.* New York University School of Law, October, 1988
Delegate, Criminal Justice and Criminology Delegation to the People's Republic of China, Eisenhower Foundation, 1985
NDEA Title IV Fellowship, Department of Industrial Engineering, State University of New York at Buffalo, June 1968-June 1971

PUBLICATIONS:

Books:

Tyler, T., A. Braga, J. Fagan, et al. (eds.), *Legitimacy, Criminal Justice, and the State in Comparative Perspective.* New York: Russell Sage Foundation Press (2008).
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Changing Borders of Juvenile Justice: Transfer of Adolescents to the Criminal Court, edited by Jeffrey Fagan and Franklin Zimring. Chicago: University of Chicago Press (2000)

EXPERT TESTIMONY:

David Floyd, et al. v. City of New York, et al., U.S. District Court, Southern District of New York, No. 08 Civ. 1034 (S.D.N.Y.)
State v. Raheem Moore, Circuit Court # 08CF05160, State of Wisconsin, Criminal Division, Milwaukee County
Connecticut v Arnold Bell, Docket # CR02-0005839, District Court of Connecticut, New Haven
Jessica Gonzales v. United States, Petition No. 1490-05, Inter Am. C.H.R., Report No. 52/07, OEA/Ser.L./V/II.128, doc. 19 (2007)
U.S. v. Joseph Brown and Jose Lavandier, U.S. District Court for the District of Vermont, Docket No. 2:06-CR-82-2
United States v. Khalid Barnes, 04 Cr. 186 (SCR), U.S. District Court for the Southern District of New York
Loggins v.State, 771 So. 2d 1070 (Ala. Crim. App. 1999)

TECHNICAL REPORTS (SELECTED):

Project Safe Neighborhoods in Chicago: Three Year Evaluation and Analysis of Neighborhood Level Crime Indicators, Final Technical Report (J. Fagan, A. Papachristos, T.L. Meares), Grant # 2004-GP-CX-0578, Bureau of Justice Assistance, U.S. Department of Justice (2006).
Social and Ecological Risks of Domestic and Non-Domestic Violence against Women in New York City (J. Fagan, J. Medina-Ariza, and S.A. Wilt). Final Report, Grant 1999-WT-VW-0005, National Institute of Justice, U.S. Department of Justice (2003).
The Comparative Impacts of Juvenile and Criminal Court Sanctions on Recidivism among Adolescent Felony Offenders(J. Fagan, A. Kupchik, and A. Liberman). Final Report, Grant 97-JN-FX-01, Office of Juvenile Justice and Delinquency Prevention (2003).
Drug Control in Public Housing: The Impact of New York City's Drug Elimination Program on Drugs and Crime (J. Fagan, J. Holland, T. Dumanovsky, and G. Davies). Final Report, Grant No. 034898, Substance Abuse Policy Research Program, Robert Wood Johnson Foundation (2003).
The Effects of Drug Enforcement on the Rise and Fall of Homicides in New York City, 1985-95 (J. Fagan). Final Report, Grant No. 031675, Substance Abuse Policy Research Program, Robert Wood Johnson Foundation (2002).
Getting to Death: Fairness and Efficiency in the Processing and Conclusion of Death Penalty Cases after Furman (J. Fagan, J. Liebman, A. Gelman, V. West, A. Kiss, and G. Davies). Final Technical Report, Grant 2000-IJ-CX-0035, National Institute of Justice (2002).

EDITORIAL:

Senior Editor, *Criminology and Public Policy*, 2001 - present
Advisory Board, *Family and Child Law Abstracts*, Legal Scholarship Network, 1999-present
Editorial Advisory Board, *Journal of Criminal Law and Criminology*, 1996-present

Editorial Board, *Criminology*, 1997-2001
Editorial Board, *Journal of Quantitative Criminology*, 2001-present
Editorial Board, *Crime and Justice: A Review of Research*, 1998-present
Editorial Board, *Journal of Research in Crime and Delinquency*, 1997-present
Editor, *Journal of Research in Crime and Delinquency*, 1990 - 1995
Editor, *Contemporary Drug Problems*, Special Issues on Crack (Winter 1989, Spring 1990)

ADVISORY BOARDS AND COMMITTEES:

Research Advisory Board, The Innocence Project (2009 – present)
Committee on Law and Justice, National Academy of Sciences (2000-2006) (Vice Chair, 2004-6)
Member, Committee to Review Research on Police Policy and Practices, National Research Council, National Research Council (2001-2003)
Working Group on Law, Legitimacy and the Production of Justice, Russell Sage Foundation (2000-present)
Working Group on Incarceration, Russell Sage Foundation (2000-2006)
Academic Advisory Council, National Campaign Against Youth Violence (The White House) (1999-2001)
Fellow, Aspen Roundtable on Race and Community Revitalization (1999 - 2001)
Fellow, Earl Warren Legal Institute, University of California School of Law (1998 - present)
Research Network on Adolescent Development and Juvenile Justice, MacArthur Foundation (1996-2006)
National Consortium on Violence Research, Carnegie Mellon University (NSF) (1996-present)
Committee on the Assessment of Family Violence Interventions, National Research Council, National Academy of Sciences (1994-1998)
Advisory Board, Evaluation of the Comprehensive Gang Intervention Program, University of Chicago (1997-present)
Committee on Opportunities in Drug Abuse Research, Institute of Medicine, National Academy of Sciences (Special Consultant) (1995 - 1996).
Initial Review Group, Violence and Traumatic Stress Research Branch, National Institute of Mental Health, National Institute of Health (1994-1998)
Chair, Working Group on the Ecology of Crime in Inner Cities, Committee for Research on the Urban Underclass, Social Science Research Council (1989-1994)
Advisory Board, Evaluation of the Jobs Corps, U.S. Department of Labor (1993-present)
Advisory Board, National Service Action Corps, Robert F. Kennedy Memorial (1993-1997)
Advisory Board, Evaluation of Family Violence Prevention and Services Act, The Urban Insitute (1993-1994)
Scientific Core Group, Program on Human Development and Criminal Behavior, MacArthur Foundation (1991-1992)
Injury Control Panel on Violence Prevention, Centers for Disease Control and Prevention, U.S. Department of Health and Human Services (1990-1991)
Princeton Working Group on Alternatives to Drug Prohibition, Woodrow Wilson School of Public and International Affairs, Princeton University (1990-1994)
Racial Disparities in Juvenile Justice, Pennsylvania Juvenile Court Judges Commission (1991-92)
Racial Disparities in Juvenile Justice, Missouri Department of Law and Public Safety (1990-91)

Conditions of Confinement of Juveniles, National Institute for Juvenile Justice and Delinquency Prevention (1990-1992)
Research Program on "Linking Lifetimes -- Intergenerational Mentoring for Youths at Risk and Young Offenders," Temple University (1989-91)
Research Program on Juvenile Court Sanctions for Family Violence, National Council of Juvenile and Family Court Judges, Bureau of Justice Assistance, U.S. Department of Justice (1987-1988)
School Crime Research and Development Program, Office of Juvenile Justice and Delinquency Prevention, National Institute for Juvenile Justice and Delinquency Prevention (1986-1988)
Research and Development Project on Sexually Exploited Children, Tufts University, New England Medical Center Hospital, Boston, MA (1980-83)
Administration of Justice Program, National Urban League, New York, NY (1982-1987)

PROFESSIONAL ASSOCIATIONS:

American Society of Criminology
American Sociological Association
Law and Society Association
American Association for the Advancement of Science
American Public Health Association

RESEARCH GRANTS:

Principal Investigator, "Evaluation of Project Safe Neighborhoods in Chicago," May 2004 – September 2006, Grant # 2004-GP-CX-0578, Bureau of Justice Assistance, Office of Justice Programs, U.S. Department of Justice.
Principal Investigator, "Capital Sentencing of Adolescent Murder Defendants," March – December 2004, Grant #20012433 from the Open Society Institute. Additional support from the Wallace Global Fund.
Principal Investigator, "Legitimacy, Accountability, and Social Order: Majority and Minority Community Perspectives on the Law and Legal Authorities," September 2002 - August 2003, Russell Sage Foundation.
Principal Investigator, "Social Contagion of Violence," Investigator Awards in Health Policy Program, Robert Wood Johnson Foundation, September 2002 – June 2004
Principal Investigator, "Getting to Death: Fairness and Efficiency in the Processing and Conclusion of Death Penalty Cases after Furman," Grant #2000-IJ-CX-0035, September 2000 - August 2001, National Institute of Justice, U.S. Department of Justice.
Co-Principal Investigator, "Columbia Center for the Study and Prevention of Youth Violence," Grant R49-CCR218598, October 1, 2000 - September 30, 2005, Centers for Disease Control, U.S. Department of Health and Human Services.
Principal Investigator, "Neighborhood Effects on Legal Socialization of Adolescents," John D. and Catherine T. MacArthur Foundation, October 1, 2000 - September, 30, 2002.
Principal Investigator, "Violence Prevention through Legal Socialization," 1 R01-HD-40084-01, October 1, 2000 - September 30, 2003, National Institute of Child and Human Development, U.S. Department of Health and Human Services.
Principal Investigator, "The Effects Of Incarceration On Crime And Work In New York City: Individual And Neighborhood Impacts," Russell Sage Foundation, Grant 85-00-11, September 2000 - August 2002.

Principal Investigator, "Community Courts And Community Ecology: A Study of The Red Hook Community Justice Center," Grant 2000-MU-AX-0006, June 1, 2000 - December 31, 2002, National Institute of Justice, U.S. Department of Justice.

Principal Investigator, "Age, Crime and Sanction: The Effect of Juvenile Versus Adult Court Jurisdiction on Age-specific Crime Rates of Adolescent Offenders," Grant JR-VX-0002, June 1999 - August 2000, Office of Juvenile Justice and Delinquency Prevention, U.S. Department of Justice.

Principal Investigator, "Social and Ecological Risks of Domestic and Non-domestic Violence Against Women in New York City," Grant WT-VX-0005, April 1999 - December 2000, National Institute of Justice, U.S. Department of Justice.

Principal Investigator, "Drug Control in Public Housing: An Evaluation of the Drug Elimination Program of the New York City Public Housing Authority," September 1998 - August 2001, Robert Wood Johnson Foundation.

Principal Investigator, "The Criminalization of Delinquency: Comparative Impacts of Juvenile and Criminal Court Sanctions on Adolescent Felony Offenders," March 1997 - September 2000, Office of Juvenile Justice and Delinquency Prevention, Annie E. Casey Foundation, Open Society Institute.

Co-Principal Investigator, "Post-Traumatic Stress Among Police," October 1997 - April 2000, National Institute of Mental Health, 1 R01 MH56350-01, National Institute of Health (subcontract from University of California at San Francisco).

Principal Investigator, "The Rise and Fall of Drug-Related Homicides in New York City: 1985-95," July 1997 - June 2000, Robert Wood Johnson Foundation.

PEER REVIEW:

Scholarly Journals

Law and Society Review
Journal of Contemporary Ethnography
American Sociological Review
Crime and Justice: An Annual Review of Research
Sociological Methods and Research
Justice Quarterly
Violence and Victims
Social Science Quarterly
Social Problems
American Journal of Sociology
Journal of Drug Issues
Journal of Quantitative Criminology
Journal of Criminal Justice
Alcohol Health and Research World
Criminal Justice Ethics
Contemporary Drug Problems

University Presses

Rutgers University Press
State University of New York Press
Temple University Press
University of Chicago Press
Cambridge University Press
Oxford University Press
Princeton University Press

Other Presses

MacMillan Publishing
St. Martins Press
Greenwood Publications
Sage Publications

Research Grant Reviews

National Institute on Mental Health, Violence and Traumatic Stress Branch
Centers for Disease Control and Prevention, National Center for Injury Prevention and Control, USPHS
Law and Social Science Program, National Science Foundation

Sociology Program, National Science Foundation
National Institute on Drug Abuse, Prevention Branch
National Institute on Drug Abuse, Epidemiology Branch
National Institute of Justice
Office of Juvenile Justice and Delinquency Prevention
The Carnegie Corporation of New York
The W.T. Grant Foundation

COURSES TAUGHT:

Juvenile Justice
Pro-Seminar on Community Justice and Problem-Solving Courts
Seminar Regulation in the Criminal Law
Law and Social Science
Seminar on Criminology
Foundations of Scholarship
Seminar on Violent Behavior
Seminar on Drugs, Law and Policy
Seminar on Communities and Crime
Research Methods in Criminal Justice and Criminology
Advanced Research Methods
Qualitative Research Methods
Criminal Justice Policy Analysis
Administration of Juvenile Corrections
Research Methods
Seminar on Deterrence and Crime Control Theory

CONSULTATIONS:

New Jersey Commission on Law Enforcement Standards and Practices, 2006-7
London School of Economics, Urban Age Colloquium, 2005
Inter-American Development Bank, Urban Security and Community Development, 2002-3
Trans.Cité (Paris, France), Security in Public Transportation, 2002
Institute for Scientific Analysis, Domestic Violence and Pregnancy Project, 1995-96
Department of Psychology, University of Wisconsin (Professor Terrie Moffitt), 1995-1999
National Funding Collaborative for Violence Prevention (Consortium of foundations), 1995
National Council on Crime and Delinquency, 1989-94
Victim Services Agency, City of New York, 1994-2000
National Conference of State Legislatures, 1994-2001
U.S. Department of Labor, 1994
City of Pittsburgh, Office of the Mayor, 1994
Center for the Study and Prevention of Violence, Colorado University, 1993 - 2000
Washington (State) Department of Health and Rehabilitative Services, 1993
National Council of Juvenile and Family Court Judges, 1993
Center for Research on Crime and Delinquency, Ohio State University, 1992, 1993
New York City Criminal Justice Agency, 1992, 1993
Violence Prevention Network, Carnegie Corporation, 1992-3
Research Triangle Institute, 1993
National Institute of Corrections, 1992, 1993
Colorado Division of Criminal Justice, 1991

Juvenile Delinquency Commission, State of New Jersey, 1991
University of South Florida, Dept. of Criminology, 1991-92
Florida Mental Health Institute, 1991
Rand Corporation, 1991-92
Juvenile Corrections Leadership Forum, 1990
Texas Youth Commission, 1990
California State Advisory Group on Juvenile Justice, 1989
New York State Division of Criminal Justice Services, Family Court Study, 1989
Juvenile Law Center, Philadelphia, 1988
American Correctional Association, 1988
Institute for Court Management, National Center for State Courts, 1987-present
Correctional Association of New York, 1987
Eisenhower Foundation, Washington DC, 1987-1990
New York City Department of Juvenile Justice, 1987-1990
Juvenile Justice and Delinquency Prevention Council, Colorado Division of Criminal Justice, 1983-87
Office of Criminal Justice Services, State of Ohio, 1983
Utah Youth Corrections Division, Salt Lake City, Utah, 1982
Office of Criminal Justice, State of Michigan, 1982,1986
National Center for the Prevention and Control of Rape, NIMH, 1980

SERVICE:

Columbia University
University Senate, Mailman School of Public Health, 2003-present
Director, JSD Program, Columbia Law School, 2001-present

Professional
Chair, Sutherland Award Committee, American Society of Criminology, 2006-7
Chair, National Policy Committee, American Society of Criminology, 2002-2003
Delegate from the American Society of Criminology to the American Association for the Advancement of Science, 1995-1999
Executive Counselor, American Society of Criminology, 1994-97
Chair, Nominations Committee, American Society of Criminology, 1995-96.
Counsel, Crime, Law and Deviance Section, American Sociological Association, 1993-94
Nominations Committee, American Society of Criminology, 1993-94
Site Selection Committee, American Society of Criminology, 1992
Program Committee, American Society of Criminology, 1988, 1990, 2000
Awards Committee, Western Society of Criminology, 1988

Public
Domestic Violence Working Group, New Jersey Administrative Office of the Courts, 1991-1998
Prevention Task Force, New Jersey Governor's Commission on Drug and Alcohol Abuse, 1990

State Judicial Conference, State of New Jersey, Administrative Office of the Courts, 1990
Task Force on Youth Gangs, State of New York, Division for Youth, 1989-90

Appendix B.

Sample of 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)
- ☐ 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.
- ☐ Other Reasonable Suspicion Of Criminal Activity (Specify)

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

Appendix C.

Crime Codes for Suspected Crimes and Crime Complaints

Appendix C.
Crime Codes for Suspected Crimes and Crime Complaints

1. Sample of Raw Codes to Create Suspected Crime Codes from UF-250 Records
2. Categories for Suspected Crimes Provided by NYPD with Supplemental Codes based on Actual Codes
3. Classification of Crime Suspected into Aggregate Crime Codes
4. Higher Order Classification of Aggregate Crime Codes into Meta-Categories
5. Histogram of Frequency of Aggregate Crime Codes
6. Histogram of Frequency of Meta-Categories

Appendix C1. Sample of Raw Codes to Create Suspected Crime Codes from UF-250 Records (First 25 lines and last 25 lines of a 50,000 line script)

```
replace crimecode1=14 if (crimsusp=="BURG" )
|(crimsusp=="BURG.")|(crimsusp=="BURGLARY" )|(crimsusp=="FELONY-
BURGLARY" ) |(crimsusp=="FEL/BURG" )|(crimsusp=="FEL/ BURG"
)|(crimsusp=="FEL/BURGLARY" ) |(crimsusp=="FEL/BURGLARY/Y"
)|(crimsusp=="FELONY/BURLARY")
replace crimecode1=14 if (crimsusp=="BRUG" )|(crimsusp=="BRUGLARY")
|(crimsusp=="BUGLARY" )|(crimsusp=="BURG (FEL)" )|(crimsusp=="BURG
(FELONY)") |(crimsusp=="BURGLARY (FEL)" )|(crimsusp=="BURG/FEL"
)|(crimsusp=="BURGALRY") |(crimsusp=="BURGLAR")
replace crimecode1=14 if (crimsusp=="BURGLARY (FELONY)")
|(crimsusp=="BURLARY" )|(crimsusp=="BURLGARY" )|(crimsusp=="FEL-BURG")
|(crimsusp=="FELONY/ BURGLARY" )|(crimsusp=="FELONY/BURG")
replace crimecode1=31 if (crimsusp=="CRIM TRESS" )|(crimsusp=="CRIM
TRES") |(crimsusp=="CRIM. TRESP." )|(crimsusp=="CRIM TRESPASS")
|(crimsusp=="CRIMINAL TRESPASS" )|(crimsusp=="CRIMINAL TRESPASSING")
|(crimsusp=="TRESPASS" )|(crimsusp=="TRESPASSING")
replace crimecode1=31 if (crimsusp=="C/T" )|(crimsusp=="CT")
|(crimsusp=="TRES" )|(crimsusp=="TRES(MIS)" )|(crimsusp=="C.TRES" )
|(crimsusp=="CRIM TRE" )|(crimsusp=="CRIM TREPASS" )|(crimsusp=="CRIM
TRES (MISD)" )|(crimsusp=="CRIM TRESP")
replace crimecode1=31 if (crimsusp=="CRIMINAL TREPASS"
)|(crimsusp=="CRIMINAL TRESSPASS" )|(crimsusp=="CRIMINAL TRESSPASSING"
)|(crimsusp=="CRI MTRES") |(crimsusp=="CRIM TRES" )|(crimsusp=="CRIM
TRESS" )|(crimsusp=="CRIM TRES (MISD)")
replace crimecode1=31 if (crimsusp=="140.15")|(crimsusp=="140.1")
|(crimsusp=="140.10" )|(crimsusp=="140.17" )|(crimsusp=="MIS/CRIM
TRES") |(crimsusp=="MISD/ CRIMINAL TRESPASS" )|(crimsusp=="MISD/CRIM
TRES") |(crimsusp=="MISD/CRIM TRESPASS")
replace crimecode1=31 if (crimsusp=="CRIM TRESPASS (MISD)"
)|(crimsusp=="CRIM RESPASSING" )|(crimsusp=="CRIM TRESS (MISD)"
)|(crimsusp=="CRIM TRESS PASS" ) |(crimsusp=="CRIM TRESS- MISD"
)|(crimsusp=="CRIM TRESS/FEL" ) |(crimsusp=="CRIM TRESSPASS")
replace crimecode1=31 if (crimsusp=="CRIM-TRES" )|(crimsusp=="CRIM.
TRES." ) |(crimsusp=="CRIM. TRES" )|(crimsusp=="CRIM. TRESPASS"
)|(crimsusp=="CRIM. TRESSPASS" )|(crimsusp=="CRIMIAL TRESPASS"
)|(crimsusp=="CRIMIINAL TRESPASS")
replace crimecode1=31 if (crimsusp=="CRIMINAL  TRESPASS" )
|(crimsusp=="CRIMINAL TRES" )|(crimsusp=="CRIMINAL TRESASS" )
|(crimsusp=="CRIMINAL TRESPAS" )|(crimsusp=="CRIMINAL TRESS" )
|(crimsusp=="CRIMINAL TRESPASSS" )|(crimsusp=="CRIMINAL TRSPASS")
replace crimecode1=31 if (crimsusp=="CRIMINALTRESPASS" )
|(crimsusp=="CRIMINIAL TRESPASS" )|(crimsusp=="CRIMINLA TRESPASS" )
|(crimsusp=="CRIMNAL TRESPASS" )|(crimsusp=="CRIMTRES" )
|(crimsusp=="CRIMTRESSPASS" )|(crimsusp=="CRININAL TRESPASS")
replace crimecode1=31 if (crimsusp=="CRMINAL TRESPASS" )|(crimsusp=="CT
2" ) |(crimsusp=="CT2" )|(crimsusp=="CTRES" )|(crimsusp=="MIS/CRIM
TRESC" ) |(crimsusp=="MIS/TRES")
replace crimecode1=46 if (crimsusp=="G.L.A." )|(crimsusp=="FEL/GLA" )
|(crimsusp=="GLA" )|(crimsusp=="GRAND LARCENY AUTO" )|(crimsusp=="AUTO
LARCENY" )|(crimsusp=="FELONY-GLA" )|(crimsusp=="FEL/ GLA" )
|(crimsusp=="FELONY/GLA" )|(crimsusp=="G L A")
```

```
replace crimecode1=46 if (crimsusp=="GLA/FELONY" )|(crimsusp=="GLA/FEL"
) |(crimsusp=="FEL - GLA" )|(crimsusp=="FEL-GLA" )|(crimsusp=="FELONY
GLA" ) |(crimsusp=="FELONY/ GLA" )|(crimsusp=="G.L.A" )|(crimsusp=="GL
VEH" ) |(crimsusp=="GLA (FEL)")
replace crimecode1=46 if (crimsusp=="GLA (FELONY)" )|(crimsusp=="GLA /
FELONY" )|(crimsusp=="GLA FELONY" )|(crimsusp=="GLA- FELONY" )
|(crimsusp=="GLA(FEL)")
replace crimecode1=45 if (crimsusp=="GRAND LARCENY"
)|(crimsusp=="LARCENY" ) |(crimsusp== "GL" )|(crimsusp=="G.L"
)|(crimsusp== "FEL/GL" )|(crimsusp =="FEL/G/L"
)|(crimsusp=="FELONY/GRAND LARCENY" )|(crimsusp=="GRAND LARC" )
|(crimsusp=="GRAND LARC.")
replace crimecode1=45 if (crimsusp=="AUTO BREAK" )|(crimsusp=="AUTO
BREAKS" ) |(crimsusp=="FEL - GRAND LARCENY" )|(crimsusp=="FEL-GRAND
LARCENY" ) |(crimsusp=="FEL/ GRAND LARCENY" )|(crimsusp=="FEL/G.
LARCENY" ) |(crimsusp=="FEL/GRAND LARCENY")
replace crimecode1=45 if (crimsusp=="FELO/ GRAND LARCENY" )
|(crimsusp=="FELO/GRAND LARCENY" )|(crimsusp=="FELONY / GL" )
|(crimsusp=="FELONY / GRAND LARCENY" )|(crimsusp=="FELONY/ GRAND
LARCENY" ) |(crimsusp=="G LARCENY" )|(crimsusp=="G. LARCENY")
replace crimecode1=45 if (crimsusp=="G.L." )|(crimsusp=="G.L. FROM
AUTO" ) |(crimsusp=="G/L" )|(crimsusp=="G.LARCENY"
)|(crimsusp=="G/L/FEL" ) |(crimsusp=="GL FR AUTO" )|(crimsusp=="GL FROM
AUTO" )|(crimsusp=="GLAR" ) |(crimsusp=="GR LARCENY" )|(crimsusp=="GR.
LARCENY")
replace crimecode1=45 if (crimsusp=="GRAN LARC" )|(crimsusp=="GRAND
LANCENY") |(crimsusp=="GRAND LAR" )|(crimsusp=="GRAND LARCENCY"
)|(crimsusp=="GRAND LARCENY (FELONY)" )|(crimsusp=="GRAND LARCENY FROM
AUTO" )|(crimsusp=="GRAND LARCENY-FELONY")
replace crimecode1=45 if (crimsusp=="GRAND LARCNEY" )
|(crimsusp=="GRANDLARCENY" )|(crimsusp=="LARC" )|(crimsusp=="LARC FROM
AUTO") |(crimsusp=="LARCENY FROM AUTO")
replace crimecode1=85 if (crimsusp=="ROB" )|(crimsusp=="ROBB" )
|(crimsusp=="ROBBERY" )|(crimsusp=="FEL/ROBBERY" )|(crimsusp==
"FELONY/ROBBERY" )|(crimsusp=="ROBB/FEL" )|(crimsusp=="ROB(FEL)" )
|(crimsusp=="ROBBERY/FEL" )|(crimsusp=="ROBBERY/FELONY")
replace crimecode1=85 if (crimsusp=="BANK ROBBERY" )|(crimsusp=="FEL -
ROBBERY" )|(crimsusp=="FEL-ROBB" )|(crimsusp=="FEL-ROBBERY" )
|(crimsusp=="FEL/ ROBBERY" )|(crimsusp=="FEL/ROB"
)|(crimsusp=="FEL/ROBB" ) |(crimsusp=="FELO/ ROBBERY")
replace crimecode1=85 if (crimsusp=="FELO/ROBBERY" )|(crimsusp=="FELONY
ROBBERY" )|(crimsusp=="FELONY-ROBBERY" )|(crimsusp=="FELONY/ ROBBERY" )
|(crimsusp=="FELONY/ROBBER")
replace crimecode1=20 if (crimsusp== "C P W" )|(crimsusp=="FEL/CPW" )
|(crimsusp=="FEL/CPW/Y" )|(crimsusp=="C.P.W" )|(crimsusp== "CPW" )
|(crimsusp=="CRIMINAL POSSESION WEAPON" )|(crimsusp=="SHOOTING"
)|(crimsusp== "SHOTS" )|(crimsusp== "WEAPON" )|(crimsusp=="WEAPONS")
replace crimecode1=20 if (crimsusp=="FELONY-CPW" )|(crimsusp=="FEL/
CPW" ) |(crimsusp=="FELONY/CPW" )|(crimsusp=="MIS/CPW"
)|(crimsusp=="MISD/ CPW" ) |(crimsusp=="MISD/CPW" )|(crimsusp=="C.P.W."
)|(crimsusp=="CPW (MIS)" ) |(crimsusp=="CPW (MISD)" )|(crimsusp=="CPW
3")
replace crimecode1=     14      if crimsusp=="C P B T BURGLARY"
replace crimecode1=     14      if crimsusp=="CPCP/BURG"
replace crimecode1=     14      if crimsusp=="CPL BURGLARY"
replace crimecode1=     14      if crimsusp=="CR BURG"
replace crimecode1=     14      if crimsusp=="DEL/BURGLARY"
```

```
replace crimecode1=      14      if crimsusp=="GRAPHIT/BURGLARY"
replace crimecode1=      14      if crimsusp=="LYNS POSS / BURG TRESS"
replace crimecode1=      14      if crimsusp=="LYNS POSS. / BURG DEALING"
replace crimecode1=      9       if crimsusp=="220.30/120.00"
replace crimecode1=      9       if crimsusp=="280.20 ASSULT"
replace crimecode1=      9       if crimsusp=="280.20/ ASSAULT"
replace crimecode1=      9       if crimsusp=="282.20/ASSAULT"
replace crimecode1=      9       if crimsusp=="CPS/ASSAULT"
replace crimecode1=      9       if crimsusp=="DISPUTE ASSAULT"
replace crimecode1=      9       if crimsusp=="DISPUTE WITH
GROUPS/ASSAULT"
replace crimecode1=      9       if crimsusp=="DISPUTE/ASSAULT"
replace crimecode1=      9       if crimsusp=="DISPUTE/ASSAULT 3"
replace crimecode1=      9       if crimsusp=="DOMESTIC VIOL"
replace crimecode1=      9       if crimsusp=="DOMESTIC VIOLENCE"
replace crimecode1=      9       if crimsusp=="DOMESTIC VIOLENCE ASSAULT"
replace crimecode1=      9       if crimsusp=="DOMESTIC/CUSTODIAL"
replace crimecode1=      9       if crimsusp=="GRAND ASSAULT"
replace crimecode1=      9       if crimsusp=="GRAND ASSAULT (POSSIBLE
BANG M"
replace crimecode1=      9       if crimsusp=="VERBAL DISPUTE/ASSAULT"
replace crimecode1=      9       if crimsusp=="VERBAL DISPUTE/ATT
ASSAULT"
```

