

Quantifying Educational Impacts Under the NYPD's Stop-And-Frisk Era

by
MATTHEW STANTON

**A capstone project submitted to the Graduate Faculty in Data Analysis and
Visualization in partial fulfillment of the requirements for the degree of Master of
Science, The City University of New York**

2024

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This manuscript has been read and accepted for the Graduate Faculty in Data Analysis and Visualization in satisfaction of the capstone project requirement for the degree of Master of Science.

30 Dec 2024

Date



Dr. Timothy Shortell

Thesis Advisor

15 Jan 2025

Date



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Executive Officer

THE CITY UNIVERSITY OF NEW YORK

ABSTRACT

Quantifying Educational Impacts Under the NYPD's Stop-And-Frisk Era

by

Matthew Stanton

Advisor: Dr. Timothy Shortell

This project examines the educational and economic impacts of the New York Police Department's "Stop, Question, and Frisk" (SQF) program, implemented predominantly under "Operation Impact" from 2003 to 2022. Using data from the NYPD and the American Community Survey, the study explores correlations between high rates of stop-and-frisk encounters and reduced educational attainment among targeted demographics, primarily Black and Hispanic young men. It contextualizes the socio-economic consequences of SQF policies, including their effect on lifetime earnings and community trust. The project highlights the limitations of data correlation, advocates for further longitudinal and qualitative studies, and suggests frameworks for mitigating inequities caused by aggressive policing practices.

Relevant URLs for associated elements in this project include the following:

Website: <https://pingstanton.com/nypdsqf/>

Github: <https://github.com/pingstanton/nypdsqf>

Dropbox:

<https://www.dropbox.com/scl/fo/4j5bvlgnsvkeim2ipt2r8/AL4buYDMJ4FmeZTTpvk1Rk4?rlkey=f87shv0msi436viwg8oe3t8fo&st=rzn5ewsq&dl=0>

First sources are listed in the Digital Manifest section of this document.

ACKNOWLEDGEMENTS

There are many individuals from the CUNY Graduate Center Data Analysis and Visualization program to thank for their expertise, patience, and encouragement throughout this project.

Dr. Timothy Shortell was the first to introduce me to data analysis, Python, IPUMS, and core ethical principles for responsible data use. Dr. Shortell also provided deep moral support and sociological data guidance throughout this work, including facilitating a meeting with Dr. Alex Vitale, coordinator of the Policing and Social Justice Project and author of published works that inspired this project.

Michelle McSweeney has been exceptional in teaching data visualization theory and guiding students into working with large language models - crucial skills in the rapidly evolving market shaped by artificial intelligence integration. She has a remarkable talent for distilling complex technical concepts into clear, concise explanations that anyone can grasp. Her boundless enthusiasm, professional knowledge, and unwavering positivity enriched every student interaction, impacting all who were fortunate to learn in her classes.

Building on these foundational lessons, Ellie Frymire brought her extensive experience in visualizing data across journalism, politics, and finance to enhance students' technical expertise in D3 further. Her shared enthusiasm for teaching matched her ability to provide detailed technical guidance and insightful critical feedback, ensuring students gained both confidence and precision in their work.

Dr. Howard Everson presented data analysis methods with clarity and an easygoing manner that made even the most complex topics approachable, writing out manual computations and hand calculations in comparison to automated processes in Stata and Python to keep analysis functions grounded.

As a journalist with limited experience in programming, the special topics courses taught by Filipa Calado (Python) and Stephen Zweibel (JavaScript) were a streamlined and accessible introduction to coding, making the onboarding process both quick and practical.

Finally, this project would not have been possible without consistent personal advisement and help from Jason Nielsen, Nicole Cote, and Sam O'Hana - and especially the DA/DV program's leadership by Dr. Matthew Gold, director of Graduate Center Digital Initiatives.

Outside the CUNY Graduate Center program, thanks are also due to New York Times data editor John Keefe for his help in mapping U.S. Census tract data to NYPD precincts, former Vera Institute of Justice data visualization designer Quinn Hood, and many friends and family who shared their support.

DEDICATION

To my mother and unwavering advocate,
Sandra Ann Stanton
(April 16, 1944 - Oct. 14, 2024)

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DIGITAL MANIFEST

First Sources

NYPD Stop, Question and Frisk Data:

<https://www.nyc.gov/site/nypd/stats/reports-analysis/stopfrisk.page>

https://www.dropbox.com/scl/fo/gd7ci4cq5apv0lv9etjj2/ALyVkxa77BJe1O_LPF71g_4?rlkey=zk7zi3m08ovas5b9ybs2lcuy0&st=04ro5ag5&dl=0

American Community Survey S1501 | Educational Attainment:

<https://data.census.gov/all?q=Educational%20Attainment>

<https://www.dropbox.com/scl/fo/o76amfwoqcll4vh23ckvx/AAtGQ-f1ACCPkfiulawFGMQ?rlkey=6988lrfxmi11v9hveg05ppsil&st=6na6e9dm&dl=0>

Project Manifest

I. Capstone Whitepaper (PDF)

II. Project Files

A. Project Website: <https://pingstanton.github.io/nypdsqf/website/>

B. Source Files

i. Via Github:

https://github.com/pingstanton/nypdsqf/rawdata_acs/

https://github.com/pingstanton/nypdsqf/rawdata_nypdsqf/

ii. Via Dropbox:

https://www.dropbox.com/scl/fo/gd7ci4cq5apv0lv9etjj2/ALyVkxa77BJe1O_LPF71g_4?rlkey=zk7zi3m08ovas5b9ybs2lcuy0&st=wacgjwsr&dl=0

<https://www.dropbox.com/scl/fo/o76amfwoqcll4vh23ckvx/AAtGQ-f1ACCPkfiulawFGMQ?rlkey=6988lrfxmi11v9hveg05ppsil&st=m4k9j5pk&dl=0>

C. Cleaned Data Files

i. Via website: <https://pingstanton.com/nypdsqf/dataset26/>

ii. Via Github: <https://github.com/pingstanton/nypdsqf/>

iii. Via Dropbox:

https://www.dropbox.com/scl/fo/7x0qilps49ybauv6wma3x/AHxc2XPfus6wSJ7_l78JgXY?rlkey=3jic74f7941kqx1ejet9mjdpe&st=8u3989pn&dl=0

iv. Data Dictionary/Codebook:

https://github.com/pingstanton/nypdsqf/blob/main/data_dictionary_codebook.txt

http://pingstanton.com/nypdsqf/data_dictionary_codebook.txt

D. Digital Edition

Public archived version at <https://pingstanton.com/nypdsqf/>

NOTE ON TECHNICAL SPECIFICATIONS

Data cleaning was done through a mix of custom search-and-replace AppleScripts integrated into the BBEdit code/text editor and Python functions written into a notebook on Google Colab.

The following Python libraries were imported for general use as needed throughout the notebook:

- pandas, for data manipulation and analysis (<https://pandas.pydata.org/>)
- NumPy, for arrays, high-level mathematics, scientific computing (<https://numpy.org/>)
- Statsmodels, for statistical models (<https://www.statsmodels.org/>)
- Matplotlib, for plotting charts and graphics (<https://matplotlib.org/>)
- Seaborn, for an API on top of Matplotlib (<https://seaborn.pydata.org/>)

Critical functions in the main notebook involved concatenated dataframes (`pd.concat`); grouping by years, precincts, and demographics (`df.groupby`); correlation measurements (`df.corr`); linear regression testing using the Ordinary Least Squares (OLS) method (`sm.OLS`); and various simple charts generated through Matplotlib.

Mapbox GL JS (<https://www.mapbox.com/mapbox-gl-js>) is a client-side JavaScript library for building web maps and web applications with Mapbox's modern mapping technology. An Access Token that associated API requests with a specific Mapbox account was acquired via a free Mapbox account (<https://console.mapbox.com/account/access-tokens/>).

GeoJSON data files for census tracts and NYPD precinct map boundaries were acquired from the United States Census Bureau (<https://www.census.gov/geographies/mapping-files.html>). Additional data for gradient fills were calculated in Microsoft Excel from cleaned data and added to the GEOJSON files using BBEdit.

HTML, CSS, and JavaScript file markups were done manually in BBEdit.

DATA DICTIONARY

https://pingstanton.com/nypdsqf/data_dictionary_codebook.txt

https://github.com/pingstanton/nypdsqf/blob/main/data_dictionary_codebook.txt

https://www.dropbox.com/scl/fi/3dnfsqa079y4983cy8isa/data_dictionary_codebook.txt?rlkey=8ckihohqxvo2f5g9r5izjqb6s&st=ng41vxc1&dl=0