Appendix C2. Categories for Suspected Crimes Provided by NYPD with Supplemental Codes Based on Actual Codes

Abandonment Of A Child
Abortion
Absconding
Adultery
Aggravated Assault
Aggravated Harassment
Aggravated Sexual Abuse
Arson
Assault
Auto Stripping
Bigamy
Bribe Receiving
Bribery
Burglary
Coercion
Computer Trespass
Course Of Sexual Conduct
Criminal Possession of Stolen Property
Criminal Possession of a Weapon
Creating A Hazard
Criminal Contempt
Criminal Mischief
Criminal Possession of Controlled Substance
Criminal Possession of Computer Material
Criminal Possession of Forged Instruments
Criminal Possession of Marijuana
Criminal Sale of Controlled Substance
Criminal Sale of Marijuana
Criminal Tampering
Criminal Trespass
Custodial Interference
Eavesdropping
Endanger The Welfare Of A Child
Escape
Falsify Business Records
Forgery
Forgery of a VIN
Fortune Telling
Fraud
Fraudulent Accosting
Gambling
Grand Larceny

Grand Larceny Auto
Harassment
Hazing
Hindering Prosecution
Incest
Insurance Fraud
Jostling
Kidnapping
Loitering
Making Graffiti
Menacing
Misapplication of Property
Murder
Obscenity
Obstructing Firefighting Operations
Obstructing Governmental Administration
Official Misconduct
Petit Larceny
Possession of Burglar Tools
Possession of Graffiti Instruments
Prohibited Use of Weapon
Prostitution
Public Display of Offensive Sexual Material
Public Lewdness
Rape
Reckless Endangerment
Reckless Endangerment Property
Resisting Arrest
Riot
Robbery
Sexual Abuse
Sexual Misconduct
Sodomy
Tampering With a Public Record
Tampering With Consumer Product
Terrorism
Theft Of Services
Trademark Counterfeiting
Unlawfully Dealing With Fireworks
Unauthorized Recording
Unauthorized Use Of A Vehicle
Unlawful Assembly
Unlawful Possession of Radio Device
Unlawful Use of Credit Card, Debit
Unlawful Wearing a Body Vest
Unlawful Imprisonment

Unlawfully Dealing With a Child
Vehicular Assault
Forcible Touching
Disorderly Conduct
Car Stop
Quality Of Life
Blank/No Entry
Riding Bike On The Sidewalk
Criminal Possession of Drug Paraphernalia
Alcohol Violation
Other Minor Sex Crimes
Sex Crimes
Uninterpretable Drug Offense
Knife Offenses-Non CPW
Other
Data Entry Error/ Not A Crime
Uncoded

Appendix C3. Classification of Crimes Suspected into Aggregate Crime Codes

Aggregate Category	Suspected offenses
Murder	Murder
Violent Crime	Aggravated Assault Aggravated Harassment Aggravated Sexual Abuse Assault Kidnapping Rape Robbery
Minor Violent Crime	Harassment Hazing Jostling Menacing Reckless Endangerment Resisting Arrest Riot Unlawful Imprisonment Vehicular Assault
Hard Drug Crime	Criminal Possession of Controlled Substances Criminal Sale of Controlled Substances Criminal Possession of Drug Paraphranalia Other Drug Offenses
Marijuana Possession	Criminal Possession of Marijuana
Marijuana Sale	Criminal Sale of Marijuana
Part I Property Crime	Arson Burglary Grand Larceny Grand Larceny Auto
Minor Property Crime	Auto Stripping Computer Trespass Criminal Possession of Stolen Property Criminal Mischief Criminal Possession of Computer Materials Criminal Possession of Forged Instruments Criminal Tampering Misapplication of Property Petit Larceny Possession of Burglar Tools Reckless Endangerment of Property Theft of Services

	Unauthorized Use of a Vehicle
Fraud and Related	Falsifying Business Records Forgery Forgery of a VIN Fraud Fraudulent Accosting Insurance Fraud Tampering with a Public Record Unlawful Use of Credit Card, Debit
Trespass	Criminal Trespass
Prostitution and Related	Prostitution
Terrorism	Terrorism
Quality of Life/Disorder	Eavesdropping Fortune Telling Gambling Loitering Making Graffiti Obscenity Obstructing Firefighting Operations Obstructing Governmental Administration Possession of Graffiti Instruments Trademark Counterfeiting Unlawfully Dealing with Fireworks Unauthorized Recording Unlawful Assembly Disorderly Conduct Quality of Life Riding Bike on the Sidewalk Alcohol Violation
Sex Crimes and Related	Abortion Adultery Bigamy Course of Sexual Conduct Incest Public Display of Offensive Sexual Material Public Lewdness Sexual Abuse Sexual Misconduct Sodomy Forcible Touching Other Sex Crimes Other Minor Sex Crimes

Bribery and Official Misconduct	Bribe Receiving Bribery Official Misconduct
Weapons and Related	Criminal Possession of a Weapon Prohibited Use of Weapon Unlawful Wearing a Body Vest Knife Offenses - Non-CPW
Domestic Violence and Crimes against Children	Abandonment of a Child Criminal Contempt Custodial Interference Endangering the Welfare of a Child Unlawfully Dealing with a Child
Other Felonies	Coercion Escape Hindering Prosecution Tampering with Consumer Product
Other Misdemeanors	Absconding Creating a Hazard Unlawful Possession of Radio Device
Vehicle and Traffic Laws	Car Stop
Other	Other
Missing	Missing
Error	Data Entry Error/Not a Crime Blank/No Entry

Appendix C4. Higher Order Classification of Aggregate Crime Codes into Meta-Categories

Stops were classified based on the suspected crime noted as generating the stop (the "crimsusp" field in the database). A 30-character string, the suspected crime is entered by officers at the time of a stop, and can take on virtually any value, including misspellings, mischaracterizations, and typographical errors. As a result, over the six years of data used for this analysis contained nearly 50,000 (49,952) unique values indicating crime suspected.

To identify analytical variables from these thousands of unique "crime suspected" values, a team of law students and other research assistants classified each value into one of 102 mutually exclusive offense categories, listed in Table XX. When the crime suspected was missing (<0.01% of cases), uninterpretable (0.26% of cases), erroneous, or denoted something other than a criminal activity (18.23% of cases), this too was noted. When more than one offense type was listed, the two most serious offenses were noted.

To enable use of the "crime suspected" variable in analysis, these 102 categories, and three categories of unusable crime categories were aggregated to 23 summary categories for both the first crime listed, and if stated, a second offense. (Second offenses were only stated in 3% of stops, and only were able to be coded in around half of these.) These 23 summary categories are further aggregated to create seven "meta-categories" used in our statistical models. These meta-categories are defined as follows:

Violent Crime: First or second offense listed as either murder or other violent crime.

Weapons Offenses: First or second offense is listed as a weapons offense, with no violent offense listed.

Property Crime: First or second offense is listed as a part one property offense, with no violent or weapon offense listed

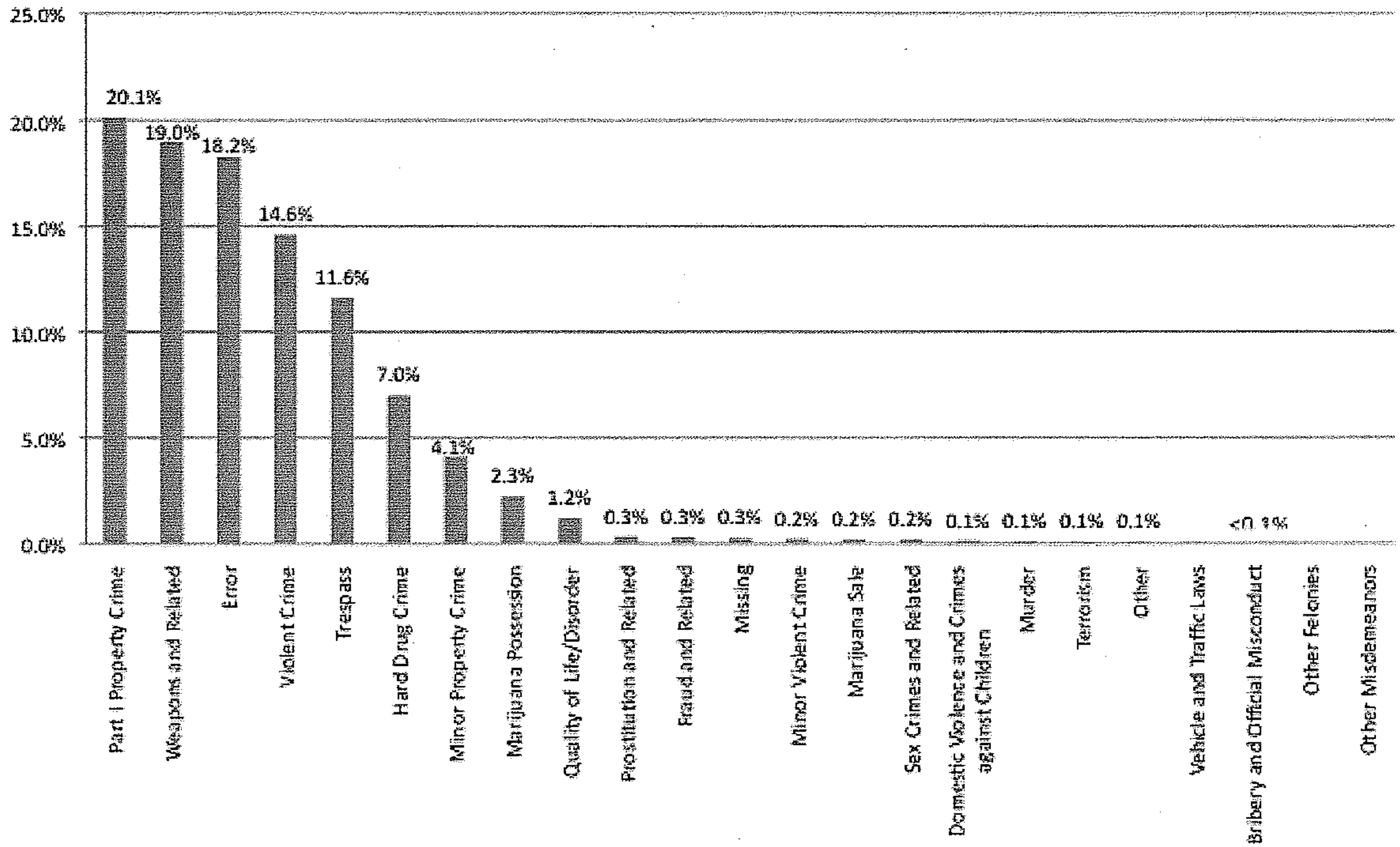
Drug Offenses: First or second offense is listed as a drug offense (hard drugs, marijuana possession, or marijuana sales) with no violent, property, or weapon offense listed.

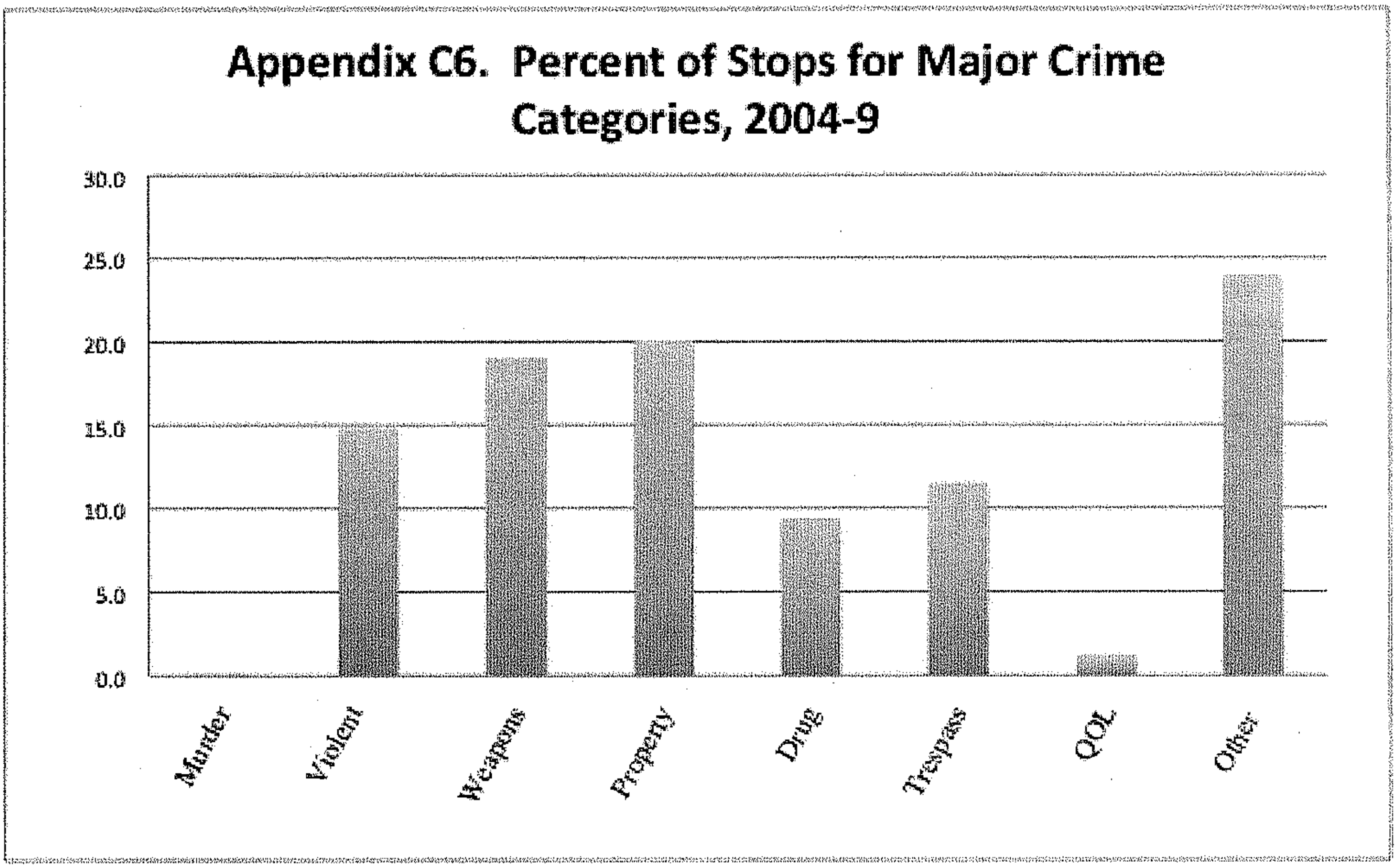
Trespass Offenses: First or second offense is listed as a trespass offense with no violent, property, weapon, or drug offense listed.

Quality of Life Offenses: First or second offense is listed as a quality of life offense with no violent, property, weapon, drug, or trespass offense listed.

Other Crime: All other stops, including erroneous crime code

Appendix C5:
Frequency of Crimes Suspected in SQF Activity, 2004-9




Appendix C6. Percent of Stops for Major Crime Categories, 2004-9
30.0
25.0
20.0
15.0
10.0
5.0
0.0
Murder
Violent
Weapons
Property
Drug
Trespass
QOL
Other

Appendix D.

Analysis of Stop Factors and Memorandum on Case Law

Appendix D. Current Case Law on SQF Stop Factors

A. Applicable Statutory Law

Under New York law, "stops" and "frisks" are considered separately. Based on this separation, it may be permissible for a police officer to stop a suspect but not to frisk the suspect given the circumstances. Stops are governed by the following statutory provision:

> In addition to the authority provided by this article for making an arrest without a warrant, a police officer may stop a person in a public place located within the geographical area of such officer's employment when he reasonably suspects that such person is committing, has committed or is about to commit either (a) a felony or (b) a misdemeanor defined in the penal law, and may demand of him his name, address and an explanation of his conduct.

N.Y. Crim. Proc. Law § 140.50(1) (2007). Frisks are governed by a slightly different standard, but all frisks require a legitimate "stop" as a predicate:

> When upon stopping a person under circumstances prescribed in subdivisions one and two a police officer or court officer, as the case may be, reasonably suspects that he is in danger of physical injury, he may search such person for a deadly weapon or any instrument, article or substance readily capable of causing serious physical injury and of a sort not ordinarily carried in public places by law-abiding persons. If he finds such a weapon or instrument, or any other property possession of which he reasonably believes may constitute the commission of a crime, he may take it and keep it until the completion of the questioning, at which time he shall either return it, if lawfully possessed, or arrest such person.

Id. § 140.50(3). In many cases, reasonable suspicion that a person is engaging in violent or dangerous crime (such as murder, burglary, assault, etc.) will justify both a stop *and* a frisk.

B. Applicable Law for Specific Factors Justifying Stops based on the UF-250 Categories

1. Carrying Objects in Plain View Used in Commission of Crime (such as a "Slim Jim", Pry Bar etc.)

Standing alone, the fact that an individual is in possession of objects commonly used in the commission of crimes does not provide an officer with the reasonable suspicion necessary to stop or frisk that individual. *See People v. Saad*, 859 N.Y.S.2d 906 (N.Y. Crim. Ct. 2008) (holding that officers lacked reasonable suspicion to stop a man seen walking down the street, pushing a shopping cart with a tire iron protruding, and looking into parked cars). A stop will, however, be justified if there is evidence to suggest that the object has been or will be used in a crime. *See People v. Brown*, 344 N.Y.S.2d 356, 357 (N.Y. 1973) (holding that an officer did not probable cause to effect an arrest for possession of a burglar's tool and stolen property, but could have make an "investigatory stop" of a man seen exiting a building holding a crowbar and a car battery that had torn cables on it). Nevertheless, an officer cannot stop or frisk an individual simply because they possess an object that could either be contraband or be innocently possessed. *See People v. Francis*, 847 N.Y.S.2d 398, 401-02 (N.Y. Sup. Ct. 2007) (holding that an officer who observed that an object that looked like a knife, which was clipped inside a suspects pocket, did not have reasonable suspicion to believe that the knife was an illegal gravity knife and not a permissible knife).

2. Suspect Fits Description

If the source of information is anonymous and does not point to a specific suspect, this factor is impermissible as the sole basis for a stop. *See People v. Benjamin*, 414 N.E.2d 645, 647 (N.Y. 1980) (explaining that radio call based on anonymous tip does not justify stop and frisk of persons in the area, but "when considered in conjunction with other supportive facts, it may thus collectively, although not independently, support a reasonable suspicion justifying intrusive police action"). Even if the anonymous information describes a specific person, this factor alone cannot justify a stop and frisk. *See People v. William II*, 772 N.E.2d 1150, 1153 (N.Y. 2002) (finding frisk unjustified under *Florida v. J.L.*, 529 U.S. 266 (2000), where anonymous tip provided description of defendant and indicated that he was armed because "[t]he tip not only lacked predictive information that would permit the police to test the caller's knowledge, but was also rendered suspect when directly contradicted by the police officer's observation that Cruz was not dressed in a manner that would permit him to conceal a weapon on his person. Furthermore, the anonymous tip did not identify defendant, nor did it provide any relevant information to suggest that he possessed a weapon or that he had engaged in any criminal activity."). An anonymous tip can only provide the basis for a stop if it contains predictive information "so that the police can test the reliability of the tip." *People v. Moore*, 6 N.Y.3d 496, 499 (N.Y. 2006). If the predictive information is corroborated by the police officer's observations, a stop and frisk can be justifiable. *See, e.g., People v. Alvarez*, 778 N.Y.S.2d 27, 27--28 (1st Dep't 2004) (finding that pat down was proper where, inter alia, police responded to radio call based on anonymous tip, heard suspicious noises coming from apartment, and witnessed suspect attempting to flee scene by climbing a fence).

A radio run based on a non-anonymous source need not be as specific and will require less corroboration by police. *See People v. Herold*, 726 N.Y.S.2d 65, 68 (1st Dep't 2001) (upholding frisk based on radio report describing suspect based on description of caller from specific address and distinguishing *Florida v. J.L.* as a case that "turned on the inherent unreliability of the unknown informant's information," a concern that did not apply when officers knew address of informant). This is because an identified citizen informant is presumed to be reliable. *People v. Schwing*, 787 N.Y.S.2d 715, 717 (3rd Dep't 2005).

Finally, in cases where a radio call indicates that a suspect has been seen with a weapon but no longer possesses the weapon, a frisk is not justified without additional factors present. *See People v. Russ*, 460 N.E.2d 1086, 1087 (N.Y. 1984) (finding that anonymous tip which identified suspect's car and location justified stop but did not justify frisk because there was no reason to suspect danger "either in the information received, which indicated that defendant had given a gun to the man but provided no basis for inferring that she had another or that it had been returned to her, or in what occurred during the officer's encounter with defendant"). This is because a frisk is only permissible if the police have reasonable suspicion that the suspect "is armed and may be dangerous." *People v. Gonzalez*, 743 N.Y.S.2d 112, 183-84 (1st Dep't 2002) (quoting *People v. Russ*, 460 N.E.2d 1086, 1087 (N.Y. 1984)).