Variable	Type	Description
YEAR	integer	year of collected data
PRECINCT	integer	NYPD precinct of reported incident
SQF_SEXF	integer	sex: female
SQF_SEXM	integer	sex: male
SQF_SEXZ	integer	sex: other or unlisted
SQF_RACEASIAN	integer	race: Asian
SQF_RACEBLACK	integer	race: Black
SQF_RACENATIVE	integer	race: Native American/Indigenous
SQF_RACEHISPB	integer	race: Hispanic/Black
SQF_RACEHISPW	integer	race: Hispanic/White
SQF_RACEUNK1	integer	race: unknown or unlisted
SQF_RACEWHITE	integer	race: White
SQF_RACEUNK2	integer	race: unknown or unlisted
SQF_RACEOTHER	integer	race: other
SQF_AGE0_17	integer	bin created for age: 17 or younger
SQF_AGE18_24	integer	bin created for age: 18 to age: 24
SQF_AGE25_34	integer	bin created for age: 25 to age: 34
SQF_AGE35_44	integer	bin created for age: 35 to age: 44
SQF_AGE45_64	integer	bin created for age: 45 to age: 64
SQF_AGE65_older	integer	bin created for age: 65 or older
POP_AGE18_24	integer	age: 18 to 24
POP_AGE18_24_M	integer	age: 18 to 24, sex: male
POP_AGE18_24_F	integer	age: 18 to 24, sex: female
POP_25OVER	integer	age: 25 or older
POP_25OVER_M	integer	age: 25 or older, sex: male
POP_25OVER_F	integer	age: 25 or older, sex: female
UNDERHS_AGE18to24	integer	max. educational attainment: under 9th grade, ages: 18-24
GRAD_AGE18to24	integer	max. educational attainment: high school graduate, ages: 18-24
COLLEGE_AGE18to24	integer	max. educational attainment: some college, no degree, ages: 18-24

BACHELORS_AGE18to24	integer	max. educational attainment: bachelor's degree or higher, ages: 18-24
UNDERHS_AGE18to24_M	integer	max. educational attainment: under 9th grade, ages: 18-24, sex: male
GRAD_AGE18to24_M	integer	max. educational attainment: high school graduate, ages: 18-24, sex: male
COLLEGE_AGE18to24_M	integer	max. educational attainment: some college, no degree, ages: 18-24, sex: male
BACHELORS_AGE18to24_M	integer	max. educational attainment: bachelor's degree or higher, ages: 18-24, sex: male
UNDERHS_AGE18to24_F	integer	max. educational attainment: under 9th grade, ages: 18-24, sex: female
GRAD_AGE18to24_F	integer	max. educational attainment: high school graduate, ages: 18-24, sex: female
COLLEGE_AGE18to24_F	integer	max. educational attainment: some college, no degree, ages: 18-24, sex: female
BACHELORS_AGE18to24_F	integer	max. educational attainment: bachelor's degree or higher, ages: 18-24, sex: female
UNDER9th_25OVER	integer	max. educational attainment: under 9th grade, ages: 25 or older
UNDERHS_25OVER	integer	max. educational attainment: high school, no graduation, ages: 25 or older
GRAD_25OVER	integer	max. educational attainment: high school degree or equivalent, ages: 25 or older
COLLEGE_25OVER	integer	max. educational attainment: some college, ages: 25 or older
BACHELORS_25OVER	integer	max. educational attainment: bachelor's degree or higher, ages: 25 or older
UNDER9th_25OVER_M	integer	max. educational attainment: under 9th grade, ages: 25 or older, sex: male
UNDERHS_25OVER_M	integer	max. educational attainment: high school, no graduation, ages: 25 or older, sex: male
GRAD_25OVER_M	integer	max. educational attainment: high school degree or equivalent, ages: 25 or older, sex: male
COLLEGE_25OVER_M	integer	max. educational attainment: some college, ages: 25 or older, sex: male
BACHELORS_25OVER_M	integer	max. educational attainment: bachelor's degree or higher, ages: 25 or older, sex: male
UNDER9th_25OVER_F	integer	max. educational attainment: under 9th grade, ages: 25 or older, sex: female
UNDERHS_25OVER_F	integer	max. educational attainment: high school, no graduation, ages: 25 or older, sex: female
GRAD_25OVER_F	integer	max. educational attainment: high school degree or equivalent, ages: 25 or older, sex: female
COLLEGE_25OVER_F	integer	max. educational attainment: some college, ages: 25 or older, sex: female
BACHELORS_25OVER_F	integer	max. educational attainment: bachelor's degree or higher, ages: 25 or older, sex: female

REFERENCES

Software and online services used in this project included the following:

Adobe Photoshop release 23.5.1 (<https://www.adobe.com/products/photoshop.html>)