Nevertheless, courts in New York have recognized one pertinent exception to the rule that an officer must have "reasonable suspicion to believe a suspect has committed a crime *and* a reasonable suspicion that the suspect is armed and dangerous." MATTHEW BENDER & CO., NEW YORK SEARCH AND SEIZURE § 2.05 (2008). Courts have held that a frisk is permitted when an officer has reasonable suspicion that the suspect has committed a violent crime. *See, e.g. People v. Smith*, 739 N.Y.S.2d 697 (1st Dep't 2002) (burglary).

Fits Description" could possibly justify a stop as the sole indicator of suspicion, but it has cannot uniformly justify a stop because an anonymous tip cannot provide the basis for a stop. If the officer conducted the stop based on a report from an identified caller or a victim that he interviewed, he would presumably indicate that "Report From Victim/Witness" was one of the "Additional Circumstances/Factors." Similarly, an officer who stopped a person because he fit the description of a wanted suspect would presumably list "A and "Ongoing Investigations, e.g. Robbery Pattern" as one of the "Additional Circumstances/Factors."

3. Actions Indicative of Casing a Victim or Location

Though "casing" is a term that can describe a number of different and potentially innocuous behaviors, actions legitimately indicative of casing can justify a stop and frisk. *See Terry v. Ohio*, 392 U.S. 1, 28 (1968) (upholding stop and frisk when officer suspected three men of casing a store in preparation for a daytime robbery); *People v. Richard*, 668 N.Y.S.2d 386, 387 (1st Dep't 1998) ("Reasonable suspicion supporting the forcible detention of defendant was supplied by lengthy police observations of defendant's complex, unusual, and suspicious pattern of 'casing'-type behavior, strongly suggestive of a known series of armed robberies in the neighborhood that targeted movie theaters in particular, coupled with the fact that defendant met a general description of one of the robbers.").

4. Actions Indicative of Acting as a Lookout

Absent additional factors, the simple fact that a person is observing a location and appears to be on the lookout for something is insufficient to justify a stop and frisk. *See People v. Howard*, 542 N.Y.S.2d 536, 538 (1st Dep't 1989) (finding that police had no reasonable suspicion to frisk suspect who repeatedly looked up and down street and down subway stairs at 10:00 P.M. in high crime area and who had reached into his jacket several times). Nevertheless, police officers may stop and frisk a person found standing watch in the vicinity of known criminal activity *if* circumstances indicate that he is acting as a lookout. *See People v. Mateo*, 504

N.Y.S.2d. 760, 763 (2nd Dep't 1986) (upholding the stop and frisk of a man who arrived at the scene of a drug transaction with a suspected drug seller and then "stood watch over the parking lot where the drug transaction was conducted" while it was raining outside).

5. Suspicious Bulges/Suspicious Objects

Without more evidence or information available to the officer, the observation of a bulge in a suspect clothes, even a suspects waistband, insufficient cannot lead to reasonable suspicion and justify a stop or a frisk. *See People v. Barreto*, 555 N.Y.S.2d 303, 304 (1st Dep't 1990) (holding that an officer who saw a suspect run holding his waste and saw bulge in the suspects waistband lacked reasonable suspicion); *People v. Williams*, 554 N.Y.S.2d 23, 24 (1st Dep't 1990) (noting that case law consistently holds that "mere observation of an unidentifiable bulge in a person's pocket is insufficient" as basis for handgun frisk). Nevertheless, an officer may frisk an individual if he observes a bulge that is plainly shaped like a firearm. *People v. Prochilo*, 41 N.Y.2d 759, 762 (N.Y. 1977).

Carrying a suspicious object, even if sufficient to justify a stop, does not justify a frisk unless there are other indications of dangerousness. *See People v. Hudson*, 527 N.Y.S.2d 919, 919 (4th Dep't 1988) (finding frisk improper where officer observed suspect "in an area where numerous burglaries had occurred, carrying a three-foot-long object wrapped in a sheet" who walked away from approaching officer).

6. Actions Indicative of Engaging in Drug Transaction

To justify a stop based on *Actions Indicative of a Drug Transaction*, the officer must observe the exchange of either currency or an object that might contain drugs. *Actions Indicative of a Drug Transaction* that do *not* include an observed exchange of currency or an object that might contain drugs cannot provide the basis for a lawful stop even in a drug prone location. *People v. Thompson*, 791 N.Y.S.2d 872, 872 (2nd Dep't 2004) (holding that an officer did not have the authority to request that a suspect reveal what was in his hand because the suspect engaged in "some sort of exchange" in a drug prone location). The exchange of currency for a small object or movements indicative of a hand to hand drug transaction that involve an exchange of currency can provide the basis for a stop based on reasonable suspicion in a drug prone location. *People v. Shaw*, 871 N.Y.S.2d 808 (2nd Dept't 2008) (holding that an officer had the authority to request that a suspect reveal what was in his hand because the suspect received currency from a man and then slapped hands with the man in return).

It is currently unclear whether such actions standing alone can justify a stop *and* frisk. *Compare People v. Perolta-Rua*, 579 N.Y.S.2d 283, 285 (4th Dep't 1992) (finding that experienced officer's knowledge "that drug dealers often carry weapons" was one factor supporting stop and frisk), *with United States v. Gonzalez*, 362 F. Supp. 415, 424 (S.D.N.Y. 1973) (deciding, under New York law, that stop and frisk was improper because "[n]one of the agents who testified expressed any concern that Torres might be armed and dangerous, and it is evident, even from their own testimony, that they grabbed his paper bag because they hoped to find narcotics, not a weapon"), *and People v. Brown*, 613 N.Y.S.2d 70, 71 (4th Dep't 1994) (finding frisk improper where defendant was frisked for selling drugs but where no additional factors suggesting danger were present). Despite the purported link between guns and drugs, the fact that a suspect might have participated in a drug transaction does not instantly ensure that an officer has reasonable suspicion to believe a suspect has committed a crime *and* a reasonable suspicion that the suspect is armed or dangerous.

"Actions Indicative of Engaging in Drug Transactions" is not coded as an unconditionally justified stop factor because cases in which such actions are found to give rise to reasonable suspicion also involve other factors ("Additional Circumstances") including, at a minimum, the equivalent of "Area has High Incidence of Reported Offense of Type Under Investigation."

7. Furtive Movements

The term "furtive movements" can be used to refer to an almost infinite number of actions which an officer might find suspicious. Nevertheless, the term often arises in cases in which an individual is suspected of carrying a firearm. Without more, furtive movements potentially indicative of carrying a firearm cannot give rise to reasonable suspicion. *See People v. Powell*, N.Y.S.2d 725, 727-28 (1st Dep't 1998) (holding that officers did not have reasonable suspicion to frisk a suspect walking with his arm stiffly against his body in a high crime area); *United States v. McCrae*, 2008 U.S. Dist. LEXIS 2314, *9-*10 (E.D.N.Y. January 11, 2008) (holding that an officer did not have reasonable suspicion to stop a suspect who moved his hand from the center of his stomach to the left side of his waist in a manner that the officer claimed was similar to how an officer handles firearms while in plain clothes); *United States v. Doughty*, 2008 U.S. Dist. LEXIS 74248, *18 (S.D.N.Y. Sept. 18, 2008) (holding that an officer did not have reasonable suspicion to stop a suspect who adjusted his waistband in a manner consistent with carrying a firearm).

During an otherwise lawful stop, movements indicating that suspect might be armed are generally sufficient to justify frisks. *See, e.g., People v. Woods*, 64 N.Y.2d 736, 737 (N.Y. 1984) ("It was also not unreasonable, in light of his past experience with defendant, for one of the officers to pat defendant in the chest area when defendant quickly reached toward the breast area of his jacket, and for that officer, upon feeling a hard object, to reach inside the jacket and retrieve it."). If there is no basis for a stop or other investigation, however, such movements do not justify a frisk. *See People v. Miller*, 504 N.Y.S.2d 407, 410 (1st Dep't 1986) (finding that movement, which could have been act of tucking in shirt or pushing gun down into waistband, did not justify frisk).

8. Actions Indicative of Engaging in Violent Crimes

Reasonable suspicion that a person may have been involved in a violent crime can support a frisk, even without other evidence of dangerousness. *See People v. Mack*, 258 N.E.2d 703, 707 (N.Y. 1970) ("Where . . . the officer confronts an individual whom he reasonably suspects has committed, is committing or is about to commit such a serious and violent crime as robbery or, as in the instant case, burglary, then it is our opinion that that suspicion not only justifies the detention but also the frisk, thus making it unnecessary to particularize an independent source for the belief of danger."); *see also People v. Schollin*, 682 N.Y.S.2d 48, 49 (2d Dep't 1998) (upholding pat down of suspect when officer believed that victim had been shot in face); *People v. Paul*, 658 N.Y.S.2d 275, 276 (1st Dep't 1997) (upholding stop and frisk where officers heard numerous gunshots and saw two persons running from location where shots were fired).

Nevertheless, "Actions Indicative of Engaging in Violent Crimes" is not a factor that, standing alone, can serve as the basis of a lawful stop. The actions at issue could be any number of "Furtive Movements." As noted below, furtive movements, even those indicative of intent to commit violent crimes are almost never sufficient justification for a stop and frisk. *See People v. Howard*, 542 N.Y.S.2d 536, 538 (1st Dep't 1989) (finding that police had no reasonable suspicion to frisk suspect who repeatedly looked up and down the street and down subway stairs at 10:00 P.M. in high crime area and who had reached into his jacket several times).

9. Wearing Clothes/Disguises Commonly Used in Commission of Crime

This factor is a sweeping and amorphous one that could encompass an almost innumerable verity of clothing. Balaclavas, clothing in gangs colors, bullet proof vests, and seasonally inappropriate attire could all fit under this general heading.

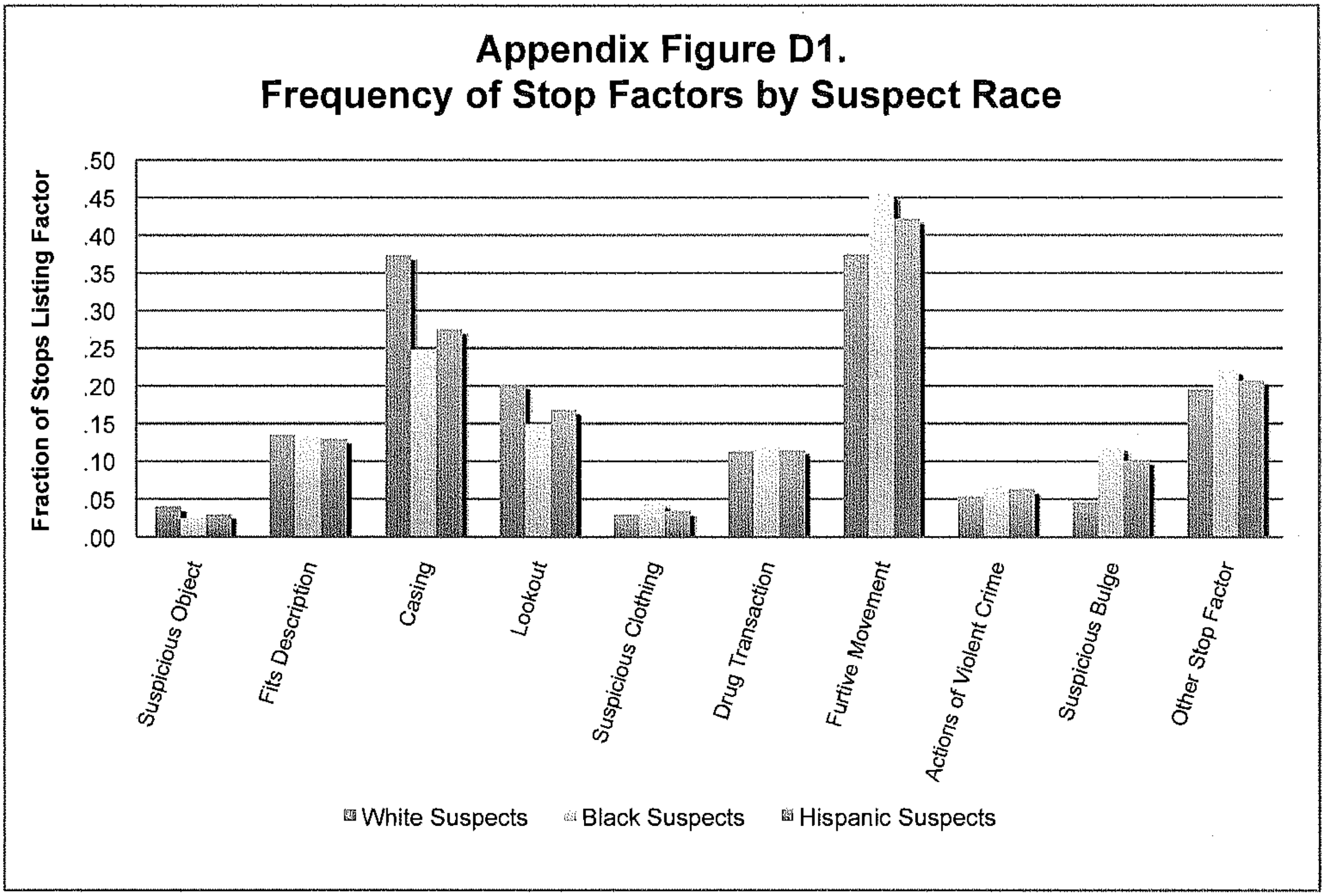
The way in which the courts have addressed bullet proof vests is an informative starting point for how this category should be addressed because bullet proof vests are a highly unusual type of clothing and are commonly associated with violent crime. The wearing of a bullet proof vest does not automatically give rise to reasonable suspicion, but it can be one factor giving rise to it. *See People v. Batista*, 672 N.E.2d 581, 583--84 (N.Y. 1996) (noting "inherent linkage between a [bulletproof] vest and possession of a firearm" but also explaining that "more is usually required to justify a frisk of the suspect"). Since a bulletproof vest is an article of clothing that "uniquely" signals that an individual is preparing to "engage in gun battle" or use a firearm, it is a factor that will weigh heavily in favor of a finding that a stop and frisk was lawful. *People v. Carvey*, 89 N.Y.2d 707 (N.Y. 1997) (holding that during a car stop an officer had reasonable suspicion to believe that a weapon was located within the vehicle because the defendant was wearing a bulletproof vest and bent down to place something under his seat as officers approached his vehicle).

The wearing of seasonally inappropriate attire is a matter that lies at the opposite end of the spectrum. Standing alone, seasonally inappropriate attire does not justify a stop or frisk because "wearing a long winter coat on a hot summer night . . . is no more than 'odd' behavior" and odd behavior alone cannot justify a stop and frisk." *People v. Giles*, 647 N.Y.S.2d 4, 6 (N.Y. App. Div. 1996). Other factors may, however, lead to the conclusion that "inappropriate garb is [being] worn for the very purpose of hiding something" like weapons or contraband. *Id.* (holding that a stop was justified because the defendant wore seasonally inappropriate attire, walked down the middle of a street, and adjusted an object in his rear waistband).

Appendix Table D1. Fraction of Stops Based on Each Stop Factor and Additional Circumstance

Stop Factor	*All Stops*	*White Suspect*	*Black Suspect*	*Hispanic Suspect*
Suspicious Object	.028	.040	.025	.030
Fits Suspect Description	.131	.134	.131	.129
Casing	.270	.373	.248	.274
Lookout	.161	.201	.149	.168
Clothing Indicative of Crime	.039	.030	.044	.034
Drug Transaction	.115	.113	.118	.114
Furtive Movement	.431	.374	.455	.422
Actions - Violent Crime	.063	.054	.066	.063
Bulge	.104	.046	.118	.101
Other	.213	.195	.220	.207
Reported Crime	.090	.112	.086	.086
Active Investigation	.122	.135	.124	.119
Proximity to Crime	.170	.138	.182	.159
Evasive Actions	.168	.172	.175	.163
Criminal Associates	.035	.042	.036	.032
Change Direction	.249	.254	.254	.245
High Crime Area	.557	.550	.575	.542
Time of Day	.346	.364	.361	.324
Sights and Sounds	.018	.033	.015	.018
Other	.042	.046	.040	.042

* Percent of all stops including each factor either alone or in conjunction with others, totals exceed 100%


Appendix Figure D1.
Frequency of Stop Factors by Suspect Race
Fraction of Stops Listing Factor
.50
.45
.40
.35
.30
.25
.20
.15
.10
.05
.00
Suspicious Object
Fits Description
Casing
Lookout
Suspicious Clothing
Drug Transaction
Furtive Movement
Actions of Violent Crime
Suspicious Bulge
Other Stop Factor
White Suspects
Black Suspects
Hispanic Suspects

Appendix E.

Calculation of Patrol Strength

Appendix E. Patrol Strength

The total patrol strength for each precinct in each calendar quarter was calculated from data on patrol strength provided by the New York City Police Department. The number of officers in each of the active command units were provided by calendar quarter, and assigned to precincts based on the descriptions of the command. See Appendix E2 for a listing of all the command codes that were provided. Estimations of patrol strength were limited to those commands that were listed by officers on UF-250 forms (and in the databases). Other command codes were not assigned to precincts. Using the procedures described below, 95% of the officers who conducted stops from 2004-2009 were allocated to a precinct.

The "command unit" field was a string of up to 30 characters, leaving the potential for typographical errors and inconsistencies in labeling[1]. The most heavily populated commands included precinct patrol, HPSA (housing), and Transit. Patrol strength data were also limited by missing observations.[2] In those instances, missing observations were replaced by interpolated data from the observations for that command for the calendar quarters preceding and following the missing datapoint.

Precinct patrol officers were directly allocated to precincts as provided in the database, with interpolations to supplement when data were missing. In Staten Island (i.e., the 121st, 122nd, and 123rd precincts), detective squad patrol strength was listed separately for each precinct in Q2 of 2004, and these officers were folded into the precinct totals.

Housing officers were provided at the level of the Housing Police Service Area (HPSA, each of which spans multiple precincts. These officers were allocated across the precincts contained in each HPSA, in proportion with the precincts' uniformed patrol officers. Transit officers were provided at the level of the transit district, and were similarly allocated: precincts were identified as overlapping with transit districts if they contained any stations from the transit district in question[3], and officers were allocated in proportion with the precincts' uniformed patrol officers. Other officers were listed by Patrol Borough unit, and were allocated

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[1] For example, the command code "023 PRECINCT", denoting the 23rd precinct, appeared for each of the 24 calendar quarters between 2004 and 2009. On the other hand, "114 PRECINCT" appeared only 23 times, while "11 4" PRECINCT appeared once; these two codes were combined to comprise the patrol strength records of the 114th precinct.

[2] For example, the 14th, 17th, and 18th precincts are each missing patrol strength data for Q2 of 2004. We approximate these totals by averaging the totals of Q1 and Q3 of 2004 in each of these precincts.

[3] Transit district allocation was also complicated by incomplete labeling. For example, Transit District 1 was listed more than the 24 times that would correspond to a single calendar quarter per unit, while Transit Districts 11 and 12 were listed fewer than 24 times. Officers were allocated across precincts, but accuracy may be limited by mislabeling.

across all precincts in the borough, in proportion with the precincts' uniformed patrol officers[4].

Officers in borough-wide commands were assigned to precincts in that borough based on the known patrol strength in that precinct.

Officers that could not be allocated to precincts, fewer than 5% of total documented officers, were excluded from the analyses.

[4] Patrol Borough commands include substantially fewer officers than either the precinct units or the housing and transit units.

Appendix E2. Command Codes

Code	Command Abbreviation	Command Name
1	001 PCT	001 PRECINCT
5	005 PCT	005 PRECINCT
6	006 PCT	006 PRECINCT
7	007 PCT	007 PRECINCT
9	009 PCT	009 PRECINCT
10	010 PCT	010 PRECINCT
13	013 PCT	013 PRECINCT
14	MTS PCT	014 PCT-MIDTOWN SO. PCT
17	017 PCT	017 PRECINCT
18	MTN PCT	018 PCT-MIDTOWN NO. PCT
19	019 PCT	019 PRECINCT
20	020 PCT	020 PRECINCT
23	023 PCT	023 PRECINCT
24	024 PCT	024 PRECINCT
25	025 PCT	025 PRECINCT
26	026 PCT	026 PRECINCT
28	028 PCT	028 PRECINCT
30	030 PCT	030 PRECINCT
32	032 PCT	032 PRECINCT
33	033 PCT	033 PRECINCT
34	034 PCT	034 PRECINCT
40	040 PCT	040 PRECINCT
41	041 PCT	041 PRECINCT
42	042 PCT	042 PRECINCT
43	043 PCT	043 PRECINCT
44	044 PCT	044 PRECINCT
45	045 PCT	045 PRECINCT
46	046 PCT	046 PRECINCT
47	047 PCT	047 PRECINCT
48	048 PCT	048 PRECINCT
49	049 PCT	049 PRECINCT
50	050 PCT	050 PRECINCT
52	052 PCT	052 PRECINCT
60	060 PCT	060 PRECINCT
61	061 PCT	061 PRECINCT
62	062 PCT	062 PRECINCT
63	063 PCT	063 PRECINCT
66	066 PCT	066 PRECINCT
67	067 PCT	067 PRECINCT
68	068 PCT	068 PRECINCT
69	069 PCT	069 PRECINCT

70	070 PCT	070 PRECINCT
71	071 PCT	071 PRECINCT
72	072 PCT	072 PRECINCT
73	073 PCT	073 PRECINCT
75	075 PCT	075 PRECINCT
76	076 PCT	076 PRECINCT
77	077 PCT	077 PRECINCT
78	078 PCT	078 PRECINCT
79	079 PCT	079 PRECINCT
81	081 PCT	081 PRECINCT
83	083 PCT	083 PRECINCT
84	084 PCT	084 PRECINCT
88	088 PCT	088 PRECINCT
90	090 PCT	090 PRECINCT
94	094 PCT	094 PRECINCT
100	100 PCT	100 PRECINCT
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109	109 PCT	109 PRECINCT
110	110 PCT	110 PRECINCT
111	111 PCT	111 PRECINCT
112	112 PCT	112 PRECINCT
113	113 PCT	113 PRECINCT
114	114 PCT	114 PRECINCT
115	115 PCT	115 PRECINCT
120	120 PCT	120 PRECINCT
122	122 PCT	122 PRECINCT
123	123 PCT	123 PRECINCT
125	C/PRV S	CRIME PREV SECT
126	AUTO CD	AUTO CRIME DIVISION
127	PSB RMS	PSB RESOURCE MANAGEMENT SECT.
128	SC UNIT	STREET CRIME UNIT
129	HOMLESS	HOMELESS OUTREACH UNIT
130	P S B	PATROL SERVICES BUREAU
131	PSB FAU	PSB FISCAL ANALYSIS UNIT
132	PSB IES	PSB INVEST AND EVALUATION SECT
133	PSB PLS	PSB PROGRAM LIAISON SECTION
134	PSB CRS	COORDIN/REVIEW SECT
135	TRF CD	TRAFFIC CONTROL DIVISION

136	PBMS TF	PATROL BORO MAN SOUTH T/F
137	PBMN TF	PATROL BORO MAN NORTH T/F
138	PBBX TF	PATROL BORO BX T/F
139	PBBS TF	PATROL BORO BKLYN SOUTH T/F
140	PBBN TF	PATROL BORO BKLYN NORTH T/F
141	PBQN TF	PATROL BORO QUEENS T/F
142	FTU 01	FIELD TRNG UNIT 01
143	FTU 02	FIELD TRNG UNIT 02
144	FTU 03	FIELD TRNG UNIT 03
145	FTU 04	FIELD TRNG UNIT 04
146	FTU 05	FIELD TRNG UNIT 05
147	FTU 06	FIELD TRNG UNIT 06
148	FTU 07	FIELD TRNG UNIT 07
149	FTU 08	FIELD TRNG UNIT 08
150	FTU 09	FIELD TRNG UNIT 09
151	FTU 10	FIELD TRNG UNIT 10
152	FTU 11	FIELD TRNG UNIT 11
153	FTU 12	FIELD TRNG UNIT 12
154	FTU 13	FIELD TRNG UNIT 13
155	FTU 14	FIELD TRNG UNIT 14
156	FTU 15	FIELD TRNG UNIT 15
157	FTU 16	FIELD TRNG UNIT 16
158	FTU 17	FIELD TRNG UNIT 17
159	FTU 18	FIELD TRNG UNIT 18
160	FTUS/I	FIELD TRNG UNIT S/I
161	PBMS	PATROL BORO MAN SOUTH
162	PBMN	PATROL BORO MAN NORTH
163	PBBX	PATROL BORO BRONX
164	PBBS	PATROL BORO BKLYN SOUTH
165	PBBN	PATROL BORO BKLYN NORTH
166	PBQ	PATROL BORO QUEENS
168	YTH SS	YOUTH SERVICES SECTION
169	PBQ/N	PATROL BORO QUEENS NORTH
170	PBQNT/F	PATROL BORO QNS NORTH T/F
171	PBQ/S	PATROL BORO QUEENS SOUTH
172	PBQST/F	PATROL BORO QNS SOUTH T/F
174	MN IRT	PBMN IMPACT RESPONSE TEAM
175	BN IRT	PBBN IMPACT RESPONSE TEAM
180	TAXI SQ	TAXI SQUAD
181	PBMS AC	PBMS ANTI-CRIME UNIT
182	PBMN AC	PBMN ANTI-CRIME UNIT
183	PBBX AC	PBBX ANTI-CRIME UNIT
184	PBQN AC	PBQN ANTI-CRIME UNIT
185	PBQS AC	PBQS ANTI-CRIME UNIT
186	PBBS AC	PBBS ANTI-CRIME UNIT