Applescript 2.7 Script Editor version 2.11 (<https://support.apple.com/guide/script-editor/>)

BBEEdit version 13.5.7 (<https://www.barebones.com/products/bbedit/>)

Google Colab / Colaboratory (<https://colab.research.google.com/>)

* Google Gemini (as integrated into Colab for Python debugging) (<https://gemini.google.com/>)

Microsoft Excel for Mac version 16.49 (<https://www.microsoft.com/en-us/microsoft-365/mac/microsoft-365-for-mac>)

Transmit version 4.4.13 (<https://www.panic.com/transmit>)

NARRATIVE

My partner and I have been together for almost a decade. I was born in 1969, a middle-class white male in Wisconsin, and I pursued a 30-year career in local journalism. She was born in 1969, a middle-class Black woman in New York City, and she pivoted from a successful career in education to becoming a clinical social worker with her own psychotherapy practice.

Early in our relationship, in October 2017, we attended the wedding of two friends living in Chicago. The night before the ceremony, we slowly drove through a mostly unlit Chicago public park to find the event venue and help put up decorations. A police squad car appeared behind us, red and blue lights flashing, and the stark differences in our lived experiences snapped into sharp focus.

In my mind, having professionally dealt with police in various municipalities throughout in my career, I was encouraged: "Oh good, I can ask this cop for directions." My partner, however, began begging to speed away and avoid any interaction with the police. She expressed genuine fear about what might happen next. The gap in our positionalities felt like a matter of life and death.

Elsewhere in Chicago that same night, 17-year-old Laquan McDonald was murdered by Chicago Police Officer Jason Van Dyke. Police claimed McDonald lunged at officers with a knife, but video of the encounter showed the teen had been walking away when Van Dyke fired on him 16 times with his gun. A second-degree murder conviction on Van Dyke and the city's \$5 million settlement with McDonald's family would come much later.

The 2017 events in Chicago happened just three years after Eric Garner had been choked to death by New York City Police Officer Daniel Pantaleo in Staten Island. Garner was approached on suspicion of selling single cigarettes, a trivial offense. While being choked, Garner reported pleading, "I can't breathe" 11 times before losing consciousness, and his death in front of a beauty supply store would later be ruled a homicide by the medical examiner.

I moved to New York City in 2005, long after Mayor Rudy Giuliani's "quality-of-life" paradigm and "broken windows theory" policing had "cleaned up" much of the city, or so some veteran New Yorkers told me. Crime rates had been in decline, and the civic unity triggered in the aftermath of the Sept. 11 terrorism attacks still echoed among local residents.

As I contemplated my own career pivot into higher education, I also read Kim Phillips-Fein's *Fear City: New York's Fiscal Crisis and the Rise of Austerity Politics* about the events of 1975, a natural lead into two books by Alex S. Vitale, *City of Disorder: How the Quality of Life Campaign Transformed New York Politics*, and his later work, *The End of Policing*. All these works led to a borough-by-borough measure of high school

graduation rates compared to the number of Stop, Question, and Frisk stops, but such efforts were not nearly granular enough to show meaningful correlations.

Getting and preparing NYPD Stop, Question, and Frisk data was consistent and easy, and in spring 2022, I had a working dataset. My initial proposal meeting with Dr. Shortell happened on May 17, 2024. At that time, Dr. Shortell warned that a direct correlation would not be possible with the available public data and without tracking individual case studies, a step beyond the scope of this semester. Ultimately, he was exactly correct.

Preparing educational data proved more elusive as IPUMS did not parse results to the census tract level. In August 2024, I found the educational attainment metrics at the tract level in the American Community Survey from the U.S. Census data site. Although it tied to some demographics (location, gender, age), it did not contain racial information for direct correlation to NYPD SQF data. Also, the data proved much more inconsistent and required substantially more cleaning before being used in analysis datasets.

On Sept. 27, 2004, Dr. Shortell arranged for his Brooklyn College colleague Dr. Alex S. Vitale to join us via Zoom to discuss the project, especially regarding finding ways to control for other socioeconomic factors such as parental education attainment, poverty, or household income. Because the stop-and-frisk data skewed overwhelmingly male, Dr. Vitale suggested a comparison between sex metrics could provide a sort of control, but further analysis discouraged this approach.

In early October 2004, I experienced a family medical emergency with my mother out of state, removing me from graduate studies for several weeks. In the unexpected aftermath of my mother's death, funeral planning, and dissolution of her assets, project work did not resume until December, prompting a reevaluation of what would be possible this term.