187	PBBN AC	PBBN ANTI-CRIME UNIT
201	DET BUR	DET BUREAU
202	DPT INV	NYC DEPT OF INV SQD
203	CI&RDIV	CENTRAL INVEST & RESOURCE DIV
204	PHOTO-U	PHOTO UNIT
205	DA NY	DA SQ NY COUNTY
206	CENROBB	CENTRAL ROBBERY SECTION
207	DB LPS	LATENT PRINT SECTION
211	DB BCIU	DET BORO BKLYN CRIM ID UNIT
212	SP FRDS	SPECIAL FRAUDS SQUAD
216	SP INV	SPECIAL INV DIV
217	DB O&IT	ORGANIZED & IDENTITY THEFT T/F
218	M CCIU	MAN CAREER CRIM INVEST UNIT
219	MC/SQD	MAJOR CASE SQUAD
220	C C M U	CAREER CRIM MONITORING UNIT
221	C C A U	CAREER CRIM APPREHENSION UNIT
222	BX CCIU	BRONX CAREER CRIM INVEST UNIT
223	BK CCIU	BKLYN CAREER CRIM IVEST UNIT
224	QN CCIU	QN CAREER CRIM INVEST UNIT
227	A-E-DIV	ARSON AND EXPLOSION DIV
228	BOMB SQ	BOMB SQUAD
229	MP SQD	MISSING PERSONS SQUAD
230	DB MAN	DET BORO MANHATTAN
231	DB MCID	DET BORO MAN CRIM ID UNIT
232	DB MSHM	DET BORO MAN SO HOMICIDE T/F
233	DB MNTF	DET BORO MAN NORTH T/F
234	001 DET	001 DET SQUAD
235	005 DET	005 DET SQUAD
236	006 DET	006 DET SQUAD
237	007 DET	007 DET SQUAD
238	009 DET	009 DET SQUAD
239	010 DET	010 DET SQUAD
240	013 DET	013 DET SQUAD
241	MTS DET	MTS DET SQUAD
242	017 DET	017 DET SQUAD
243	MTN DET	MTN DET SQUAD
245	019 DET	019 DET SQUAD
246	020 DET	020 DET SQUAD
247	CPK DET	CENTRAL PK DET SQ
248	023 DET	023 DET SQUAD
249	024 DET	024 DET SQUAD
250	025 DET	025 DET SQUAD
251	026 DET	026 DET SQUAD
252	028 DET	028 DET SQUAD
253	030 DET	030 DET SQUAD

254	032 DET	032 DET SQUAD
255	034 DET	034 DET SQUAD
256	DB MSVS	DET BUREAU MAN SPEC VIC SQUAD
257	MNROBSQ	MANH ROBBERY SQUAD
258	033 DET	033 DET SQUAD
259	049 DET	049 DET SQUAD
260	DB BX	DET BORO BRONX
261	DA BX	DA SQ BRONX COUNTY
262	DBBXCIU	DET BORO BRONX CRIM ID UNIT
263	040 DET	040 DET SQUAD
264	041 DET	041 DET SQUAD
265	042 DET	042 DET SQUAD
266	043 DET	043 DET SQUAD
267	044 DET	044 DET SQUAD
268	045 DET	045 DET SQUAD
269	046 DET	046 DET SQUAD
270	047 DET	047 DET SQUAD
271	048 DET	048 DET SQUAD
272	050 DET	050 DET SQUAD
273	052 DET	052 DET SQUAD
274	DB BXHM	DET BORO BX HOMICIDE T/F
275	BXROBSQ	BRONX ROBBERY SQUAD
276	DB BXSV	DET BUREAU BRONX SPEC VIC SQD
277	DB SVD	DET BUREAU SPECIAL VICTIMS DIV
278	BKROBSQ	BKLYN ROBBERY SQ
280	DB BKLN	DET BORO BKLYN
281	DA BKN	DA SQ KINGS COUNTY
282	060 DET	060 DET SQUAD
283	061 DET	061 DET SQUAD
284	062 DET	062 DET SQUAD
285	063 DET	063 DET SQUAD
286	066 DET	066 DET SQUAD
287	067 DET	067 DET SQUAD
288	068 DET	068 DET SQUAD
289	069 DET	069 DET SQUAD
290	070 DET	070 DET SQUAD
291	071 DET	071 DET SQUAD
292	072 DET	072 DET SQUAD
293	076 DET	076 DET SQUAD
294	078 DET	078 DET SQUAD
295	073 DET	073 DET SQUAD
296	075 DET	075 DET SQUAD
297	077 DET	077 DET SQUAD
298	079 DET	079 DET SQUAD
299	081 DET	081 DET SQUAD

300	083 DET	083 DET SQUAD
301	084 DET	084 DET SQUAD
302	088 DET	088 DET SQUAD
303	090 DET	090 DET SQUAD
304	094 DET	094 DET SQUAD
305	DB BSVS	DET BUREAU BKLYN SPEC VIC SQD
306	DBBS OP	DET BORO BKLYN SOUTH OPER
307	DB BSTF	DET BORO BKLN SOUTH TASK FORCE
308	DBBN OP	DET BORO BKLYN NORTH OPER
309	DB BNTF	DET BORO BKLN NORTH TASK FORCE
310	DB QNS	DET BORO QUEENS
311	DA QNS	DA SQUAD QUEENS COUNTY
312	DB QCIU	DET BORO QUEENS CRIM ID UNIT
313	DB BSHM	DET BORO BKLYN SO HOMICIDE T/F
314	DBMNHTF	DET BORO MAN NO HOMICIDE T/F
315	DB BNHM	DET BORO BKLYN NO HOMICIDE T/F
316	DB QNHM	DET BORO QNS HOMICIDE T/F
317	INT RIS	REGIONAL INTEL SUPPORT CENTER
318	TRT CS	INTELL-CRIMINAL SECTION
319	INT PSS	INTELL-PUBLIC SECURITY SECTION
320	INT CIS	INT CRIMINAL INTELLIGENCE SECT
321	INT EPU	INTEL-MSS-EXEC. PROTECTION
322	INT UOU	INTEL-MSS-UNIFORMED OPERATIONS
327	DB QSVS	DET BUREAU QUEENS SPEC VIC SQD
328	DBMS OP	DET BORO MAN SOUTH OPER
329	DBMN OP	DET BORO MAN NORTH OPER
330	100 DET	100TH DET SQUAD
331	101 DET	101ST DET SQUAD
332	102 DET	102ND DET SQUAD
333	103 DET	103RD DETECTIVE SQUAD
334	104 DET	104TH DET SQUAD
335	105 DET	105TH DET SQUAD
336	106 DET	106TH DET SQUAD
337	107 DET	107TH DET SQUAD
338	108 DET	108TH DET SQUAD
339	109 DET	109TH DET SQUAD
340	110 DET	110TH DET SQUAD
341	111 DET	111TH DET SQUAD
342	112 DET	112TH DET SQUAD
343	113 DET	113TH DET SQUAD
344	114 DET	114TH DET SQUAD
345	115 DET	115TH DET SQUAD
347	QNROBSQ	QUEENS ROBBERY SQUAD
351	DB QNTF	DET BORO QUEENS TASK FORCE
352	TNG UNT	TRAINING UNIT

353	D C M B	DEP COMM MANAGEMENT & BUDGET
354	PRG BUD	PROGRAM BUDGET SECTION
355	PAY SEC	PAYROLL SECTION
356	POL PEN	POLICE PENSION FUND
357	LIC DIV	LICENSE DIVISION
358	BUD&ACC	BUDGETING & ACCOUNTING SECTION
359	M I S D	MANAGEMENT INFORM. SYSTEMS DIV
360	PAY&BEN	PAYROLL AND BENEFITS DIVISION
361	L.I.M.S	LEAVE INTEGRITY MGT. SECTION
362	QC UNIT	QUALITY CONTROL UNIT
363	FM DIV	FACILITES MANAGEMENT DIVISION
364	EQP SEC	EQUIPMENT SECTION
365	QM SEC	QUARTERMASTER SECTION
366	BM SEC	BUILDING MAINTENANCE SECT
367	NAR DIV	NARCOTICS DIVISION OCCB
368	MAILDIS	MAIL & DISTRIBUTION UNIT
369	HQ CUST	HEADQUARTERS CUSTODIAL SECT
370	PLT MGT	PLANT MANAGEMENT UNIT
371	HLTH IN	HEALTH INSURANCE SECTION
372	FIN MGT	FINANCIAL MANAGEMENT DIVISION
373	CON ADM	CONTRACT ADMINISTRATION UNIT
375	PER BUR	PERSONNEL BUREAU
376	A P DIV	APPLICANT PROCESSING DIV
378	PB REC	PB RECRUITMENT SECTION
379	STAFFSV	STAFF SERVICE SECTION
380	OEEO	OFF OF EQUAL EMPLY OPRTY
381	PB EMPL	EMPLOYMENT SECTION
382	SPL TRN	SPECIALIZED TRAINING SECTION
383	P C C U	POLICE CADET CORPS UNIT
384	POL ACD	POLICE ACADEMY
385	LDS DEV	LEADERSHIP DEVELOPMENT SECTION
386	OFSCSRG	OFFICE SUPV CHIEF SURGEON
388	MED DIV	MEDICAL DIVISION
391	PB EMD	EMPLOYEE MANAGEMENT DIV
393	PB POS	PERSONNEL ORDERS SECTION
394	POS PDU	PERSONNEL DATA UNIT
396	M E L D	MILITARY & EXTEND LEAVE DESK
397	F.T.S.	FIREARMS & TACTICS SECTION
398	DR.ED&T	DRIVER ED. AND TRAINING UNIT
399	MEL STF	MIL & EXTENDED LEAVE STAFF
400	TRF DIV	TRAFFIC DIVISION
401	TRF/MTF	MANHATTAN TRAFFIC TASK FORCE
402	TR/BKTF	BROOKLYN TRAFFIC TASK FORCE
403	TR/BXTF	BRONX TRAFFIC TASK FORCE
404	TR/QTF	QUEENS TRAFFIC TASK FORCE

405	TR/STED	SURFACE TRANSP. ENF. DIST.
406	BUS UT	BUS UNIT
410	HWY DST	HIGHWAY DISTRICT
411	HWY 01	HIGHWAY UNIT NO 1
412	HWY 02	HIGHWAY UNIT NO 2
413	HWY 03	HIGHWAY UNIT NO 3
414	HWY 04	HIGHWAY UNIT NO.4
415	HWY SEU	HWAY DIST/SAFETY ENFORC UNIT
420	MOUNTED	MOUNTED UNIT
431	120 DET	120 DETECTIVE SQUAD
432	122 DET	122 DETECTIVE SQUAD
433	123 DET	123 DETECTIVE SQUAD
434	SI WARR	STATEN ISLAND WARRANT SQUAD
435	HQ SEC	HEADQUARTERS SECURITY
436	S O D	SPECIAL OPERATIONS DIVISION
437	PBSI AC	PBSI ANTI-CRIME UNIT
438	TC SISE	TRAFF CONTROL SI SUMMONS ENF.
439	SI PROP	S/I CRIMES VS PROPERTY SQD
440	ESS 05	EMER SERV SQ 05
441	SIHU	STATEN ISLAND HOUSING UNIT
442	HWY 05	HIGHWAY UNIT NO.5
443	S.I. CT	STATEN ISLAND COURT SECTION
444	DA S/I	S/I DA SQUAD
445	HES/SI	HIGHWAY EMER SERV S/I
446	PBSI TF	PBSI TASK FORCE
447	PBSI	PATROL BORO S/I
448	DB SI	DET BORO STATEN ISLAND
449	SI PERS	S/I CRIMES VS PERSONS SQD
450	E S U	EMER SERV UNIT
451	ESS 01	EMER SERV SQ 01
452	ESS 02	EMER SERV SQ 02
453	ESS 03	EMER SERV SQ 03
454	ESS 04	EMER SERV SQ 04
456	ESS 06	EMER SERV SQ 06
457	ESS 07	EMER SERV SQ 07
458	ESS 08	EMER SERV SQ 08
459	ESS 09	EMER SERV SQ 09
460	ESS 10	EMER SERV SQ 10
465	ESU CAN	CANINE TEAM
470	HARBOR	HARBOR UNIT
480	AV.UNIT	AVIATION UNIT
483	CPK PCT	CENTRAL PARK PRECINCT
489	VED M/S	VICE.ENF.DIV. MANHATTAN SOUTH
490	TV UNIT	MOVIE AND T.V. UNIT
491	VED M/N	VICE.ENF.DIV. MANHATTAN NORTH

492	VED BX	VICE.ENF.DIV. BRONX
493	VED Q	VICE.ENF.DIV. QUEENS
494	VE BSSI	VICE.ENF.DIV.BROOKLYN SOUTH/SI
495	VE BK/N	VICE.ENF.DIV.BKLYN NORTH
496	VICE ED	VICE ENFORCEMENT DIVISION
497	I.A.B.	INTERNAL AFFAIRS BUREAU
498	QA DCSI	QUALITY ASSURANCE DIV DC S INT
499	INS SB	INSPECTIONAL SERVICES BUREAU
500	P C O	POLICE COMM OFFICE
501	C C I B	CIV COMPLAINT INVEST BUREAU
502	1ST D.C	FIRST DEP COMM OFFICE
503	OFF/CIV	OFF/CIV & STAFF DEV
504	DC OPER	DEPUTY COMM. OF OPERATIONS
505	T.A.R.U	TECH. ASSIST. & RESPONSE UNIT
506	PRINTS	PRINTING SECTION
507	P.E.R.L	PUBLIC ED & RESOURCE LIAISON U
508	DC ADM	DEPUTY COMM ADMINISTRATION
509	PROPCLK	PROPERTY CLERK DIV
510	PCO C U	P C O CEREMONIAL UNIT
511	PCO L U	P C O LIAISON UNIT
512	PCO RTC	PCO REAL TIME CRIME CENTER
513	CA SECT	COMMUNITY AFFAIRS SECTION
515	D.A.R.E	DRUG ABUSE RESIST. ED. UNIT
517	D C TRL	DEP COMM OF TRIALS
518	D C L M	DEP COMM OF LEGAL MATTERS
519	LEG BUR	LEGAL BUREAU
520	CRJ BUR	CRIMINAL JUSTICE BUREAU
521	EMP REL	EMPLOYEE RELATIONS SECTION
523	C A B	COMMUNITY AFFAIRS BUREAU
524	D C P I	DEP COMM OF PUBLIC INFO
525	P/INFO	PUBLIC INFORMATION DIVISION
526	COD SAS	CH DEPT STRATEGIC ANALYSIS SEC
527	EM OPS	NYPD EMERGENCY OPERATIONS CTR
530	CD IRS	CHIEF OF DEPT INV REVIEW SECT
532	DC INT	DEPUTY COMM INTELLIGENCE
533	INT DIV	INTELLIGENCE DIVISION
536	F S D	FIREARMS SUPPRESSION DIVISION
537	INSUPDV	INVESTIGATIVE SUPPORT DIVISION
538	O C C B	ORGANIZED CRIME CONTROL BUREAU
539	O C I D	ORGANIZED CRIME INVEST DIV
540	D-E T/F	DRUG ENFORCEMENT TASK FORCE
541	NARCBQN	NARC BORO QNS
542	Q/N-ND	QUEENS NORTH NARCOTICS DIST.
543	Q/S-ND	QUEENS SOUTH NARCOTICS DIST.
544	NARCBMN	NARC BORO MN NORTH

545	M/N-NW	MANHATTAN NORTH NARCOTICS WEST
546	M/N-NE	MANHATTAN NORTH NARCOTICS EAST
547	NARCBBN	NARC BORO BK NORTH
548	BNNARCD	BKLYN NORTH NARC DIST
549	SNAG-BN	B.N. STRATEGIC NARC.& GUN TEAM
550	DPT ADV	DEPARTMENT ADVOCATE'S OFFICE
551	CD OFF	CHIEF OF DEPARTMENT OFFICE
552	P A T U	POLICE ACADEMY TRAINING UNIT
553	CD OP/D	CHIEF OF DEPT OPER DIV
554	DIS CTL	DISORDER CONTROL UNIT
555	CD OP/U	CHIEF OF DEPT OPER UNIT
556	DB HATE	HATE CRIME TASK FORCE
557	C C A S	COLD CASE APPREHENSION SQUAD
558	JUV CRM	JUVENILE CRIME SECTION
559	FUG ENF	FUGITIVE ENFORCEMENT DIVISION
560	AUX P.S	AUXILIARY POLICE SECT
561	CR PREV	CRIME PREVENTION SECTION
562	S S B	SUPPORT SERVICES BUREAU
563	FOR INV	FORENSIC INVESTIGATIONS DIV.
564	BARRIER	BARRIER SECTION
565	DC S IN	DEP COMM STRATEGIC INITIATIVE
566	DC C TR	DEPUTY COMM COUNTER TERRORISM
567	JT T/F	JOINT TERRORIST TASK FORCE
568	C/SCENE	CRIME SCENE UNIT
569	FC-DIV	FIELD CONTROL DIV OCCB
570	FLT SVC	FLEET SERVICES DIVISION
571	JB/R/TF	NYC JOINT BANK ROB T/F
572	O.E.M.	OFFICE OF EMERGENCY MANAGEMENT
573	C TERR	COUNTER TERRORISM DIVISION
575	COMMDIV	COMMUNICATIONS DIV
576	COMMSEC	COMMUNICATIONS SECT
577	BK N WS	BROOKLYN NORTH WARRANT SQUAD
578	CT DIV	COURT DIV
579	MAN CT	MAN COURT SECTION
580	WARRSEC	WARRANT SECTION
581	MN C BK	MAN CENTRAL BOOKING
582	BKLN CT	BROOKLYN COURT SECTION
583	BK C BK	BKLYN CENTRAL BOOKING
584	BX CT	BRONX COURT SECT
585	QNS CT	QNS COURT SECTION
586	O M A P	OFF MGMT ANALYSIS & PLANNING
587	OFF/L R	OFFICE OF LABOR RELATIONS
588	BX C BK	BRONX CENTRAL BOOKING

589	QN C BK	QNS CENTRAL BOOKING
590	DC TRNG	DEPUTY COMM OF TRAINING
591	OFF I/T	OFFICE OF INFORMATION TECH.
592	GANG DV	GANG DIVISION
593	GANG SI	GANG SQUAD STATEN ISLAND
594	GANG BN	GANG SQUAD BROOKLYN NORTH
595	GANG BS	GANG SQUAD BROOKLYN SOUTH
596	GANG Q	GANG SQUAD QUEENS
597	GANG BX	GANG SQUAD BRONX
598	GANG M	GANG SQUAD MANHATTAN
599	GANG IU	GANG INTELLIGENCE UNIT
605	CEN REC	CENTRAL RECORDS DIV
606	ID SECT	IDENTIFICATION SECTION
607	CRS/AU	CRIMINAL REC SEC / AIDED UNIT
608	AID UN	AIDED UNIT
609	S P I S	STOLEN PROPERTY INQUIRY SECT
610	CARCRMS	CAREER CRIM SECT
612	PI&REQ	PUBLIC INQUIRY AND REQUEST SEC
675	DBSV Z1	DET BUR SPEC VIC DIV ZONE #1
676	DBSV Z2	DET BUR SPEC VIC DIV ZONE #2
677	DBQ MC	DET BORO QUEENS MAJOR CRIMES
678	DBBK MC	DET BORO BROOKLYN MAJOR CRIMES
679	DBBX MC	DET BORO BRONX MAJOR CRIMES
680	DBM MC	DET BORO MAN MAJOR CRIMES
681	DBM ZN1	DET BORO MANHATTAN ZONE #1
682	DBM ZN2	DET BORO MANHATTAN ZONE #2
683	DBM ZN3	DET BORO MANHATTAN ZONE #3
684	DBM ZN4	DET BORO MANHATTAN ZONE #4
685	DBM ZN5	DET BORO MANHATTAN ZONE #5
686	DBM ZN6	DET BORO MANHATTAN ZONE #6
687	DBBX Z7	DET BORO BRONX ZONE #7
688	DBBX Z8	DET BORO BRONX ZONE #8
689	DBBX Z9	DET BORO BRONX ZONE #9
690	DBBKZ10	DET BORO BROOKLYN ZONE #10
691	DBBKZ11	DET BORO BROOKLYN ZONE#11
692	DBBKZ12	DET BORO BROOKLYN ZONE #12
693	DBBKZ13	DET BORO BROOKLYN ZONE #13
694	BDBKZ14	DET BORO BROOKLYN ZONE #14
695	DBBKZ15	DET BORO BROOKLYN ZONE #15
696	DBQ Z16	DET BORO QUEENS ZONE #16
697	DBQ Z17	DET BORO QUEENS ZONE #17
698	DBQ Z18	DET BORO QUEENS ZONE #18
699	DBQ Z19	DET BORO QUEENS ZONE #19
701	PBMSD01	PATROL BORO MAN SO DIV 01
702	PBMSD02	PATROL BORO MN SO DIV 02

703	PBMSD03	PATROL BORO MN SO DIV 03
704	PBMND04	PATROL BORO MN NO DIV 04
705	PBMND05	PATROL BORO MN NO DIV 05
706	PBMND06	PATROL BORO MN NO DIV 06
707	PBBXD07	PATROL BORO BX DIV 07
708	PBBXD08	PATROL BORO BX DIV 08
709	PBBXD09	PATROL BORO BX DIV 09
710	PBBSD10	PATROL BORO BKN SO DIV 10
711	PBBSD11	PATROL BORO BKN SO DIV 11
712	PBBSD12	PATROL BORO BKN SO DIV 12
713	PBBND13	PATROL BORO BKN NO DIV 13
714	PBBND14	PATROL BORO BKN NO DIV 14
715	PBBND15	PATROL BORO BKN NO DIV 15
716	PBQND16	PATROL BORO QN DIV 16
717	PBQND17	PATROL BORO QN DIV 17
718	PBQND18	PATROL BORO QN DIV 18
719	PBSID19	PATROL BORO S/I DIV 19
730	NARCBBX	NARC BORO BX
731	BX/S-ND	BRONX SOUTH NARCOTICS DISTRICT
732	BX/N-ND	BRONX NORTH NARCOTICS DISTRICT
740	NARCBBS	NARC BORO BS
741	B/S-WND	B'KLYN SOUTH WEST NARC. DIST.
742	B/S-END	B'KLYN SOUTH EAST NARC. DIST.
750	NARCBMS	NARC BORO MS
751	M/S-ND	MANHATTAN SOUTH NARCOTICS DIST
752	M/S-DND	MANH. SO. DOWNTOWN NARC. DIST.
755	NARCBSI	NARC BORO S/I
756	SINARCD	S/I NARC DISTRICT
757	SNAG-SI	S.I. STRATEGIC NARC.& GUN TEAM
758	JOCNTF	JOINT ORG CRIME NARC T/F
759	OCDE-SF	ORG CRIME DRUG ENF STRIKE FORC
760	100 SSU	100 SCHOOL SAFETY UNIT
761	101 SSU	101 SCHOOL SAFETY UNIT
762	102 SSU	102 SCHOOL SAFETY UNIT
763	103 SSU	103 SCHOOL SAFETY UNIT
764	104 SSU	104 SCHOOL SAFETY UNIT
765	105 SSU	105 SCHOOL SAFETY UNIT
766	106 SSU	106 SCHOOL SAFETY UNIT
767	107 SSU	107 SCHOOL SAFETY UNIT
768	108 SSU	108 SCHOOL SAFETY UNIT
769	109 SSU	109 SCHOOL SAFETY UNIT
770	110 SSU	110 SCHOOL SAFETY UNIT
771	111 SSU	111 SCHOOL SAFETY UNIT
772	112 SSU	112 SCHOOL SAFETY UNIT
773	113 SSU	113 SCHOOL SAFETY UNIT

774	114 SSU	114 SCHOOL SAFETY UNIT
775	115 SSU	115 SCHOOL SAFETY UNIT
780	SS DIV	SCHOOL SAFETY DIVISION
781	PBMS SS	PBMS SCHOOL SAFETY
782	PBMN SS	PBMN SCHOOL SAFETY
783	PBBX SS	PBBX SCHOOL SAFETY
784	PBBS SS	PBBS SCHOOL SAFETY
785	PBBN SS	PBBN SCHOOL SAFETY
786	PBQS SS	PBQS SCHOOL SAFETY
787	PBQN SS	PBQN SCHOOL SAFETY
788	PBSI SS	PBSI SCHOOL SAFETY
789	SS INV	SCHOOL SAFETY INVEST UNIT
800	HSG BUR	HOUSING BUREAU
801	PSA 1	HOUSING PSA 1
802	PSA 2	HOUSING PSA 2
803	PSA 3	HOUSING PSA 3
804	PSA 4	HOUSING PSA 4
805	PSA 5	HOUSING PSA 5
806	PSA 6	HOUSING PSA 6
807	PSA 7	HOUSING PSA 7
808	PSA 8	HOUSING PSA 8
809	PSA 9	HOUSING PSA 9
810	H OPER	HOUSING OPERATIONS
811	HB DET	HOUSING DETECTIVE
820	H INV U	HOUSING INVESTIGATIONS UNIT
821	H BKLYN	HOUSING BROOKLYN
822	H MAN	HOUSING BOROUGH MANHATTAN
823	H BX/Q	HOUSING BX/QNS
824	HBK IRT	HB BKLN IMPACT RESPONSE TEAM
825	HBM IRT	HB MANH. IMPACT RESPONSE TEAM
826	BX/Q IM	HB BX/QNS IMPACT RESPONSE TEAM
833	H SP OP	HB SPECIAL OPERATIONS SECTION
834	H VANDL	HOUSING ELEVATOR VANDALISM UNT
835	H OTHER	HOUSING MISC. COMMANDS
840	OFF/TRP	OFFICE CHIEF OF TRANSPORTATION
845	TRP BUR	TRANSPORTATION BUREAU
850	TB	TRANSIT BUREAU
851	TB LIAS	TRANSIT AUTHORITY LIAISON
852	TB INV	TRANSIT BUR. INVEST. UNIT
853	TB C/AN	TRANSIT BUR. CRIME ANALYSIS
854	TB SIU	TRANSIT BUR. SPEC. INV. UNIT
855	TD OPS	TRANSIT PATROL OPERATIONS
856	TB MANH	TRANSIT BORO MANHATTAN
857	TB BX	TRANSIT BORO BRONX
858	TB QNS	TRANSIT BORO QUEENS

859	TB BK	TRANSIT BORO BROOKLYN
860	TB DT01	TRANSIT BUREAU DISTRICT 1
861	TB DT02	TRANSIT BUREAU DISTRICT 2
862	TB DT03	TRANSIT BUREAU DISTRICT 3
863	TB DT04	TRANSIT BUREAU DISTRICT 4
864	TB DT11	TRANSIT BUREAU DISTRICT 11
865	TB DT12	TRANSIT BUREAU DISTRICT 12
866	TB DT20	TRANSIT BUREAU DISTRICT 20
867	TB DT23	TRANSIT BUREAU DISTRICT 23
868	TB DT30	TRANSIT BUREAU DISTRICT 30
869	TB DT32	TRANSIT BUREAU DISTRICT 32
870	TB DT33	TRANSIT BUREAU DISTRICT 33
871	TB DT34	TRANSIT BUREAU DISTRICT 34
872	TB M/TF	TRANSIT BORO MANH TASK FORCE
873	TB BXTF	TRANSIT BORO BX TASK FORCE
874	TB Q/TF	TRANSIT BORO QNS TASK FORCE
875	TB BKTF	TRANSIT BORO BKLN TASK FORCE
876	TB H/O	TB HOMELESS OUTREACH UNIT
877	TD CAN	TRANSIT DIV. CANINE UNIT
878	TB VTF	TB CITYWIDE VANDALS TASK FORCE
879	TB SOD	TB SPECIAL OPERATIONS DISTRICT
880	TB/OTR	TRANSIT BUREAU OTHER
881	TC PED	TC PARKING ENFORCEMENT DIST.
882	TB TAGS	TB TRANSIENT AND GRAFFITI SEC
883	TC INTL	TRAFF CONTROL INTEL.UNIT
884	CWS ENF	CITY WIDE SUMMONS ENFORCEMENT
885	INT CU	INTERSECTION CONTROL UNIT
886	TC MSE	TRAFF CONTROL MAN SUMMONS ENF.
887	TC QSE	TRAFF CONTROL QNS SUMMONS ENF.
888	TC BXSE	TRAFF CONTROL BX SUMMONS ENF.
889	TC BKSE	TRAFF CONTROL BK SUMMONS ENF.
890	TC MIN	TRAFF CONTROL MAN INTERSECTION
891	TC BKIN	TRAFF CONTROL BK INTERSECTION
892	TC QIN	TRAFF CONTROL QNS INTERSECTION
893	TOW OPS	TRAFF CONTROL TOW OPERATIONS
894	TC VTOW	TRAFF CONTROL VIOLATION TOW UT
895	TARGTOW	TRAFF CONTROL TARGET TOW UNIT
897	ND BKSI	NARC.DIV.BK SOUTH INIT.
898	ND BXCI	NARC.DIV.BRONX CENTRAL INIT.
899	ND Q/NI	NARC.DIV.QUEENS NORTH INIT.
900	SAT B/N	STRATEGIC & TACTICAL CMD B/N
901	SATNOPS	SAT NARC OPS B/N
902	SATHOPS	SAT HOUS OPS B/N
903	SATPOPS	SAT PAT OPS B/N
904	SATDOPS	SAT DET OPS B/N

905	005 SSU	005 SCHOOL SAFETY UNIT
906	006 SSU	006 SCHOOL SAFETY UNIT
907	007 SSU	007 SCHOOL SAFETY UNIT
908	001 SSU	001 SCHOOL SAFETY UNIT
909	009 SSU	009 SCHOOL SAFETY UNIT
910	ND NMI	NARC DIV NORTHERN MANH. INIT.
911	ND BXSI	NARC DIV BRONX SOUTH INIT.
912	ND SEQI	NARC DIV SOUTHEAST QUEENS INIT
913	ND CH I	NARC.DIV.CENTRAL HARLEM INIT.
914	ND EH I	NARC.DIV.EAST HARLEM INIT.
915	ND SI I	NARC.DIV.STATEN ISLAND INIT.
916	010 SSU	010 SCHOOL SAFETY UNIT
917	017 SSU	017 SCHOOL SAFETY UNIT
918	MTN SSU	MTN SCHOOL SAFETY UNIT
919	019 SSU	019 SCHOOL SAFETY UNIT
920	020 SSU	020 SCHOOL SAFETY UNIT
921	013 SSU	013 SCHOOL SAFETY UNIT
922	CPK SSU	CENTRAL PARK SCHOOL SAFETY UT
923	023 SSU	023 SCHOOL SAFETY UNIT
924	024 SSU	024 SCHOOL SAFETY UNIT
925	025 SSU	025 SCHOOL SAFETY UNIT
926	026 SSU	026 SCHOOL SAFETY UNIT
927	MTS SSU	MTS SCHOOL SAFETY UNIT
928	028 SSU	028 SCHOOL SAFETY UNIT
930	030 SSU	030 SCHOOL SAFETY UNIT
932	032 SSU	032 SCHOOL SAFETY UNIT
933	033 SSU	033 SCHOOL SAFETY UNIT
934	034 SSU	034 SCHOOL SAFETY UNIT
940	040 SSU	040 SCHOOL SAFETY UNIT
941	041 SSU	041 SCHOOL SAFETY UNIT
942	042 SSU	042 SCHOOL SAFETY UNIT
943	043 SSU	043 SCHOOL SAFETY UNIT
944	044 SSU	044 SCHOOL SAFETY UNIT
945	045 SSU	045 SCHOOL SAFETY UNIT
946	046 SSU	046 SCHOOL SAFETY UNIT
947	047 SSU	047 SCHOOL SAFETY UNIT
948	048 SSU	048 SCHOOL SAFETY UNIT
949	049 SSU	049 SCHOOL SAFETY UNIT
950	050 SSU	050 SCHOOL SAFETY UNIT
952	052 SSU	052 SCHOOL SAFETY UNIT
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Appendix F.

Transcript of March 9, 2010 Forum on Stop and Frisk

The Association of the Bar of the City of New York

CITY UNIVERSITY OF NEW YORK - JOHN JAY COLLEGE OF CRIMINAL JUSTICE

The New York Police Department's Stop and Frisk Policies

March 9, 2010
6:00 PM to 8:00 PM

Ubiqus/Nation-Wide Reporting & Convention Coverage
22 Cortlandt Street, Suite 802 - New York, NY 10007
Phone: 212-227-7440 • 800-221-7242 • Fax: 212-227-7524

The New York Police Department's Stop and Frisk Policies: Are they Effective? Fair? Appropriate?

[START MZ000001]

MR. HARLAN LEVY: I'm glad to welcome everyone here tonight. My name is Harlan Levy, and I am the Chair of the Council on Criminal Justice of the New York City Bar Association. And we are, along with the Committee on Civil Rights, sponsoring tonight's program. We're very excited to sponsor this program, because it reflects the intersection of public safety on the one hand and issues of fairness on the other. And those are two key issues in our city right now. And the latter issue, the issue of fairness, is also which this Bar Association has long been dedicated to.

There are two people that I want to mention tonight just to get this panel started. I know that Dan Richmond [phonetic] is here tonight. Dan is a member of the Council on Criminal Justice, is a professor at Columbia Law School, and he was fundamental in terms of identifying exactly the right people to be here tonight, which we have, and in recruiting them to be here. So we're all grateful to Dan's assistance.

I also want to introduce to you our moderator, and in many respects, the leader of our discussion tonight, Jeremy Travis. Jeremy came to us last year and said that he wanted to find a place that was a safe place for a reasoned and intelligent discussion of these issues. And he thought the City Bar was the right place to do that. And we were grateful for that, and are very grateful to host this program.

Jeremy is the President of John Jay Criminal Justice. He is the former Director of the National Institute of Justice, the Department of Justice in Washington, DC He's been the Deputy Commissioner for Legal Matters at the New York City Police Department. And last year, he gave the Orison Marden Lecture at the New York City Bar Association on Race, Crime and Criminal Justice: A New Look at Old Questions. And I am delighted to turn the program over to him tonight.

[applause]

MR. JEREMY TRAVIS: After Harlan Levy speaks, you always have to adjust the mic. Welcome to all of you. I'm very appreciative of all of you taking time from your schedules to be here this evening for this very important discussion. I'm very honored that the Bar Association has asked me to moderate this panel, and very grateful to both the Council on Criminal Justice and the Committee on Civil Rights of the Bar for serving as sponsors. And very pleased that they seeded to this notion that the Bar Association would be an important and appropriate place for a important conversation.

As everyone here knows, there is considerable debate in the city regarding the efficacy of the practices we're discussing tonight. In fact, the title of the panel captures the questions: The New York City Police Department's Stop and Frisk Policies: Are They Effective? Fair? Appropriate?

Now, strong claims are made on both sides of this debate. Proponents of these practices claim that they have made substantial contributions to the crime decline in New York City, and they have become an essential tool in the Police Department's crime prevention tool kit. Critics of these practices claim that the Stop, Question and Frisk Policies have had an unwarranted disparate impact on communities of color, and have undermined the legitimacy of the police operations and of the justice system.

So our hope for this evening is that we will shed some light on the issues underlying this debate. And to do that, I'm pleased to note that the Center for Race Crime and Justice at John Jay College, under the leadership of Dr. Delores Jones-Brown, has prepared a, what we call a primer on Stop, Question and Frisk that, hopefully, you've all received as you came in, where we attempted to present in a straightforward way, the basic facts describing these practices. And in a moment, I will share just five slides—no extensive Power Point here—five slides from the primer so that this audience starts with a common understanding of the dimensions of the practice that we will be discussing.

We are very fortunate to have four experts who have examined the practices of Stop, Question and Frisk from very different perspectives. I'll introduce them in the order in which they will speak.

Our first speaker will be Heather MacDonald, the John M. Olin Fellow at the Manhattan Institute, and Contributing Editor to City Journal. She has written extensively on policing and the controversies regarding racial profiling.

Next, we will hear from Tracey Meares, Deputy Dean and Walton Hale Hamilton Professor at Yale Law School. Her scholarly work explores the issues of legitimacy of the police functions, particularly in communities of color.

Our third speaker will be Dr. Jeffrey Fagan, Professor of Law and Public Health at Columbia Law School, and Director of the Center for Crime, Community, and Law at that institution. He is currently a Visiting Professor of Law at Yale University. Dr. Fagan has conducted extensive research on Stop, Question and Frisk issues. He is indeed one of the prime scholars in this area in New York City and police citizen interactions generally.

And our final speaker will be John Timoney, Former Chief of Police of Miami-Dade, Commissioner of Police in Philadelphia, and First Deputy Commissioner of New York City Police Department under Commissioner William Bratton, who's also with us tonight. Chief Timoney has explored the challenges facing modern policing in a book. I'm here to shamelessly plug his book appropriately titled, Beat Cop to Top Cop: A Tale of Three Cities. And that will come out when, John? Do we want to give the...

MR. JOHN TIMONEY: First week of May.

MR. TRAVIS: First week of May. And you can now order it on...

MR. TIMONEY: You can get it on Amazon now.

MR. TRAVIS: Right. I knew you'd work that in. I should note that the New York City Police Department was invited to participate on this panel, but declined the invitation citing pending litigation challenging the current Stop, Question, Frisk policies that we are discussing tonight.

So here's the plan. Following what I hope will be a very brief overview, the slides aforementioned, each of our speakers will make a presentation lasting no more than 15 minutes. And I will give each of them a 2-minute warning if they get close. I hope to ensure that we stay on schedule, so that we have ample time for Q&A following their presentations. That's the real meat, I hope, of the discussion tonight.

Please note that we are taping and filming the discussion this evening so that we can prepare a video and a monograph that will capture the discussion. It will be released by our Center.

So let's take a quick look—if you'll stick with me—at five summary slides that tell, I hope, at a very macro level the story of Stop, Question, Frisk practices in New York City. We will describe how many people are stopped according to official records, what is the racial and ethnic profile of those stopped, why they are stopped, what happens during the stops, and where those stops occur. We are using, as you note in the primer, by and large available data presented by the NYPD on their website. And the primer also notes that there a couple of points of missing data where we have used data provided by the Center for Constitutional Rights.

Now, I recognize that these slides will present questions. And that's the point. But we're not going to answer them until we get to the Q&A. Okay? So the idea is to give you a brief overview. So you with me? That's what we're about to do.

So first slide. So the first question is: What is the magnitude of the phenomenon that we're talking about? These are official NYPD records in almost all years. This shows, as you'll see, a significant increase in stops over the past seven years. The annual number of stops, as recorded by the police department, has tripled over that time period from 160,000 approximately in 2003, to 575,000 in 2009.

Second slide. Second slide—those of you who are closer will have a little easier time reading it, but it's all in the primer. Shows that African Americans, actually blacks, since we are—you'll see that there's some coding issues here in the data here—but blacks and Hispanics represent a significant majority of all stops. So if you were to put these years together, you'd find that for the years 2005 to 2008, approximately 80% of those stopped are either African American or Hispanic, 20% white. If you look at the 2009 data, you'll see that there's a slight increase in that number. About 85% are black or Hispanic, and 15% white. You notice I'm making no commentary. We're just presenting some data here.

There we go. The third slide shows the reasons for the stop. These data are collected by, in essence, the police officers that make the stops. They are data collection agents. They check a box for the reasons for the stop that then gets recorded and made public by the police department. The reason for initiating stop sighted least frequently—if you go to the far left of this spectrum—in 2008, that's the only year we're presenting here, was that the person was carrying a crime object in quote plain view. The reason cited at the other end of the spectrum—the tallest bar on the bar chart—cited most frequently was that the person was engaged in quote furtive movements. So that the largest number on the right—furtive movements. That was cited in almost half or 246,000 of the stops presented here.

The next slide answers the question: What happens during these stops? And, again, we're using only 2008 data here. It shows that during roughly half of all stops in that year—54% to be precise, 54.4% to be really precise—officers reported that they frisked the subject, the person stopped. And, as you know, an officer is legally authorized to pat down the outer clothing of a suspect to determine if that person's carrying a weapon. So that happened in half, slightly over half of the cases. In about a quarter, 23% of the cases, there was physical force used. Go to the other end of the spectrum—6% of the stops resulted in an arrest, 6.4% resulted in a summons, and slightly around 1%—it's actually 1.09%—resulted in confiscation of a knife or other weapon, and .15% resulted in the confiscation of a gun. So we see a very different distribution of the outcomes of these stops.

And the final slide that I'll show you is just to give you a city picture in terms of where these stops are occurring. This is looking at, again, we've combined data here from 2003 to 2008, of the nearly 3 million documented stops that occurred between those years. Five precincts have the greatest number. And those are the 23rd Precinct in East Harlem, Upper East Side; the 73rd Precinct in Ocean Hill Brownsville in Brooklyn; the 75th Precinct in East New York, also Brooklyn; the 79th, the Bed-Stuy in Brooklyn; and the 103rd Precinct in Jamaica Queens. So there's a big picture, 40,000-feet-above-street-level view of what we're talking about tonight.

So we'll go back to the title of the presentation. And we are about to hear our first presenter. So we welcome to the podium, Heather MacDonald.

[applause]

MS. HEATHER MACDONALD: Thank you so much President Travis. And how do I move this even after you're taller. There we go. Is this good? Thank you. And I'm very honored to be here tonight, and especially on such a distinguished panel.

The most startling thing that William Bratton did upon assuming control of the New York Police Department in 1994 was to announce that he would lower crime in his first year by 10%. No police chief in living memory had ever made so reckless a pledge. It signaled Bratton's break with reigning law enforcement ideology that held that police could not prevent crime, they could only respond after the fact by making an arrest. Bratton not only met his 10% target, he bested it, bringing crime down 12% in 1994 while crime nationally dropped 1%. The next year, he upped the ante, promising a 15% reduction in crime. 1995 closed with a 16% crime drop while crime stayed flat in the rest of the country.

Bratton accomplished this unprecedented feat by the managerial revolution that came to be known as CompStat. The department started gathering and analyzing crime data daily, and deploying officers where crime patterns where emerging. If officers observed suspicious behavior in a violence-plagued area, they were expected to intervene pursuant to their legal authority before a crime actually occurred. Precinct commanders were held ruthlessly accountable for the safety of their precincts. And the department stopped tolerating the disorder that had engulfed so many public spaces.

CompStat created a sense of urgency about fighting crime that has never dissipated. In the 1990s, New York's crime drop was twice the national average. Homicides, robberies, larcenies and burglaries dropped 70%. And in the 2000s, while the crime decline in the rest of the country flattened out, crime in New York dropped an additional 34%. New York's crime profile no longer resembles that of a big metropolis. The city's homicide rate is two-fifths that of Chicago, for example. Juveniles under the age of 17 are killed in New York at one-quarter the rate of those in the Windy City.

The benefits of this crime decline have been disproportionately concentrated in the city's poorer neighborhoods since that is where the costs of crime hit the hardest. Blacks and Hispanics have made up 79% of the decline in homicide victims since 1993. Over 10,000 black and Hispanic males are alive today who would have been dead had homicide rates remained at their early 1990s levels.

With robberies and burglaries plummeting in once desolate neighborhoods in the late 1990s, economic activity and property values there rose dramatically. Senior citizens could go shopping without fear of getting mugged, and children no longer needed to sleep in bathtubs to avoid stray bullets.

Despite the benefits of proactive policing, however, it has generated a backlash in certain quarters. The John Jay handout, which we've been provided today, provides a classic demonstration of how the public debate regarding stop and frisks inevitably proceeds. The booklet gives us the racial breakdown of stops and the racial breakdown of the city's population. It leaves out, however, the most relevant factor in analyzing police activity—crime rates. In the CompStat era, it is absurd to talk about policing patterns without discussing crime since crime drives everything that the department does.

We learn, according to the primer, that blacks made up 55% of stops in 2009, and are 24% of the city's population. Here's what you will never ever hear in such a discussion. Blacks committed 66% of all violent crimes in the first half of 2009. How do we know that? That's what the victims of and witnesses to those crimes reported to the police. Victims who are overwhelmingly minority themselves. Blacks committed 80% of all shootings in the first half of 2009, again, according to victim and witness reports. Together, blacks and Hispanics committed 98% of all shootings. Blacks committed nearly 70% of all robberies their victims reported to the police. These ratios have held steady for years.

Whites, by contrast, committed 5% of all violent crimes in the first half of 2009, though they are 35% of the city's population. They committed 1.8% of all shootings, and less than 5% of all robberies. Any given violent crime is 13 times more likely to be committed by a black than by a white perpetrator. Compared to their rates of violent crime, 66% in other words, blacks are being significantly under-stopped at 55% of all stops.

Now, crime rates are not a perfect benchmark for police stops. Ideally, you would include as well community requests for police service and calls reporting suspicious activity. But crime rates are a heck of a better benchmark for stops than census data, which is wholly irrelevant to police deployment. Police presence and stops are going to be heaviest in minority neighborhoods, because that is where the overwhelming majority of victimization is going on.

If customers are being held up at knifepoint at ATM machines in East Flatbush, cops will be more intensively deployed there. Two teens intently watching an ATM user from across the street, who quickly move away when they see an officer observing them, may be questioned. If there has been a string of robberies against senior citizens in East New York, someone walking closely behind an elderly lady in the 75th Precinct and looking furtively over his shoulder stands a good chance of getting seen and stopped by an officer who has been deployed there just for that purpose.

Anyone who thinks that stop rates should mirror census data must explain why public safety would be better served by stripping officers from the areas that need the most, and deploying them in neighborhoods where people are not being victimized anywhere near to the same degree. Yesterday, a 2-year-old girl was shot in the 73rd Precinct of Brooklyn. A 10-year-old girl was shot in the 81st Precinct in Brooklyn. The man who shot the 10-year old managed to kill his intended victim as well, a 22-year-old man. There were no shootings in the 50th Precinct, which is largely white. I fail to see how the police officers, which are being deployed today in the 73rd and 81st Precinct and are making stops, should be instead deployed to the 50th Precinct for the sake of racial balance.

Community demands for police attention is the second major factor driving deployment decisions and tactics—one is that completely ignored by conventional racial profiling analysis. The New Republic's Jeff Rosen argues that broken windows policing discriminates against the poor. He has obviously never attended an inner city policy community meeting in his life. There are no fiercer proponents of public order and quality of life policing than law-abiding residents of poor neighborhoods. Go to any precinct meeting in Brooklyn or Harlem and this is what you will hear: a) We want more cops, b) Please get the drug dealers off the corner. You arrest them and they're back the next day, c) Please crack down on neighborhood disorder.

A few years ago, I heard an elderly woman in the 28th Precinct tell the police, "Teenagers are hanging out in front of my building. Why can't you arrest them for loitering?" The commander had to explain to her that loitering laws had been sharply circumscribed by the courts. The irony is that the police cannot respond to these heartfelt requests for public order without also generating disproportionate stop data that can be used against them in a racial profiling lawsuit such as the Center for Constitutional Rights is now bringing against the NYPD.

The other charge against proactive policing concerns the absolute number of stop and frisks. In 2009, as the slide that President Travis showed us, the NYPD conducted 575,000 stops. This number is presented as prima facie evidence of an out-of-control department. Perhaps it is. But I would like to know what the critics thinks is the proper number of stops, and what formula they used to arrive at that number. In 2009, the department made over 400,000 arrests and issued 500,000 summons. Given that the probable cause standard for making an arrest is considerably higher than the reasonable suspicion standard for questioning someone, the number of stops is not out of proportion to the number of arrests.

Few cities collect stop-and-frisk data with anywhere near the rigor of the NYPD. One city that does, however, is Los Angeles thanks to a federal consent decree. In 2008, the Los Angeles Police Department conducted nearly a quarter million pedestrian stops, and made over 184,000 arrests. The ratio of pedestrian stops to arrests, and the ratio of pedestrian stops to the city's population are identical in Los Angeles and New York. A federal judge just lifted the consent decree from the LAPD. Critics of the NYPD's stop numbers need to explain why stop data that are consistent with civil rights in Los Angeles violate civil rights in New York.

Critics also charge that the percentage of stops that conclude with an arrest or summons, 12%, shows that the NYPD is abusing its authority. This criticism misunderstands the purpose and evidentiary basis of stops. But in any case, I would once again like to know what these critics think a proper stop-to-arrest ratio is. Moreover, it is not true, as the New York Times's Bob Herbert asserts, that just because a stop does not result in arrest, that the persons stopped was necessarily quote totally innocent. Someone stopped in a high-crime area because he appears to be casing a location or victim or acting as a lookout could well have been engaged in that activity, but there will be no evidence of casing on which to base an arrest. Nevertheless, that stop will likely have prevented a crime by alerting the participants that the police are on to them.

The fact that no drugs or guns were found on someone engaged in the familiar choreography of a drug ring does not mean that he was not acting as a runner or lookout. But even if a person stopped is totally innocent, it does not follow that this stop was not legally justified or that it was not part of sound public policy to deter crime, however frustrating and humiliating it may be for the person stopped.

Officers need to do a far better job of courteously explaining to people why they were stopped if the officer's suspicions proved unfounded. Occasionally accosting innocent people is a real cost of proactive policing. Whether that cost outweighs the benefits of lowered victimization in high-crime areas is obviously a decision society needs to make on an ongoing basis.

Finally, according to data posted on the web by the Center for Constitutional Rights, as part of its lawsuit against the NYPD, an identical ratio of stops of whites, blacks, and Hispanics result in arrests and recover weapons. The Center argues that this data is further proof of racial profiling. I'm puzzled by this claim. Analysis of hit and arrest rates is complex. But the fact that they are identical across different racial groups suggests that the police are using identical quantum of reasonable suspicion in making a stop.

No other public policy change of the last quarter century has had as positive an impact on the wellbeing of the city's poor as CompStat policing. Commissioner Ray Kelly is undoubtedly pressing the department hard to keep crime going down, but there's no sign yet of diminishing returns. In 2009, the recession notwithstanding, homicides dropped 19% and overall crime dropped 10% in New York City. Perhaps some would argue that crime is low enough already, and it's time to back off of proactive policing. Last year, in the 75th Precinct in East New York, there were 24 murders and 678 robberies. Good enough?