The project successfully articulated the "thought experiment" of including educational attainment as one of the measured impacts of this - or any - public policy. The "Toward a Framework for Further Study" section of this project includes observations and discussions between Dr. Shortell and myself going back to May 2024.

Once reviewed, the concept of this study can be shared with several policy advocacy groups in New York City, including the Vera Institute of Justice, the Research Alliance for New York City Schools, the Center for New York City Affairs at The New School, the Equal Justice Initiative, and of course, the City University of New York system.

Quantifying Educational Impacts Under the NYPD's Stop-And-Frisk Era

Matthew Stanton

Master of Science Candidate, Fall 2024

CUNY Graduate Center Data Analysis and Visualization Program

Advisor:

Dr. Timothy Shortell

Professor of Sociology, Brooklyn College / CUNY Graduate Center

A master's capstone project submitted to the Graduate Faculty in Data Analysis and Visualization in partial fulfillment of the requirements for the degree of Master of Science, The City University of New York.

Introduction

Incident data shows the New York Police Department's "Stop, Question and Frisk" program, predominantly used under the name "Operation Impact" (Integrated Municipal Police Anti-Crime Teams) from 2002 to 2023, disproportionately targeted people of color and may have led to a generational loss of educational attainment and corresponding associated lifetime incomes. This project aims to identify areas, times, and demographics of people most targeted under this program and examine possibilities to quantify educational attainment impacts.

The NYPD reports to have confronted and detained New Yorkers under the "stop-question-and-frisk" program more than 2 million times. During Michael Bloomberg's administration, the "stop-and-frisk" program reached a historic annual high of 685,724 documented stops in 2011, disproportionately targeting Black and Hispanic young men. In that year, a Hispanic man was four times as likely to be subjected to a stop by the NYPD as a white man, while a Black man was 10 times more likely to be stopped. [1]

That same year marked New York's highest number of resident adults over 18 lacking a high school diploma or equivalent: 1,475,319 people, or 18.6 percent of the city's adults, dropping out of further educational attainment. Data analysis in this capstone will show moderate to strong correlations along racial lines that closely match the trend lines of the NYPD's stop-and-frisk usage, but there are challenges to proving such correlation equals any degree of causation.

One year after these record highs, U.S. District Court Judge Shira Scheindlin ruled in *Floyd, et. al. v. City of New York* that the program had been unconstitutional, showing "significant evidence that the NYPD acted with deliberate indifference" - especially toward Black and Hispanic New Yorkers. [2]

Loss of household earnings to New Yorkers has not been quantified either as a social or financial cost, a metric that would benefit understanding among affected communities, policymakers and legislators, educational institutions and advocates, social justice organizations, and those invested in resolving lingering program consequences such as legal professionals, local business leaders, and community organizers.

Methodology

Stop-and-Frisk data from 2003 to 2022 was downloaded from New York City Police Department's Stop, Question, and Frisk Data (SQF) repository on NYC.gov. Populations by New York City census tracts, including age bins and highest levels of educational attainment, were drawn from the American Community Survey S1501 Educational Attainment (ACS) 2010-2023 dataset via the U.S. Census.

Some cautions of note regarding this analysis:

- In order to compare NYPD and ACS data, tallies of individual census tract counts were combined into precinct groups. In cases where a precinct split a census tract, the tract was counted into the precinct of greatest area. Precincts with no residences (i.e. 22nd Precinct/Central Park) have been excluded from some correlations.
- Data from 2010 to 2019 were matched to 2020 census boundaries. In most cases, changes involved splitting the tract into two or more parts from a previous tract, not changing its associated NYPD Precinct. The major exception to this rule is found on Staten Island, where the 121st Precinct was created in 2013. For more information on tract revisions, see 2020 Census Reconfiguration of Statistical Geographies: A Guide for New York City by the NYC Department of City Planning's Population Division
- Any data related to Queen's 116th Precinct, created in December 2024, are included in the 105th Precinct and parts of the 113th Precinct as per prior boundaries.
- NYPD racial codes for subjects identified in Stop, Question, and Frisk reports as "P BLACK-HISPANIC" and "Q WHITE-HISPANIC" have been merged into one category, "Hispanic."
- Due to small representation in the data, stop-and-frisk tallies of racial demographics exclude individuals identifying as American Indian/Alaskan Native or Middle Eastern, or incidents where no race was listed in NYPD reports.
- Counts have not been normalized against changes in New York City demographics, particularly in the city's increasing median age and shrinking number of residents below the age of 18. Percentages of populations are limited to either same-year comparisons or an entire range spanning the dataset.
- The analysis assumes an implied association with stop-and-frisk encounters and the census tract of residence for the targeted individual. While this assumption may be true for some individuals, it is not possible to verify any personally identifiable information.