Maybe so. After all, these represented a 78% drop in murders and an 80% drop in robberies since 1990. But try telling those victims and their families in East New York that the crime rate is low enough.

For a decade now, we've been having the wrong conversation about crime and policing. We've been focusing exclusively on alleged police bias in order to avoid talking about a far more pressing problem—disproportionate rates of black crime. Not only do blacks in New York commit 66% of all violent crime, well above their population and stop rates, but nationally, black males between the ages of 16 and 24 are ten times more likely to commit homicide than similarly aged white and Hispanic males combined. It is those disparities we should be most worrying about and trying to change. Thank you very much.

[applause]

MR. TRAVIS: We promised a robust discussion. I think we're off to a good start. Thank you very much, Heather. Our next speaker is Tracey Meares.

[applause]

MS. TRACEY MEARES: Good evening, everyone. You might see me shivering up here. It's really cold. And I have sort of a circulation thing. So I might be going like this.

I want to make four points today. And I'm going to start where Heather MacDonald left off, because you might be surprised to learn this. She and I actually agree on quite a bit.

I've spent most of my scholarly career looking at neighborhoods, high-crime neighborhoods, predominantly poor ones, and the experience of crime there. And it is true, as Heather asserts—do you mind if I call you Heather?

MS. MACDONALD: Please do.

MS. MEARES: ...as Heather asserts that residents of those communities feel, believe and are right that crime is a serious problem there. Crime reduction is critical. Crime reduction is important. It's also true that police are important, and that residents of those communities desire and demand more and better policing. It's also true that police tactics such as stops, consensual searches, stops and frisks are all parts of a policing tool kit that can address crime in communities such as this.

As an aside here, I also want to engage the point of innocence in stops in a slightly different way. And you'll see why as I continue to speak. I think it's important to actually take the freight off of that term in this context. Because the reality is under the legal standard for stops, and arrests. for that matter, that most people who engage the police will never be convicted or serve any time. So in that sense, most people who engage the police are innocent. And I think if we stop focusing on innocence and guilt in this context, but instead focus on the dynamics of what's happening in the encounter itself, we'll probably make more headway.

That brings me to my second point. Numbers matter here. Hundreds of thousands people in New York are stopped every year. And what needs to be explored, I think, in New York is not the proportion or the racial proportion of stops and whether there is some relationship between people who are engaging in crime and the police tactic. Obviously, that's true. It would be absurd to think that the police tactic ought to match demographic representation in the city as opposed to the demographic representation of people who are engaged in offending. That actually tracks to the first point I was making about the legal basis for stops and arrests.

However, to make a point about the proportion of the people who are stopped and arrested is not the same as looking at the sheer numbers of people who are encountered on a daily basis in this city and the relationship between that and the crime decline. We haven't heard anything about that today.

What we know is that hundreds of thousands of people have been stopped in this city over time, and we also know that there has been a crime decline. I am sure that there are people on this panel—at least I know, because one of them is a very good friend of mine—who are capable of making and answering that concrete question. But we don't know that there's a straightforward relationship between those two things.

What we do know is that what we're getting out of this probably isn't what we thought we were getting out of it. In the primer, we saw that the yield rate from the stops—at least in terms of weapons—is extremely low. I think, if I'm remembering correctly, the slide said that there is a .15% yield rate in terms of guns and stops. That's a really, really small number for the kind of intrusion of liberty that has to be sustained. And that's a question that I think we all have to take seriously. Whether that cost of intrusion is worth that particular benefit very saliently put there.

We also know that there's been an escalation in the sheer number of stops—hundreds of thousands of them—and the crime decline itself has not moved apace. So that's another cost benefit question that can be answered apart from whether we can actually tease out the direct causal relationship between this particular strategy and a crime decline.

I do think—and this is my fourth point—that the costs are clear in one domain. And that is with respect to legitimacy. Now, I'm going to be the law professor here for a moment. And I'm going to ask you a question. Do you think that people obey the law because they fear the consequences of failing to do so? Or do you think that they obey the law because they think it's the right thing to do? Or because they think that government and legal agents have the right to dictate to them proper behavior? I think that it's the latter.

And if you believe that, then you will probably think that in investigating in a strategy that demands that law enforcers stop and frisk hundreds and thousands of people will likely be, well, maybe wrongheaded in a certain sense. Now, I want to be clear here. And I hope I made it clear from the beginning. I am, I think, police agencies are critical. I think they do work. There's a role for stops and frisks in certain strategies. It just should be smart. And there are ways in which we can predictably see that that overinvesting in this kind of strategy will backfire.

Here's the reason why. If you think that people obey the law because they believe that law enforcers have the right to dictate to them proper behavior, it's because of reasons having to do with procedural justice more than it has to do with instrumental reasons for compliance. Here's an example. If you're driving home let's say from the New York City Bar Association building at night—maybe this won't work though in New York because there are way too many people around. But let's say it's 3:00 in the morning, and you come upon a stoplight at 3:00 in the morning. And no one's around. This is probably not happening in New York. So let's imagine it's New Haven where it does happen. Where there's no one around at 3:00 in the morning. Do you stop at the stoplight or do you keep going? Well, maybe a few people in the room keep going, but most of us stop. And we stop because we know it's the right thing to do, and because there's a law that says you have to stop when there's a stoplight.

All of our changing that encourages us to stop at the stoplight when no one's around has to do with the procedural justice of the way that laws are enacted and the way that they're enforced. People are more likely to obey the law and requests by legal enforcers when they're treated with dignity, when they're treated in ways that they can identify as neutral. That is, that they're not treated differently from other people, especially in a group-based way. And they're more likely to obey a request from a law enforcer when they can trust that that person will behave benevolently toward them in the future. None of these things have to do with a law enforcer holding a club over their head. None of these reasons are instrumental. All of them encourage people to voluntarily obey the law.

Now, what does that have to do with what's going on here? Well, if people experience hundreds of thousands of stops—and in some areas of New York, I'm told, there are groups of people, young African-American men, I think between the ages of 18 and 24, where 90% of that group is stopped. They're going to have a different view of police agencies, law, and law enforcers than people who don't experience that kind of saturation of—what's the word I want to use?—

well, forced compliance essentially.

It also means that we have to pay attention to the dynamics of those encounters. Something we haven't heard anything about here. And I'm not sure how much information we have. We don't learn from the fact that there are close to 600,000 stops about the particular context of each of them. Heather's just said that it's really important that police officers explain to people why they're stopped. I agree. That's a critical aspect of the procedural justice model of compliance. It's also critical, not only that people get the reasons why they're stopped explained to them, but that they're treated politely, and that they're not tossed about and have their things taken out of their pockets and simply strewn into the street. All of those kind of tactics are inconsistent with someone viewing the encounter as a dignified one, and certainly not one in which that person will believe that they will be treated benevolently in the future.

My guess is, is that the more stops—I don't know this to be true; it's just a hypothesis—but that the more police officers stop people, the less likely they are to invest in these kinds of dignity-enhancing strategies. New York City may be different from other cities, but I doubt it. And to the extent that these things are not happening, again and again and again and again—I won't say again 600,000 times—we can predict that there will be costs to procedural justice.

Why does this matter? And this will be the last thing that I say. If you believe, as I do, that procedural justice and policing is fair, you might be pleased to learn that it's also effective. That is, social psychologists have shown that there is a relationship between these kinds of editia [phonetic], of procedural justice in policing strategies, tactics, and micro-encounters, and a person's commitment to and likelihood of obeying the law. So it turns out that you can have your cake and eat it too.

[applause]

MR. TRAVIS: Thank you very much, Tracey. And we'll hear next from Professor Jeff Fagan.

MR. JEFF FAGAN: Thank you. Pleasure to be here. Researchers are nothing without their slides.

MS. MEARES: Speak for yourself.

MR. FAGAN: We'll get to that in a second. Okay. It's a pleasure to be here. John's not the only one that gets to flog his book, although this isn't my book. But we have a chapter in here about New York City, and I'm going to actually speak from this chapter to a great degree. This book is called, Race Ethnicity in Policing: New and Essential Readings. It's edited by Steve Rice and Michael White. It's got chapters about New York and about, I believe, Los Angeles and many other cities, and the difficult questions that we are encountering here. And I get nothing for this. This is just done from, you know, just to get the word out. So pick it up at your local NYU Press book store.

Okay. I've been studying this question for well over a decade. I started in 1998. I worked with then Attorney General Elliott Spitzer on his investigation of the NYPD's stop and frisk practices. In the interim between then and when I got back into it, we published a couple of articles, Andy Gilman and myself and some others, that basically made some points about some of the issues that have been raised tonight. Issues about, for example, the racial geography of stop and frisk, the social demography of stop and frisk, questions about its efficiency, and so on and so forth. I returned to the topic in 2008 after the release of new data by the NYPD showing that the rate of stops had increased by roughly 500% since 1999. And also, for those of who whose memories are short, in the wake of the Sean Bell incident and other incidents in the city.

We published this chapter very recently in that book that shows the pattern of stops and frisks, over the course of that decade, roughly a ten-year period, from 1998 through 2006. And we're now at it again with some improvements in the data that are compared to what was available to us a decade ago. So I think we're able to make some statements that I think are a bit more conclusive, and in terms of social science, are rooted in much firmer grounds.

When we approach this, we approach this in terms of four basic questions. One of which I believe is unanswerable. First, we ask if the tactic is fair and proportional with respect to the race and ethnicity of persons stopped. We use a benchmark of population and crime, not just population and not just crime. And, in fact, we use multiple benchmarks of specific crime rates, whether they're drug crimes, weapons offenses, violent crimes, property crimes, trespass, and the like. And we ask whether the stop rates at each police precinct or neighborhood are what one would predict knowing those benchmarks. And if, in fact, the actual rate is higher than the benchmark, those excess stops suggest to us that there's some other motivation way beyond crime, well beyond crime, that's motivating the allocation of police resources and efforts in those places.

Next we ask very simply is it an efficient way to remove weapons from the street, to detect criminals and call offenders to account? A very simple question. A fancy way of saying hit rates. We ask also if it's conducted legally in comportment with state and federal law that governs the circumstances when police can intervene and conduct when it amounts to a seizure—which I'll get to in a minute—in the everyday routines of citizens. I'm not going to talk about that tonight for time, mostly for time circumstances.

And then we ask whether or not—and this is the unknowable question—whether or not this is bringing down the crime rate. There's a lot of enforcement in this city. There's a lot of marijuana arrests. There's a lot of police on every corner signaling the high risk, the possibility of detection were one to do a crime. There are trespass arrests in public housing. There are hundreds of thousands of stops and frisks every year. There's a lot of enforcement arguing there's a lot of people in state prison. So arguing that, in fact, this tactic, and this tactic alone, over and above at the margins or at the core are bringing down the crime rates. I think is probably based on bad science.

We've obtained data, mainly through litigation. It's a little bit more than what Jeremy showed in the primer. We've analyzed these trends over the course of a decade. We're addressing these questions. And in the course of which we've identified what I believe are a set of basic facts. I'm going to deal as much in two parts—one part with facts and then one part with a little bit of editorial and opinion.

So first... Okay. Between 2003 and 2006, the rate of stops per 1,000 persons increased in New York City by roughly 210%, more than double. But all of the increase took place in a set of police precincts—the ones on the right with the little dots sticking up from the main bar—that were predominantly black or Latino neighborhoods. Brownsville, East New York, Central Harlem, East Harlem, Bedford Stuyvesant, Mott Haven, and the Bronx. The rate for black New Yorkers increased during this time by about 250%, well above the average. And the increase of Latinos was 225%. The increase for whites was below 200%.

The landscape. Here's what the landscape looks like. There's a similar map in Jeremy's primer. Ours, of course, is much prettier, done by a very capable GIS artist at Columbia University, James Quinn. And you can see pretty much the same thing. Now, what's notable about this—and I guess was no surprise to folks perhaps in this room—is that if you look at that map, the bluer the neighborhood, the higher the density of stops and frisks by the police. If you took a map and you put it up there of low birth weights, of children who were born—or poverty rates, or incarceration rates, or high school dropout rates, or domestic violence rates, or any other indicia of social disadvantage, it would look the same. In effect, these are poverty traps. And the same neighborhoods, no matter how much better off they are today than they were a decade ago, are still the worst neighborhoods relative to the other neighborhoods. These are what we call poverty traps. And poverty traps are really tough to undo.

Whether or not policing contributes or helps in those poverty traps is an argument that social scientists can make. But certainly, concentrating stop and frisk activities in those neighborhoods certainly hasn't changed the temporal order, or the ordinal position of which neighborhoods are better than others.

Tracey mentioned the data that we've been looking at. In 2006, the probability of an 18- or a 19-year-old black male being stopped at least once on the street was .93, 93% odds. Even if we discount that rate to some reasonable assumptions about repeaters—a 75/25 rule for you lawyers in the room and you economists—that probability drops down to about .8. For black males, ages 18 to 24, the odds actually are .69. The comparable rate for Latino males is 29%, and for white males is 13%.

When we consider the productivity—and numbers do count, and I agree with Tracey on that... And when we consider the productivity of these practices, which I'll get to in a second in a little bit more detail, the numbers do take on some added significance. Our analyses show that stop and frisk is not necessarily targeted at crime or disorder. It is not allocated in that sense. The racial geography, as our maps show, suggest that which police precincts are the highest stop locales. When we do the models, when we do the actual statistics and we say, How many stops are there controlling for crime?, we find that, in fact, the concentration of black residents in a precinct predicts the stop rate after we control for crime, after we control for disorder, after we control for all those other poverty trap conditions. There is something more than what you would expect that's predicting what the stop rates are.

Beyond these stops, the numbers, the racial skew in the numbers are compounded by similar patterns and statistics for misdemeanor marijuana arrests and for trespass arrests. I doubt that anybody in this room seriously believes that 58% of the marijuana smokers in New York City are black. Right? If there's anybody who believes it, let's discuss this afterwards. Yet the numbers pretty much show that that's the pattern of enforcement. So if you layer that and trespass arrests and other enforcement on top of the patterns that we observe, there's a very strong racial skew that's suggesting there something other than simply crime that's going on here.

So we conclude—and this is something that I have to give one of my students on my research team the credit for, a wonderful term. In the past, we used to talk about redlining. In other words, studying neighborhoods apart, using housing discrimination, and so on, and so forth, as a way to enforce restrictive covenants and prevent integration of minorities with the larger society. Today, in fact, we see something that we call bluelining, which is, in effect, the extraordinarily high stop rates and frisks rates for young African Americans, which tends to have a fairly corrosive effect on their neighborhoods.

Let me talk quickly about efficiencies. Police are most likely to stop people based on furtive movements or other actions that seem to suggest they're about to commit a felony offense, such as a robbery. Yet the stops fail to yield any kind—they certainly stop... They don't yield felony arrests for concealed weapons, nor do they yield arrests for robberies. We find there's no sanction at all in 89% of the stops, perhaps 88%. It depends on the year. The equal hit rate across the city is a fact, but it's very misleading. Because the hit rates, in fact, vary quite a bit by neighborhood. And in neighborhoods that are the bluest up there, in fact, those are the neighborhoods with the lowest hit rates. The hit rates are higher outside of those places. The irony is the less we do, the better we do. Less, in this case, truly appears to be more.

Stops don't yield guns. If you go back and look historically over a period of 15 years to the early days of Commissioner Bratton's regime, they talk—that administration talked very forcefully about guns and the importance of getting guns off the street as an instrumental pathway to reducing the crime rate. We see extraordinarily low rates of seizures of guns. The rates of gun seizures is roughly .15. Somebody's already mentioned that. Or about one gun seized for every 666 stops, or perhaps 1.4 guns for every 1,000 stops. And it's getting worse. If you look at that crime, the blue line is the hit rate. In other words, it dropped down dramatically. It hasn't gone anywhere. The number of guns is ticked up, seized is ticked up a little bit, but mostly in proportion to the stops.

There are approximately 700 gun seizures, roughly, seized each year in New York if you look at the average. But, in fact, if you compare it to some other cities, and here in Chicago, they get more guns off the street. And they do it without a stop, question and fritz program. And they do it, in fact, in a city that is much more difficult to patrol. It's more spacious. People aren't clustered together. You don't see them as easily. And they do it with less than half the number of cops. So there are other ways to get guns off the street, and I think this perhaps suggests that where they are.

So now, that's the end of the fact portion of the show. Let me talk a little bit about the normative portion of the show. These data remind us that citizens who are stopped and who are found to have done nothing wrong suffer four distinct harms. Bill Stuntz, Law Professor at Harvard, has carefully enumerated what these harms are.

The first is a harm to the victim's privacy—the injury suffered if some agent of the state rummages around in a person's backpack at a very low level of suspicion, or perhaps examines the contents of his jacket pockets, or perhaps even his pants pockets and perhaps hers. The second is what Professor Sherry Colb, who's now at Cornell Law School, nicely labels targeting harm—the injuries suffered by one who is singled out by the police and publicly treated like a criminal suspect. As we know, these are not pleasant stops. Everything we know right now, everything we understand from what data there are—limited though it may be—suggest that these are anything but pleasant encounters. The third is the injury that flows from discrimination—the harm that a black suspect feels, for example, when he believes he is treated the way he is treated simply because he is black. And the fourth is the harm that flows from police violence—the physical injury and the associated fear of physical injury that attends the improper police use of force. We have some data that we're working on now that shows an extraordinary racial disparity in the number of incidents when police actually draw their weapon during a stop. And that's a little bit disturbing.

Remember that these risks, these harms will accrue hundreds of thousands of times each year, and in very specifically racially defined neighborhoods of our city. We, most of the folks in this room, don't see it. It is hidden from us because of the patterns of segregation and routine movements that we make. But it is there.

So federal and state case law do represent serious attempts to regulate street level policing, to forbid bad police encounters, and to encourage and sanction and actually approve and reward good ones. But it's hard not to think about the 500,000+ stops each year—especially the ones where nothing turns up—as coercive encounters. They are coercive encounters. Therefore, they tend to become seizures. Think of them, you lawyers in the room, think your basic Terry law. They are seizures.

Why are they seizures? They're not casual encounters. The truth is that ordinary people never feel free to terminate a conversation with a police officer. If the seizure standard and law means what it says, every street encounter between a police officer and a citizen is subject to Terry's reasonable suspicion standard. But that doesn't seem to be the case in New York, and we'll get to that in the next conversation that we have about this.

The conduct of street stops in New York, in fact, looks an awful lot like the early '60s. It looks like the enforcement of vagrancy laws, loitering laws, laws which went by the wayside in the late '60s, and which were discouraged and, in fact, negatively sanctioned by the Supreme Court in a series of landmark cases in the early '60s. Okay. I don't need it. Often those cases were tossed out for reasons of racial disparity. In Jacksonville, the famous loitering case involving Papachristos, for example, and many others.

What we see today is not, well, it was tossed out often for reasons of racial disparity. And that regime in those days didn't look at all like the regime that was envisioned by the architects of Terry or in the New York case, the governance stop and frisk people would be DeBoor [phonetic]. We're challenged in our city to establish mechanisms to rein in street policing, and to make it behave reasonably on the crown, and, in fact, if you go back to the less is more argument, to actually more carefully allocate it as a matter of public policy as well as a matter of strategy.

So any benefits that we see that may accrue to minority populations in terms of lower crime rates are weakened and perhaps even negated by the social costs of pervasive, inefficient police intervention. Crime is complex business. It's multiply determined. We don't know what it is in New York. And I think it's a bit of sophistry to think that this tactic, net of all the others, is what's driving the crime rate down, 'cause it's not.

It's important, I think, to understand that we are probably doing more than we need to do. And I think that's one of the things that we need to talk about. The current system that we see is unsustainable, it's bad public policy, it's probably bad legal policy. The courts will determine that, but we can make an argument in that direction. But more important, it makes little sense. It's inefficient as crime control. It exacts high social costs. It's corrosive to legitimacy.

We've asked, as have others, whether or not there's some other purpose here. We actually said what Bob Herbert said a long time before he did about maybe this is about intelligence. It turns out it might be. Maybe this is about productivity. It turns out it might be. Maybe it's about crime control. But if it is, I don't think the answer is positive there. And, in fact, if someone claims it is, I think it's a bit cynical.

So I think there are better ways to police the streets and keep the crime rate in check. Examples are there for a careful analyst to identify. It's a tailor for the context of New York. In fact, people at this table are doing that work right now. And I think moving in this direction is really a question of our will. Thanks.

[applause]

MR. TRAVIS: Thank you very much, Professor Fagan. And our final speaker is John Timoney. And I know you're all getting ready with your questions. We'll open it up as soon as we've heard from the other J.T.

MR. JOHN TIMONEY: Thank you, J.T. I want to come at this from a chief of police perspective. You've heard from the academicians and the lawyers. And I thought... First I did a little, if you'll excuse me Jeremy, a little academic exercise in math. And as you know, academic exercises are always ridiculous, but sometimes they're helpful.

If you looked at the NYPD—I won't spend too much time in the NYPD, because I want to go to Philadelphia and Miami where I was the chief. But if you look at the NYPD, there are about 36,000 police officers. And for argument's sake, let's say 11,000 are not involved in law enforcement, but the other 25,000, whether they're detectives, narcotics, uniform, are involved in law enforcement on a daily basis. That's what they do for a living. If each one of those 25,000 officers and detectives went out there and made one stop a week—not a lot of work, one stop a week for some person engaged in suspicious activity, you would have 1.1 million stops a year. So the notion, when I read it down in Miami in the New York Times, it's over a half a million, those numbers seem shocking. They seem extraordinarily high. But I think as Heather pointed out, what is the right number? When you start to look at—and I'll get back to the numbers later on, 'cause I think some of the statistics are not all that good as far as historical data. My sense is—and I'll get back to it later—that the increase isn't all it's made out to be over the last five or six years.

When I went to Philadelphia, I took a page from Ray Kelly's book and I went around visiting churches, particularly in the African-American areas. I was brought to Philadelphia because the homicide rate, while it dropped in New York and some other cities, had remained stubbornly high. Over 400 people a year were getting killed, and a whole host of others were getting shot, and robbed, and burgled, and what have you. And in the first two weeks, I went to three different churches. And the complaint—now, this was strictly African-American audience—the complaint was universal that your cops are doing nothing. We call 911. We see the drug boys out on the streets. They're plying their trade. They're carrying their guns. And your cops just drive by. Even when we call, they don't get out. They just drive by. So either they don't care, they're getting paid off, or what have you. But the bottom line is they're not doing their job.

For me, or for any chief of police, those are arguments that you have to respond to. My first meeting in Miami, my first week there, I met with a group of citizens from Overtown, which is an African-American neighborhood, really depressed neighborhood, in Miami. But about half a dozen to a dozen good citizens come in, and one older woman said, You know, Chief Timoney, just 'cause we live in Overtown doesn't mean we don't deserve a good quality of life. And you need to get your cops out of there, and get them out of the cars, and confronting the drug dealers and the people who are shooting up and urinating in the alleyways—a whole host of things. And so there is a tremendous amount of pressure from people in tougher neighborhoods who are by far disproportionately affected by crime on chiefs and the police officers that serve for them.

In Philadelphia, I was there about two or three months when the Jersey State Troopers shot the four youth on the Jersey Turnpike. And that, it was a big case at the time, but only got bigger over the next year, year and a half, where it took on all sorts of implications. And the whole notion of racial profiling became the topic du jour in policing. Any conference I went to, that was the number one issue. The organization that myself and Bill Bratton headed up, PERF, the Police Executive Research Forum in New York, brought in chiefs and community leaders from all over America to deal with this issue, this whole issue of racial profiling.

In Philadelphia, Mayor Rendel, as he was going out the door, I was able to convince him to give me ten additional lieutenants above quota. We got money from Comcast Corporation, produced a training video to deal with this stuff that we imagined or felt was a real issue for the city and that we needed to deal with. It was a whole host of training on those police officers. I set up a system where as soon as a stop was made, the officer would get on the radio and give his location, and then the race of the person stopped. This was just a pilot project to see if there's some way we can deal with this issue. Then we get six to nine months of data. We would look at the data. If there was some offending police officer that looked like there was a disproportionate number of summonses or stops of African Americans, we would set up a system where we would bring them in to counsel them.

Jim Fife, who was a professor at Temple at the time, had done a study on the Jersey State Police. And he thought that the highways and byways were the perfect venue, and that there should be no racial disparity—you're not going into the neighborhoods. So do those first. And so we looked at the highway police officers and their summonses. And we found two police officers in particular who looked like they were giving a disproportionate number of summonses to African Americans. And so they were brought in for counseling and guidance and directions. But it made for a poor picture when the white lieutenant brought in two African-American police officers, were the first two. You could see where we were going with this stuff. It was really, really difficult to deal with.

When we did get all the data, meeting with professors from the different universities. Okay. You have the data. What does it mean? What are you going to do with it? And then 9/11 happened right around that time. And the whole issue of racial profiling was off the table for us and policing. Off the table completely. But as we moved further and further away from 9/11 and things appeared to have calmed down somewhat, it's come to the forefront especially, especially in New York over the last two years. They're really picking up heat, certainly after the Sean Bell shooting, and over the last couple of months.

I know Ray Kerry very well. I don't think for a second that he's ordering his police officers to go out there and engage in overly aggressive tactics to keep crime down. I think, like most chiefs in America, the irony of all of this—you can speak to most chiefs—we have a difficult time getting our cops to work. The allegations of his is that they work too hard. I wish they worked as hard as people allege. The bottom line is they don't. We often have to go out and beat the bushes, and create all sorts of incentive plans, only to be shot down by the local police union. And so this is an extraordinarily difficult topic. I wasn't going to go into all the things that Heather and the two professors went into.

But you're complaining, or people are complaining about over-aggressive policing. I'm not advocating - - policing, because that would be the opposite. But we do, in the last five years, have an example of when a police department goes into a cocoon and basically refuses to go out there and enforce the law.

About five years ago, the city of Cincinnati suffered a series of riots, race riots, based on some police shootings. And the—as you can well imagine—the accusations flew back and forth. And I guess under the leadership of the police union, those officers were told, Don't take any chances. Don't do anything that could get you in trouble. And in no short time, the shootings and the homicides skyrocketed in Cincinnati. I'm not using that example as some kind of a lever to say give the police permission to go out there and do what they want. All I'm saying is that the opposite of this case, aggressive policing—I wouldn't even call it aggressive policing. I would call it going out and doing your job that you're paid for. The opposite of that is to have these cops, Well, I'm not going to do anything. If I'm going to get in trouble, if I'm going to be sued, then I'm going to lay back. And that's in nobody's best interest.

Finally, a comment on the New York statistics on the primer. It's interesting, the numbers are in there, and there's a reference to my old place, Philadelphia. That not only is New York bad, but look at Philadelphia. In 2007, they went from 100,000 stops to 2008, 200,000 stops. Very simple. When I left Philadelphia, the program wasn't kept in place. There was rapid regression to where it was before I got there, and in some cases worse. And a new chief of police, Chuck Ramsey, African American—and by the way, that force is majority African American so you don't even have the racial tinge that you may get in other cities where there is not a proportionate reflection of the police department and the population it serves.

In any event, Chuck Ramsey went in there. Was brought in for one reason and one reason only—to deal with those shootings and those homicides. And Chuck, a pretty aggressive police officer, he came out Washington, D.C., where he succeeded. And sure, the stop and frisks increased 100%. I would suggest to you that the 100,000 was basically nothing the year before. That they were disengaged, and that the 200,000 was more reflective of a police department going out there and doing their thing. Bottom line, though—the homicides were down his first year almost 20%, and they continue on this year.

It's a difficult situation. And I'm going to plug my book one more time. I spent a lot of time writing the book. And it's about three cities—New York, obviously, Philadelphia, and Miami. But the last chapter of the book is on race, because race permeates everything we do in policing. And I didn't think you could deal with the issue of race in policing in each section of the book—in New York, the race—because the race transcends the police departments all across America. And it was just for me to reflect on the last 40 years how far we've come.

When I joined the NYPD back in 1967, it was pretty much basically a lily white force. It's not that way now. Police departments all across America have made great strides. It's interesting that the two institutions—and I'll finish here. The two institutions that may be, or are alleged to be, the most conservative of all our institutions, the police and the military, have probably done a better job of integrating their forces than all the corporations and law schools in America.

Thank you.

[applause]

MR. TRAVIS: Thank you very much to all of the presenters. We promised a lively discussion. We've delivered on that promise so far. John Timoney will get at least one more chance to plug his book before the evening is out. Happy to provide that forum.

So here's your chance to ask some questions. So here's how we propose that we proceed from here. I'm looking around. There is... I'm sorry.

MS. MACDONALD: No, we don't have an opportunity to - - .

MR. TRAVIS: Let's do this. I want to get some questions going here. If you have something where you want to jump in, Heather, please... But I'd like to get people engaged. So just think about it with the right opportunity. And if it doesn't come by 8:00, I'll give it to you.

I see one microphone. It's right here. I'm going to make this personal. This stands under the portrait of the judge I clerked for, Ruth Bader Ginsburg, so she'll keep us on time. But if you have a question to ask, we'd like you to come to this microphone to ask your question so that it can be recorded. So no one's running to the mic. You get to ask a question, Heather. So please form a line here. Identify yourself, quick question, and we'll hope for fairly short answers, because we want lots of people to... Heather, what was your question?

MS. MACDONALD: No, I'll wait.

MR. TRAVIS: Okay, great. Who's the first guy here? Mr. McShane.

MR. JIM MCSHANE: Good evening. My name is Jim McShane, I'm a former police chief from NYPD. And I wanted to address a point to Professor Fagan about some of the data about the reduction in gun arrests, I guess, as a result of stop and frisk.

I was a precinct commander in 1994, the first year when Commissioner Bratton came to New York, and we started to engage in more proactive policing. And one of the things that happened was the number of stop and frisks began to go up, the number of arrests for guns started to go up in New York City and in my precinct as well, which is a fairly busy place. And then after awhile—and also the number of shootings started to go down. So after a few months, the number of arrests, which had been going up, peaked, and the number of arrests started to go down. But the number of shootings continued to go down.

And one of the reasons, at least in my precinct, that that happened was people on the street knew that there was a real increased risk that they were going to be stopped. If they were on a corner, if they were doing something, whether it was drinking a beer, whatever the quality of life issue was, there was a great risk that they were going to be stopped. So as a result of that, a lot of guns were not being carried on the street anymore.

So I would like to just offer another hypothesis that you might look at. Perhaps the reason that the number of arrests are down when stop and frisk are conducted is because that there are fewer guns being carried. And, you know, the strategy, I don't think, should necessarily be judged only by the number of arrests that are made as a result of a frisk. But let's look at the number of guns that are actually out there on the street. Let's look at the decreasing number of guns. And at the end of the day, let's look at the decreasing number of homicides. I just think it's another way of looking at it, and something that you should consider.

MR. TRAVIS: Thanks, Jim. Yeah, Jeff.

MR. JEFF FAGAN: I think it's a... You know, as a social scientist, I think it's a perfectly hypothesis. But the question I would ask is: How many stops do you need to make that happen? And is that the only mechanism by which people decide not to carry guns? It could just as easily be a social norm. And during the period of time you're talking about, we actually were doing street field studies, interviewing kids who were shooters. In the South Bronx and in East New York, we interviewed about 400 kids, asked them characterize 750 events. I published this stuff, my co-author Deanna Wilkinson's published this stuff. It's in her book.

And the argument that came out there were two. I hate to say this, Jim, because as a Columbia guy... They told us that the police actually were not really a significant part of their decision making. And this was during the period of time when you guys were really wrapping up. And that, in fact, much of the decision to stop carrying guns and to turn the heat down was simply something that developed indigenously within communities of African-American kids. So, you know, I have no doubt that there was some police pressure that encouraged people to stop producing guns.

But, again, like everything else, it's a very difficult, complex, multiply-determined process. My guess also is that these kids were deterred by simply the sheer presence of the number of cops on the street. So there's a lot of things going on in this. But I keep going back to the question about: How many stops do you really need to produce this effect?

MR. TRAVIS: So let's get the next question lined up. Just identify yourself. And if there's somebody on the panel you'd like to address your question to, that would be great.

MR. JOHN MARTIN: My name's John Martin, I'm a teacher at a high school in Bushwick in Brooklyn. And this past Saturday we had—a student at our school was shot and killed in a gang-related incident. So I've been trying to contact, you know, as a community, we've been trying to contact as many people as we can to get input on what we can do as a community to, you know, stop the gang-related violence.

So I guess, you know, in terms of stop and frisk, I mean, I guess my question is you know, maybe how effective is stop and frisk, you know, in terms of maybe looking at people who have, you know, seem to be involved in gang-related activities, you know, on the street where they can be identified with, you know, colors or things that like? Is it effective? And, yeah, that's my question.

MR. TRAVIS: First of all, very sorry to hear about that loss of life in your community. Anybody on the panel want to answer John?

MS. MACDONALD: Well, I would—I'm interested by the comparison to Chicago that somehow the fact... You know, we could go—Chicago, Professor Fagan is right, does not have as aggressive a policy of stop and frisks. Why we would emulate Chicago I don't know, since, again, the homicide rate in New York is 40% that of Chicago, and there's an epidemic of youth shootings there. As I say, the shootings are four times higher per capita of juveniles under the age of 17.

And I would very much agree with Mr. Shay that the possibility of getting your gun apprehended during a stop did give people permission not to carry. And that the social norm in changing was very much driven by police behavior. Because if it was simply a norm that let's stop the violence, that would have happened in Chicago as well. They are shooting each other. There's very little surcease there. But the police are not proactive. And to use gun seizure rates as the only measure of stop and frisk, again, misunderstands that this is not an arrest tactic, it's a trying to deter. And I would say the police departments that have embraced proactive policing have been the most successful in this country in being crime down.

MR. TRAVIS: Anyone else want to jump on this question? Okay. Well, next.

MR. ANDREW CASE: Hi. Good evening. My name is Andrew Case. Relevantly, I was at the CCRB for eight years until a couple of years ago. Most recently, a spokesman during which time I had some very pleasant conversations with Heather about our RNC outreach, which I'm not going to talk about today.

But my question is for Chief Timoney. One of the things we understood, because we were looking very closely at this productivity question and the stops as a proxy for officer productivity, and we understood, at least as recently as a couple years ago, that when commanding officers went into CompStat, one of the data points that they were held accountable to or looked at was the number of 250s filled out. And my understanding was that was not always true, and was not true in '94.

MR. TRAVIS: [interposing] These being the form that officers used to record...

MR. CASE: Sorry. The Stop, Question and Frisk forms.

MR. TRAVIS: Thank you.

MR. CASE: And my question is first of all, whether we were even right about that. It was secondhand knowledge. And secondly, whether that was always true, or whether you know of a time when that became one of the data points in addition to crime, and arrests, and that sort of thing.

MR. TIMONEY: I don't believe back in 1994, 1995, and 1996, myself and Bill Bratton left then. I don't believe it was one of the data points. I think it is now. But I think this goes back to my—I didn't want to waste too much time on the assertion that the statistics, I think, are misleading. I don't think that the number of stop and frisks have tripled. I think the reporting is way better as a result of the lawsuit back in 2003. I know Commissioner Kelly has put a great emphasis, they've done training, they've done a whole host of things. And there's an old adage in policing, Expect what you inspect. And this is a form of inspection. There may be an increase, but I'm guaranteeing it's not triple.

Now, by the same token, if it became a data point at CompStat, and the precinct commanders are going back and saying, Listen, when you stop somebody in the street and you frisk them, make sure you do the report. It doesn't mean that there are more people out there doing stop and frisks. It just means that they are doing reports.

MR. TRAVIS: Yes.

MR. BOB NEUGAN: I'm Bob Neugan [phonetic]. I'm a criminal lawyer and an adjunct professor at John Jay. And I have a question for Professor Meares. I understood you to say that, in general, people obey the law because they accept the law and the legal process as legitimate, and not because they're afraid of being caught by the police. And I can readily accept that that's true of most people. And I also could say that if it were true of everyone, we could get by with a much smaller police department than we have.

But I want to ask you whether you would also agree that there's some subset of people, perhaps thousands, who, for whatever psychological or sociological reasons, don't accept the law as legitimate and would be prone to commit serious crimes if there were no law enforcement. And if you believe that, what police strategy would you recommend to deal with that problem?

MS. MEARES: Okay. So when I asked the general rhetorical question in the way that law professors do, this time I get to follow up when I say do I believe that people comply because they think it's the right thing to do, or because government has the right to dictate to them proper behavior. You are right. I did not mean to suggest that penalties make no difference. It's, in fact, true that all three reasons matter. It's important that people believe that laws are legitimate and law enforcers are too. It's also true that, you know, that punishments matter.

What social psychologists have shown, however, is that the normative reasons that I have pointed to are simply much more important reasons for compliance than other ones. And so if you're designing a strategy, a tactic, a strategy, a criminal justice system, it makes sense to place emphasis on the one that really matters. That was my general point.

In response to your question about do I think that some people are motivated differentially. Of course. I mean, you know, there's going to be a distribution in the population as those kinds of reasons. And, in fact, I can refer you to a paper that I wrote that actually has a four-page exegesis on these different reasons why people might comply. It's called, "Attention Felons," and it was published in the Journal of Empirical Legal Studies.

Do I think because some people might be more susceptible to punishment than others, does that mean that we should do something totally different for them? The answer to that is no. I have another paper called, "Why Criminals Obey the Law." And in that paper, my co-authors, one of whom is sitting here on the panel, Jeff Fagan, and Andrew Papachristos, we've surveyed, actually, people on parole and people on probation for some pretty serious crimes. Because a lot of the social psychology has been done on college students. The best of it's been done on ordinary citizens. Some of you may be even sitting here in this room by a university professor Tom Tyler. He's surveyed New Yorkers pretty extensively.

And it turns out that even offenders, serious offenders, people who have spent time in prison, have the same kind of priors and nominate the same reasons for compliance, and at the same rates as people who have never set foot in prison. The difference between those people and the people sitting in this room is they have much, much, much lower opinions of the police than people in this room do. So using those two pieces of information, that they're motivated to comply for the same reasons that other people do, and the fact that they have much more dismal opinions of the police than other people do, seems like there's some areas for traction and improvement there—right?—by harnessing these ideas of legitimacy and policing to help raise compliance rates.

MS. MACDONALD: But if I could add, I totally agree with Tracey that legitimacy is extremely important. But as Chief Timoney mentioned, for a long time the racial rep against the police was that they ignored crime in minority neighborhoods. And one way for police to gain legitimacy is to be seen as effective in getting the drug dealers off the street. When people are living under the thrall of fear that people that don't live in an open-air drug market can little understand, and the police are unable to do anything about that, that undercuts the legitimacy of the police as well. And the notion that somehow criminals are aware of the regression analysis of Professor Fagan that reaches the conclusion that stops are driven not by crime, but by something else—and I would question some of that methodology. But I doubt whether that's an important factor in whether they view the police as legitimate.

I would say, agreeing with Tracey again, we both—and I think most of us on this panel agree—the behavior of the cop in making a stop is crucially important. Cops get street hardened and cynical. That is no excuse for failing to treat people with courtesy and respect. So I would say the main drivers of legitimacy are whether, in fact, you're making a difference and responding to the community's heartfelt demands for protection, and whether you're treating the people on your beat with courtesy and respect even if they are criminals.

MS. MEARES: There is an answer to that question.

MR. TRAVIS: Oh, oh, oh. Fagan's name having been mentioned, Fagan gets to say something. Then we'll take another question.

MR. FAGAN: No, I wasn't going to mention that. The conversation about stop and frisk tonight seems to suggest that there's a binary. We either de-police and withdraw, or we send large numbers of police officers proactively into communities and at relatively low levels of suspicion, stop and question and perhaps frisk people on the streets.

I think that this is a false binary that if you look around the country at cities, there are multiple experiments going on—and they're not even experiments; they've been institutionalized in some places—that show fairly effective ways to interdict gun violence and violence. I've written a little bit about it. Tracey's written a little bit about it. Jeremy Travis and Tracey are helping to develop a network that's going to disseminate some of this technology. It's not a choice between withdrawal and send in large numbers of troops. There are lots of ways to craft intelligent, carefully-designed interventions by police that actually incorporate the notions of procedural justice and fairness, and treating people with respect.

MR. TRAVIS: We've got a wonderfully long line of people who are being patient. So come on up and ask your question.

MR. FAGAN: I'll send you an article.

MR. TRAVIS: And I just have to comment. Since I live in an academic world these days, I sort of struggle the worlds where languages sometimes humor us. So I just want to point out when Tracey was talking—if you'll allow me to do this—about interviewing prisoners about their priors. You didn't mean their prior convictions. Right?

MS. MEARES: Oh, right.

MR. TRAVIS: Right. Their prior beliefs, their prior assumptions.

MS. MEARES: Yes. I did not mean prior convictions, yes.

MR. TRAVIS: Right? So, yes, hello. Hi.

MR. TERRENCE PITTS: Hi. Ms. MacDonald, you mentioned really high crime rate.

MR. TRAVIS: Please identify yourself.

MR. PITTS: Terrence Pitts.

MR. TRAVIS: Yeah.

MR. PITTS: You mentioned really high crime rates in New York City among African-American community, in particular, I believe, for homicides and felonies in comparison to the white community, white population in New York City. How do you explain the high crime rate among African Americans?

MS. MACDONALD: I think if I could change one thing, I would give black children the same chance of growing up with married parents as white children in this city have. That, to me, is the biggest handicap facing black kids is their chance of having their father in their household is very slight.

MR. PITTS: And is that based upon a particular study?

MS. MACDONALD: Well, the black illegitimacy rate is over 70%.

MR. PITTS: But is the crime rate that you're citing, are those crime rates related to studies on illegitimacy in African-American community?

MS. MACDONALD: Well, there's many—

MR. PITTS: [interposing] Is there a correlation based upon a study?

MS. MACDONALD: As Professor Fagan said, neighborhoods have a set of characteristics that tend to be correlated in poor neighborhoods, but you're asking me. Yes, it's coming from a single-parent family is correlated with high rates of crime. But other things are correlated as well.

MR. PITTS: So the high rates of—

MS. MACDONALD: [interposing] My belief... However, you're asking me what would I do.

MR. PITTS: No, I didn't ask what you would do. I was asking you how you explain the difference.

MS. MACDONALD: That's how I explain it.

MR. PITTS: So illegitimacy in the African-American community.

MS. MACDONALD: I think a culture of fatherlessness hurts children and does not give them the support that they need. I think, again, that that is an advantage that white and Asian kids in this city have. And if that's the biggest disparity—

MR. PITTS: [interposing] And what are the rates of illegitimacy among the African-American community?

MR. TRAVIS: This will be the last, 'cause...

MR. PITTS: Okay. I'm sorry.

MR. TRAVIS: - - .

MR. PITTS: What are the rates?

MS. MACDONALD: Nationally, it's—

MR. PITTS: [interposing] No, in New York City.

MS. MACDONALD: In New York City, it's probably higher.

MR. PITTS: No, what are the specific rates in New York City?

MS. MACDONALD: It's minimally 71%. In the South Bronx, the out-of-wedlock birth rate is in the 80s.

MR. PITTS: [interposing] I'm sorry. Can you speak up?

MS. MACDONALD: In the South Bronx, the out-of-wedlock birth rate is in the 80%.

MR. PITTS: And what about other areas?

MR. TRAVIS: Terrence, I think we've... If you want to talk to Ms. MacDonald afterwards about some of her data, you can do that. The next person up with a question.

MR. MICHAEL VILLACREST: Good evening. I'm Michael Villacrest [phonetic]. I'm a junior at John Jay College of Criminal Justice. My question is directed to Chief Timoney. Chief Timoney, how do you actually balance the whole... You have so many factors regarding to professionally policing any metropolis. But how do you actually balance the perception versus the reality? Whereas, if you actually are treating people with respect, that the community actually is receiving that it's respect as opposed to... 'Cause no one likes to be stopped by the police and to actually get frisked.

MR. TIMONEY: No.

MR. VILLACREST: But if you stop them because it's a random stop, and it's nothing personal, but it's just professional, 'cause just doing a random stop as we have here at the train stations where your backpack is searched randomly. How do you actually randomly... How do you actually make sure that your policing professionally is received by the public?

MR. TIMONEY: Well, I think—it's been mentioned before—you've got to do it, obviously, in a courteous fashion, explain why the stop was made, whether it was as a result of a 911 call, which a lot of these do, or because it's a high-crime area, a whole host of things.

By the way, Commissioner Kelly has instituted a pilot program in about five precincts where when you do, in fact, get stopped, not only do you get the reason, but they give you a card. And if you've got a complaint, you can call it in. But it is all about respect. The whole, you know, in Philly and Miami, I heard the term "jump-out boys," about the cops that would jump out. And so you've got to make sure—and I made sure—that the cops aren't engaged in that type of stuff. That if you're going to stop them, you stop them legally.

And we produced a video about the only time, the only time I got along with the union, I was able to convince the union president to do the video with me. And he said it better than I could say it. Nobody should ever be stopped based on the color of their skin as a sole factor. And we gave that out to the seven cops. We gave them plenty of training, a whole host of things. So you've got to do with respect, and with courtesy, and an explanation sometimes.

But sometimes it just, you know, stuff happens. I've been in those situations myself. Sometimes they're unavoidable. Sometimes the person cops an attitude. Words lead to other words. And you'll end up in unfortunate situations.

MR. VILLACREST: Thank you.

MR. TRAVIS: Tracey, you want to add to that?

MS. MEARES: I just wanted to add a quick... Everyone else is plugging books. I'd like to plug an article. I've written an article with Bernard Harcourt called "Randomization and the Fourth Amendment." And one advantage to this idea of randomization that you just brought up—it's largely theoretical, but you can imagine it happening in real life—is that it can erase or at least diminish the kind of targeting harm that Jeff mentioned earlier. Because there's no longer an association necessarily with the public police stop and wrongdoing. So it's something to keep in mind since you're a student. I'll send you the paper.

MR. FAGAN: Just to add to Tracey's point. The data on checkpoints actually suggests that they're much more efficient, for example, than what we see in New York, deterrence notwithstanding. Deterrence is a tough thing to know whether it's actually happening or not. But checkpoint data actually suggests in a way that eliminates targeting harm, that one can detect and seize contraband, find people who are out on warrants, etc., etc., etc. So it's one of those strategies, one of those other strategies that can actually make the same kind of gains without exacting the same kinds of costs.

MR. TRAVIS: But that's a polar opposite from individualized, suspicion-based...

MS. MEARES: That's right.

MR. FAGAN: It's by the numbers. Yeah, right.

MR. TRAVIS: So come on up. Yeah, hi.

MR. ALAN BARRETTE: Good evening, everybody. My name is Alan Barrette [phonetic]. I'm a grad student at John Jay. I'm also an intern for the Honorable Councilman LeRoy Comry [phonetic] of the 27th District. I have a question, and it's followed by a small statement.

My question is, you know, what are we going to do to increase communication between the NYPD and us members in here? And let me be frank. It's an honor to be in this room full of NYPD brass, professor, presidents. But two weeks ago, we got a very disturbing email in the office about one of our constituents. It said basically that, you know, my son was assaulted by the police, stopped and frisked, you know, etc., etc. The kind of stories that we naturally hear. At the end of the email, I was surprised to see that she put, Well, you know, it would be our word against theirs. But she attached a video that the bodega had. And I tried to get in contact with the New York City boss so we could put the video and show you what stop and frisk really looks like.

Basically, the young gentleman was arrested for assaulting a police officer, resisting arrest. Throughout the whole video, which the video lasted approximately 18 minutes, the young gentleman... First of all, they pulled him out of the store. Right? Handcuffed him from behind. Took everything out of his pockets. Searched—when I say thoroughly searched, I'm talking about thoroughly searched. Not only that, they slammed him into the metal gate. Put him on the floor. Stepped on his face. And at the end of the email, I kind of understand the sentiments. What do I do? What do we tell our constituents here?

I'm a big fan of the NYPD. I've interned for the NYPD. I'm a big fan of cops. But what are we going to do to increase communication? Because, frankly, I need to see one side of the room full of COs, inspectors, everybody who are currently on the job. And I don't see that. It's highly disturbing and highly reprehensible when you actually see the video what stop and frisk looks like. So what are we going to do?

[applause]

MR. TIMONEY: You're pointing out a specific incident. I don't think that is indicative of all stop and frisks. I just don't think it is. Second, but if you've got good video and you've got a good lawyer, you're on your way. I mean, I just, I'm not trying to be facetious about it, but if it's as egregious as you said... And by the way, these videos—did you see the precursor to the video? Was something going on before that?

MR. BARRETTE: The video starts off and the gentleman was in the store. Right? Two minutes later, the van just pulls up, the officers go on. And it's a marked van, but it's officers in plain clothes. They come inside the store. Pull the gentleman out, and just begin to search him for absolutely no reason at all.

MR. TIMONEY: Well, there's plenty of recourses. At a minimum, you've got CCRB, you've got Internal Affairs.

MR. TRAVIS: So, Alan, I'm just curious. What did you say to the constituent of your councilmember?

MR. BARRETTE: Well, I was trying to invite the family here, but, you know, obviously, they're a little bit intimidated to come to—

MR. TRAVIS: [interposing] I understand. But what advice did you provide in terms of their recourse?

MR. BARRETTE: We haven't provided any advice yet, because we're still trying to figure out how we're going to attack this situation, you know. I mean, basically, we've provided, you know, some kind of resources in terms of legal counsel, etc., etc., and putting them in, you know... I mean, the video speaks for itself, you know. So, I mean, we're still trying to figure out—and I'll gladly talk to anybody in here about getting more resources allocated their way.

MR. TRAVIS: Well, I think the CCRB is in the room. If you wanted to meet them afterwards... I saw Commissioner Thompson. Yeah, there she is. The commissioner in charge of the CCRB is over there.

Peter Mancuso, welcome. Alan, nice to see you.

MR. PETER MANCUSO: Good evening. My name is Peter Mancuso. I was a member of the New York City Police Department 22 years ago. I live in New Hope, Pennsylvania. And I wonder why I came here this evening. For the past several years I have been watching, and reading, and discussing with colleagues and former colleagues really this whole issue of stop, question, and frisk. And I'm formerly the Assistant Director of Training for the NYPD, and also the Chairman of Social Science Department of the Police Academy.

But it was in my role as a supervising sergeant in New York's Lower East Side here in the East Village, in 1976, I supervised a team that effected an arrest that was largely based on a stop, question, and frisk. And that arrest led to the conviction of two predicate felons. And it was later brought to the appellate division by New York's Civil Liberties Union to challenge the conviction. And the conviction was upheld. But the reason the conviction was upheld had everything to do with all of the work we had done locally in that precinct over a short period of time with minimum resources. I had to bribe the Crime Analysis guy with coffee and donuts to work up some numbers for us and some profiles for us.

And when we went out there to those target areas at a very specific time looking for very specific individuals, race became fractional. We were not looking for race; we were looking for individuals. The fact that they may have been black, Hispanic, white was only incidental. Unfortunately, what we don't have here this evening is a copy of the preliminary report. You made some reference that crime victims, Ms. MacDonald, report to the police the 66% of perpetrators are black. But when you really look at that document, you will see how much it is lacking as a true crime analysis document.

Now, the reason I came tonight is I believe that my alum, the NYPD, is in a perfect position to pull off one of the greatest coups in democratic policing. And that is colorblind policing. It now has in its grasp the technology, the computer analysis, the team, the leadership, the experience, and a low crime rate that gives it a little opportunity to reach out and look at this kind of micro-suspect profiling, looking for individuals, not for groups of individuals. And that's why I came here from New Hope tonight.

MR. TRAVIS: Thanks, that New Hope. We'll take that as a comment rather than a question, Pete. I want to make sure we get through the line. Thanks.

MS. MACDONALD: Can I just...

MR. TRAVIS: Yeah.

MS. MACDONALD: But CompStat... Mr. Mancuso, thank you so much for that statement. But as you know, CompStat is doing exactly what you say it ought to be doing—race does not come up. You may have been in some CompStat meetings before you left the department, but it works absolutely when it has an individual description, it has an individual description. Otherwise, it goes on the neighborhood, where the crime is. The police do not determine where to deploy. Crime determines where they're deploying. And if they don't have a description, they're not looking on the basis of race. They're looking for suspicious behavior.

MR. MANCUSO: Here's a tipoff, Ms. MacDonald. Look at the chart on page 8. You see those furtive movements? Is that furtive movements like I'm looking over my shoulder because I don't want to get mugged in my neighborhood? Furtive movements right there tells me that the cops are out there winging it a bit, that they really don't have the data, they're really not looking for individuals. And to me, that's a huge tipoff.

[applause]

MR. TRAVIS: Okay. Next question. We're trying to move through here. Yeah. Good evening.

MS. SHIRLEY LAYROW: Good evening. My name is Shirley Layrow [phonetic], and I'm a - - student of criminal justice.

MR. TRAVIS: Hold the mic down so we can here you.

MS. LAYROM: Hello. My name is Shirley Layrow. I'm a - - student of criminal justice. And my question is for Heather MacDonald. You gave numbers which were not found on the primer, and you gave them to give a possible explanation of why these stops are concentrated where they are. You said 80% of shootings involve blacks, and 95% of shootings involve both blacks and Hispanics. But I'm still not clear on the justification of this concentration, or just the effectiveness of these stops when only .15% of guns are found, and there's only one-tenth of a percent difference between blacks and whites in this discovery. So I just wanted your comments on its effectiveness and fairness when you look at the disparity there.

MS. MACDONALD: Well, the stops, again, can't be judged solely on the basis of whether they recover a weapon. They are deterring weapon carrying. Shootings have gone way, way down in this city. And police are deploying, as I say, yesterday a 2-year-old and a 10-year-old girl was shot. Police will be deploying in that neighborhood, looking for the shooters. And they will probably make stops of people that are not carrying guns, and that were not the shooters. That is a crime tax that is paid in neighborhoods where crime is highest, and it is unfair to the people living in those neighborhoods who have been law-abiding all their life. But the fact of the matter remains, if you're in a neighborhood that is high crime and you're a law-abiding male, you do stand a higher chance over the course of your life, of getting stopped because the police are deployed there more intensively to try and bring safety to everybody in that precinct. And it is the incidents of crime that determines police deployment.

So, you know, last year the number of guns that were collected, 762—4 machine guns, 36 assault weapons, 639 handguns. That's not an insignificant yield.

MR. TRAVIS: Just to be clear, Heather, those are as a result of stops. Right?

MS. MACDONALD: Right.

MR. TRAVIS: That's not overall.

MS. MACDONALD: Right. As a result of stops. I'm not sure... Professor Fagan suggests random checkpoints throughout the city. I'm not sure.

MS. MEARES: He didn't; I did. I want to be clear about that.

MS. MACDONALD: Okay, well, I thought both of you were sort of working together. Okay. Random checkpoints?

MS. MEARES: I wrote the paper, and he - - .

MS. MACDONALD: Okay. I'm just not sure that random checkpoints put throughout the city are going to have the same effect at getting guns off the street compared to deploying officers in neighborhoods where there has been a spate of shootings.

MR. TRAVIS: Jeff gets to say a few things, and then we'll take our next question.

MR. FAGAN: I think the idea—I think doing fairly aggressive investigations in the days that follow a tragic shooting, like the ones that Heather describes, is appropriate and necessary, and it's good policing. It would be actually quite unfortunate if it didn't happen. But I'm interested in the stops that happen in the two weeks after that or the month after that, or perhaps that shooting is cleared by an arrest. What happens in the months after that? Will there be some kind of recalibration of the stop rate based on the clearance of a tragic homicide? But the fact is—and you can sort of look at this. If you look month by month or quarter by quarter, there's a spike, or week by week, if there's a spike in crime, there's a bit of a spike in stops, but there's not necessarily a decline when the crime... They don't follow; they don't track. It's not necessarily about crime; it is about place.

MR. TRAVIS: Come on up. Another John Jay student. It's nice to see you.

MR. JEREMIAH JOHNSON: Hello. My name is Jeremiah Johnson. I'm a doctoral student at John Jay...

MR. TRAVIS: Hold the mic up.

MR. JOHNSON: ...in the Criminal Justice program. I'm also employed as a police sergeant in a municipality in Connecticut. My question is more oriented towards Professor Fagan, and it speaks to the efficiency question. And I think it's important when you're conducting this type of analysis, when you're looking at stop and frisk as a self-initiated activity conducted by police officers, to consider the element of discretion that's used by the police officers. Not only in making the stop, but also the enforcement aspect. And I'm wondering about the data collected. I saw the form, the stop and frisk form used by the police department. But I'm wondering if the form's being filled out all the time by officers; and I think also more importantly, whether contraband and possibly weapons have been found, but the officer utilizing their discretion has not made an arrest; and whether that's skewing the data somehow.

MR. FAGAN: Well, first of all, your instincts are right on both counts—on at least two of the counts. One is there is wild variation in the rates of completion of forms, and in the comprehensiveness of the completion of forms. So there are forms with minimal information that's filled out. There are forms where, for example, the suspected crime, the reason for the stop was written down as misdemeanor, or MSID. And my crew out there has spent a ridiculous number of hours, courtesy of Columbia Law School, in trying to do this hand coding and written computer code—50,000 lines of code—and try to make sense out of the scribbling that's written down there.

Now, admittedly, you know, if you're in the middle of making a stop, being really careful with your handwriting and writing out the accurate section of the penal code is not something that's on the police officer's mind, and nor it shouldn't be. But we find the number of unintelligible writings to be extremely high. So we don't know often the crime. The suspect, the reasons for the stop are often not indicated. The check—there's a little box that says Other, which is checked at a very high rate for what the suspected reason is.

MR. TRAVIS: Let me jump in. We also sense that, in many cases, even that effort isn't made. The form's not filled out [crosstalk].

MR. FAGAN: There is a lot of blanks. Now, on the discretion question, that's an excellent insight, and I hope that whoever your professors are in the room take note of this. So we break down stops by high discretion, low discretion stops. If it's a radio run, that's low discretion; cop has to respond. If it's he suspects somebody's carrying a weapon, that's low discretion; they have to act. If, on the other hand, they suspect somebody of, I think, you know, Mr. Mancuso said furtive movements with a kind of low-level crime that's suspected, maybe a trespass or misdemeanor or a marijuana offense, that's high discretion. And we see a lot of play in the data in the high discretion - - . And your instinct is absolutely right. That's where I think there could be perhaps a different kind of policing strategy that's put into play there.

MR. TRAVIS: John and then three more questioners. About five more minutes.

MR. TIMONEY: Just two things. One, cops are notoriously sloppy. I mean, - - their reports. They just are, and they've always been. That's one. Number two, my sense is on the gun seizures and also just the rest in general, that there's an undercounting. I can almost guarantee you there are plenty of arrests that came as a result of a stop and frisk, but the cop makes the arrest report—What am I going to do about the 250? And so there's a huge, I think, undercount in all of this.

MR. TRAVIS: Okay, thanks. So let's try to keep our questions and I'll ask the panel to keep their answers short. And let's see if we can get through four people who are standing there. And then we'll have a few words before we break for extended conversation. Yes, please.

MS. JOY PITTMAN: Hi. My name is Joy Pittman, and I'm a junior at City College. I just had a question. Well, from listening to everything, it seems to be very easy to draw a correlation between a large number of black and Hispanic offenders and the fact that these areas are targeted. But I'm wondering, is anybody looking into urban planning issues or social policies? Because I tend to believe that you would have more loitering, more crime areas when you have an area full of housing projects, bodegas, corner stores everywhere, all these - - as opposed to areas where you have residential homes and things like that.

MR. TRAVIS: Tracey, were you inclined to answer that question or...?

MR. TIMONEY: Just... You added a good point. There's a program started, I guess about two or three years ago, by the NYPD as a result of the clamoring in the public housing that accounts for some of the increase. I think most of the increase is better reporting. But some of it clearly is this new program, about two years ago, Clean Hallways. Where they're going in, they're confronting people who are loitering, trespassing, that don't belong in the buildings. They chase them and send them on their way. They're making out a 250.

MR. TRAVIS: Okay. We're going to try go through the last ones quickly. Yes, please, come up.

MS. VERINA POWELL: Hello, my name is Verina [phonetic] Powell. I'm a former prosecutor, and now I'm a defense attorney.

MR. TRAVIS: Come a little closer to the mic.

MS. POWELL: I guess I have a couple of comments. I guess Heather is trying to be controversial. And if that was your hope in stating that there should be more stop and frisk in communities of color, then you have definitely accomplished that. In addition, I think your statement to say the crime tax is something that has to be paid by people of color in those communities is unacceptable. Part of the problem is I think the officers in the community need to get back on the beat, interact with individuals, go to co-op board meetings, go to the schools and the like. Because to go through some of your facts, I was born and raised in St. Louis, which is a city which has a high homicide rate. I then attended law school in Boston, and I now live here in New York City. And I think growing up, even in St. Louis, police officers are only going to act a certain way in certain areas even within minority areas. 'Cause even if you go to Harlem, they're not going to act the same way in Sugar Hill as they're going to act in certain parts of East Harlem or certain parts of 125th Street. So I think a lot of it has to do with the fact that the police have to get back out there and realize that they're actually people.

Part of the problem is—and I can give you some anecdotal incidents also. I have a friend who's an investment banker who lives in Brooklyn, in downtown Brooklyn, Ford Green. Even when he runs out and wears jeans, he never wears sneakers. He always wears dress shoes because police will pay attention to little things such as shoes, and they will not stop him. Where if he's wearing the same outfit and wearing sneakers, he knows he will be stopped. And he lives in a neighborhood which is predominantly black.

So as I said, I think the crime tax is unacceptable. And I think that the police officers actually need to get out there and get to know their community.

MR. TRAVIS: Great. Okay, thank you. Here's what we're about to do because I do want people who have been patient waiting to have an opportunity to make their comment or ask their question. I'm going to ask those three folks—thank you—to come up, make your comment, ask your question. And each of the panelists gets a 30-second closing observation. They can respond to anything—Heather just had a comment made about her presentation—that they'd like to respond to. And then we'll have some closing comments. Yeah, go ahead.

MR. LUIS ROMAN: My name's Luis Roman. I'm an attorney with the Criminal Defense Practice of the Legal Aid Society. And I had a wonderful introduction to my question, which would have made you all laugh your sides off, but that's okay.

The issue, to me, is about training. Quite briefly, I was subjected, not to a stop, but to an instance where I simply hang out in the park, knew that I was under observation by a uniform police officer who was quite clearly checking me out and radioing for a description. Clearly, there was a person being sought, and he was radioing because I appeared to fit the description of that person. He did not approach me. He did not say anything to me. I knew he was there; and he knew that I knew he was there. He simply contacted his precinct to get the proper description of the person. And when he determined that I did not, in fact, fit the description of the person, simply walked away. There was no interaction between us. This, to me, was an example of the ideal form of policing there. An officer observes and then takes the moment that he has to get the proper information before determining what step he has to take first, whether it's no interaction or further interaction. What do we do in terms of training to try and reach that ideal?

MR. TRAVIS: Thanks, Luis. So come on up and make your statement or ask your question. We'll bundle them all together.

MR. WALTER TRUSDALE: Hi. My name is Walter Truesdale [phonetic]. Tonight we've talked about paper records and videotape records. What about an experiment going halfway? What if the police officer carried with him a digital tape recorder, which he turned on every time he left his car? He could state what he was doing, why he was doing it, and you would have a record of what happened. It's cheap. You could keep seven days' worth of it. And if no complaints were filed or there was no major crime, you would use them over again. But if you needed it, you'd have it. And I think the union might go along. Thank you.

MR. TRAVIS: Might go along. Thanks, Walter. And our final question or comment. Yeah.

MS. JEAN BLISCHE: Hi. My name is Jean Blische [phonetic]. I'm an attorney and I have lived Uptown West 105th Street with many black friends above 110th Street, around 125th Street, and in the projects on 131st Street on the West Side. And I watch young kids over the years being stopped dozens and dozens of times to the point where they don't know how many times they're stopped. They are given summonses here and there. They are never, ever carrying anything.

My first concern is bringing up a culture of young people of color who think that police, law enforcement, prison is normal. I'm white. I grew up in the suburbs. I didn't think that, but I learned that that's America and that has become normal.

And my other concern is the summonses that are written that are incomplete and insufficient. Because I've gone to defend people against these summonses, and the police are obviously fulfilling the quota—obviously the furtive movement and the summonses that are not even handed in. Which means that if somebody doesn't appear for the summons, there will be a warrant out for their arrest even if they had shown up and the summons would have been thrown out for insufficiency. So this is another step to criminalizing people who have done nothing, because if the officer didn't write up a summons that was sufficient with a clear charge, it meant that there wasn't anything to charge the person. Yet if they don't appear to address that, even if it would have been thrown out, they do have a record based on that. And I was told that the buybacks for guns have been more effective than the police searches.

MR. TRAVIS: Okay. Thanks, Jean. So we have some topics, and we'll start with John Timoney. Go in reverse order. Crime tax that Heather proposed. - - training and how to make sure that there's communication particularly on this fits the description idea. Digital tape recorders. Culture of growing up where prison and policing is likely. And questions of a quota. So anything you want to pick up, and just concluding comments. We'll go down and Heather will get the [crosstalk].

MR. TIMONEY: Two quick things. One, I think the training I had mentioned earlier. The training is paramount that they understand, not just a legal basis for stop and frisk, but also the moral basis and what are the implications of what's been discussed here today, the damage that it may have if it's perceived to be done not fairly and not legally. That's one.

Regarding the videos of the police officers. You know, I think when I was a cop in the South Bronx walking the beat, I had a gun and that was it. And I look at the cops today, and they've got a ton of stuff around them. To add one more piece of equipment which would be difficult as far as keeping all of this. It just seems like an impossible task.

MR. TRAVIS: Okay, thank you. Jeff, final observations?

MR. FAGAN: The New Jersey Turnpike, following this consent decree after Soto, police had video cameras mounted on their dashboards, and they're still profiling, and I can tell you the data. You know, it's really obvious when you look at the New Jersey Turnpike, the New Jersey State Police data.

But everybody's entitled to their own opinion, but no one's entitled to their own facts. And I think the claim that this particular tactic is bringing down the crime rate and keeps it low, and deters young men from picking up guns and carrying them out in the street is a claim and nothing more than a claim. And I would like to see us actually study it. And, of course, there are ways, very good detailed strong social science, that can be done to actually go in and talk to people about the issues of their experience with the police, how they perceive the risk of caught and punished, should they be carrying a weapon or committing a crime, and so on. These are knowable facts, but right now we don't know them. And I think it's very important for us to learn them.

MR. TRAVIS: Thanks, Jeff. Tracey, final word.

MS. MEARES: The relationship between procedural justice and legitimacy and the relationship between legitimacy and compliance is based on good social science. We know that to be true, and that's one of the things that I've emphasized today.

But the last thing I want to say is something that I haven't emphasized that much, at least in my comments here, but which I care about deeply. And that is smart policing. One of the big issues that I think we've been talking about today is whether this particular tactic—and this particular tactic isn't necessarily CompStat. This particular tactic isn't necessarily problem-oriented policing. But we know from looking at policing agencies all over the country that there is a smart, sharp, focused way to do policing. And it usually turns out that that sharp, focused, smart way in deploying force and deploying the power of the police can often coincide well with legitimate policing.

MR. TRAVIS: Thank you. And, Heather, final - - .

MS. MACDONALD: Well, I agree with Professor Fagan that causality is very difficult to prove in complex situations like life. But I would say that the idea of preventive proactive policing has been proven to be effective in the cities that have done it most rigorously, which is L.A. and New York. No other cities have seen a crime drop that has been sustained the way New York's has. The primary beneficiaries of that crime drop have been the residents of minority neighborhoods. I did not suggest that I was proposing a crime tax. I was merely saying that this is a burden that is borne by people that do live in high-crime neighborhoods. And it has nothing to do with race; it has to do with the incidents of crime. And the police are there, they're put there by CompStat data analysis. They're making stops because crime patterns have been breaking out. And I do think it is somewhat incumbent on the critics to give us some rough number of what they think the proper number of stops is. Given that, as I say, the ratio of stops to arrests and ratio of stops to population is identical in L.A. and New York. And a federal judge has deemed L.A. policing to be consistent with civil rights. So at this point, I would be reluctant to change what has been an extraordinarily winning formula in this city.

MR. TRAVIS: Thank you, Heather. So I want to end just by thanking everybody for coming. When we first came up with this idea, Harlan, months ago, when Dan Richmond and I thought about it—you know, you give a party, you don't know whether anybody's going to come. So it's really gratifying to look out and see how many people are here. I think there's enormous and deep and sustained interest in this topic. It is not an easy question. That's why we're here. But I encourage you to keep the conversation going. And I want to ask you, as a final request, to join me in thanking the panelists for helping us get a conversation going.

[applause]

[END MZ000001]

Appendix G.

Letter from
Police Commissioner Raymond W. Kelly to Christine C. Quinn, Speaker, New York City Council

April 29, 2009

THE POLICE COMMISSIONER
CITY OF NEW YORK

April 29, 2009

Honorable Christine C. Quinn
Speaker
New York City Council
City Hall
New York, New York 10007

Dear Speaker Quinn:

I am writing to advise you that the New York City Police Department will not be attending tomorrow's oversight hearing regarding "Analysis of NYPD Stop and Frisk Encounters." As discussed in my previous letter to you, attached for your convenience, the subject of the hearing is also the subject of a federal class action lawsuit against the City, and while we acknowledge the Council's exercise of its oversight role in this matter and its long-standing interest in the issue, we respectfully decline to participate in the hearing.

We are highly aware of the public's interest in the Police Department's exercise of its power under Criminal Procedure Law Section 140.50 to detain and frisk individuals reasonably suspected of committing a crime, of having committed a crime, or of being about to commit a crime. As you know, the New York City Police Department has since 2002 provided to the Council on a quarterly basis Stop, Question and Frisk information, pursuant to Section 14-150 of the New York City Administrative Code. Over time, this information has become more generally accessible through the development of a computerized database and the availability of the underlying data sets, first through their posting on the website of the National Archive of Criminal Justice Data in 2007 and then through their posting on the Police Department's own website in 2008.

While we believe that stop, question and frisk activity has played a major role in the reduction of crime in New York City, and that it is directly targeted to public safety needs, the level of public concern regarding how this necessary tool is exercised, especially in the wake of the tragic shooting of Sean Bell in 2006, led us to request a thorough and independent analysis of our stop, question and frisk data by the RAND Corporation.

It has been argued that the Police Department engages in racial profiling based on racial disparities between the general population of New York City, and the population of those who are stopped. There is no perfect benchmark for measuring exactly what population our stop and frisk activity should be compared to, however RAND's report, "*Analysis of Racial Disparities in the New York Police Department's Stop, Question, and Frisk Practices*" summarized the issue by stating:

"We completed analyses using several candidate benchmarks, each of which has strengths and weaknesses for providing plausible external benchmarks. For example, residential census data—that is, the racial distribution of the general population in New York—possibly provide an estimate of the racial distribution of those exposed to police but do not reflect rates of criminal participation. As a result, external benchmarks based on the census have been widely discredited."

The British Home Office also examined this issue and, in a report entitled "*Profiling Populations Available for Stops and Searches*" Police Research Series report #131 (2000), concluded:

"The research presented here shows, quite clearly, that measures of resident population give a poor indication of the populations actually available to be stopped or searched."

One of the possible benchmarks, the race/ethnicity of the criminal suspect population, while not perfect, appears to be a more reasonable benchmark. In fact when the race/ethnicity of stop rates are simply compared to suspect race/ethnicity there is little or no disparity. RAND researchers analyzed data on all street encounters between New York City Police Department officers and pedestrians that occurred during 2006, and determined that no pattern of racial profiling existed.

It has also been argued that the volume of stops conducted by the Police Department is unnecessary given New York City's current levels of crime. Further, the number of stops is often mistakenly associated with the interpretation of stop outcomes, as if a stop is a success if it generates an arrest or summons, and a failure, or misconduct, if it does not, i.e., a "hit rate."

This assertion conveniently ignores the more credible argument that the reason crime levels have dropped is that the Department has paid proper attention to its crime control responsibilities. The appropriate use of legal stop, question and frisk powers attends to those responsibilities. In a recent study by Smith and Purtell, "*Does Stop and Frisk Stop Crime,*" the authors find that increases in stops were statistically associated with citywide reductions in Robbery, Murder, Burglary and Grand Larceny Motor Vehicle complaints. The authors also question the lack of research interest in examining this relationship:

"We have made the case that the debate about police stop-and-frisk practices should include the question of whether is it is effective in reducing crime and increasing public safety. Police can be faulted for using or expanding the practice without evidence of its efficacy but critics could . . . also be questioned about their failure to even raise the issue of effectiveness as if being an innocent victim of crime is not a violation of citizens [rights] equal or [greater] than an innocent person being questioned by police."

The association of stops with a hit rate or score ignores the legally recognized difference between stops and actual enforcement actions, summonses and arrests. Officers must have "reasonable suspicion" when making a stop but must have "probable cause" to make an arrest. The act of stopping someone can also interrupt criminal activity at an early enough stage that probable cause can never be met. The fact that probable cause can never be met and an arrest or summons made does not detract from the preventive value of that police action, which in almost one half the instances involves only questioning a subject, rather than conducting a frisk or taking other physical action.

Advocates of these arguments typically discount the continuing reductions in crime in New York, particularly referring to the City's recent experience as a "leveling off" or "stabilizing." The opposite is true. During recent testimony before the Council's Public Safety Committee, Assistant Commissioner, Programs and Policies Philip McGuire was able to report that the City closed 2008 with a more than 3% reduction in the seven major felony crime categories compared to 2007, representing a cumulative 28% decline since 2001. During the first quarter of 2009 the trend has continued with a reduction of nearly 14% in major felony crimes compared to same period in 2008.

Because of the direct correlation between crime and stop and frisk activity, we have previously provided to the Council our own "*Crime and Enforcement Activity in New York City*," a detailed analysis of crime in New York City for the six-month period January – June, 2008. We have since updated that study to cover calendar year 2008, and have attached it for your information. We have shared it with every Council Member, in the hope and expectation that it will provide a proper context for your discussion of stop, question and frisk activity.

I am also attaching a new Police Department form, "What Is A Stop, Question And Frisk Encounter?" to be included in officers' memo books. The form was developed in response to a recommendation made by the RAND Corporation, which suggested that officers should explain to individuals who were stopped the reason, or reasons, why it occurred. As a result, the Department has changed its written procedure so that officers are now clearly instructed to do so. In addition, we have begun a pilot program in the 32nd, 44th and 75th Precincts, in which officers conducting a stop will now provide to the person stopped the new form, which is a palmcard that informs the individual as to the legal authority for the stop and the common reasons persons are stopped by police.

Again, we regret that pending litigation prevents the Police Department from participating in the hearing of the Public Safety and Civil Rights Committees regarding "Analysis of NYPD Stop and Frisk Encounters," and hope that the information we have provided through this letter proves helpful.

Sincerely,

Raymond W. Kelly

Raymond W. Kelly
Police Commissioner

Appendix H.

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Appendix H
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