- Stop-and-frisk data measures incidents, not individuals, so some cases may reflect the same individual appearing in the dataset multiple times within the same year and/or precinct, or multiple years and precincts.

While there may appear to be a relationship between stop-and-frisk rates and local levels of educational attainment, it is important to consider that correlation does not imply causation; other factors like income inequality or policing policies could influence these rates.

A Brief History of Stop-And-Frisk Policies

The practice of confronting and briefly detaining citizens to uncover hidden contraband such as drugs and weapons had neither originated in the 21st century, nor even begun in New York. The practice of "stop, question, and frisk" became common across America following the 1968 landmark U.S. Supreme Court decision *Terry v. Ohio* that empowered police "upon the on-the-spot observations of the officer on the beat" to perform over-the-clothing pat-downs of individuals suspected of endangering others. [3]

At the discretion of police officers, judicial approval of searches and seizures through the Fourth Amendment's warrant process of probable cause could be waived in the moment on a "case-by-case" basis. Such encounters became known as "Terry stops," so named after the man in Cleveland who became the plaintiff in the Supreme Court case.

In a footnote within the Supreme Court's ruling, the 1955 Journal of Criminal Law and Criminology article "Searching and Disarming Criminals" by L.L. Priar and T.F. Martin was cited for its description summarizing the expected intrusion made upon those stopped in public and backed up against a wall by police: "(T)he officer must feel with sensitive fingers every portion of the prisoner's body. A thorough search must be made of the prisoner's arms and armpits, waistline and back, the groin and area about the testicles, and entire surface of the legs down to the feet." [4]

Beyond this academic guideline, the reality of undergoing such stops in New York City often proved much more violent and unsettling. A study by Columbia University researchers noted 1 in 5 NYPD stops involved physical "use of force" in which "young men are often thrown to the ground or slammed against walls" and sometimes subjected to "racial invective or taunts about sexuality." [5]

By the 1990s, New York City voters elected Rudy Giuliani as mayor, in part based on his promise to curb crime, improve public faith in the New York City police department, and follow a "quality of life paradigm," a variation on "broken windows theory" that favored social controls over previous rehabilitation programs. [6]

William Bratton became the new NYPD Commissioner in 1994, and by April of his first year, the department launched COMPSTAT - short for Compare Stats or Computer Stats - a method to track crime statistics, identify patterns, and focus on target areas.

Bratton and COMPSTAT co-creator Jack Maple led a pivot to metrics-driven policing, including the use of standardized demographic descriptions of encounters between police and the public, something that "came to signify an officer's productivity in the field." [7]

"Stop, Question, and Frisk" took formal shape in January 2003 through Operation Impact and Integrated Municipal Police Anti-Crime Teams. The initiative's stated goal was to "reduce crime throughout the city by deploying more officers to high-crime hot spots, known as 'Impact Zones,'" areas NYPD Commissioner Raymond Kelly described as "isolated stubborn pockets" of urban crime. [8]

This move happened amid the conclusion of *Daniels, et al. v. the City of New York*, a class action lawsuit begun in 1999 that alleged selective NYPD targeting of residents based on their race. The city agreed to a settlement that December. [9]

Over the next decade and a half, the NYPD would continuously expand and redefine such Impact Zones every six months, primarily in precincts located in Brooklyn, Queens, and the South Bronx. Those police officers put in charge of making stop-and-frisk calls were among the least experienced on the force.

"From the outset, roughly two-thirds of the graduating classes from the Police Academy were assigned to Impact Zones," noted one analysis of the policy. "These rookie patrolmen and patrolwomen were encouraged by supervisors to conduct high volumes of investigative stops. In addition to suspicion-based stops, officers were encouraged to make arrests for low-level offenses or issue warrants for minor non-criminal infractions (such as open containers of alcohol), and conducted other stops as pretexts to search for persons with outstanding warrants." [10]

NYPD Stop-And-Frisk Disparities

Implementation of Stop, Question, and Frisk under the New York Police Department quickly rose to disproportionately target specific demographics: men, Blacks, Hispanics, and those between the ages of 18 to 34. During the program's most active tenure, almost exactly half of all stops involved people 24 years old or younger.

Figure 1: NYPD Stop-And-Frisk Targeting By Race

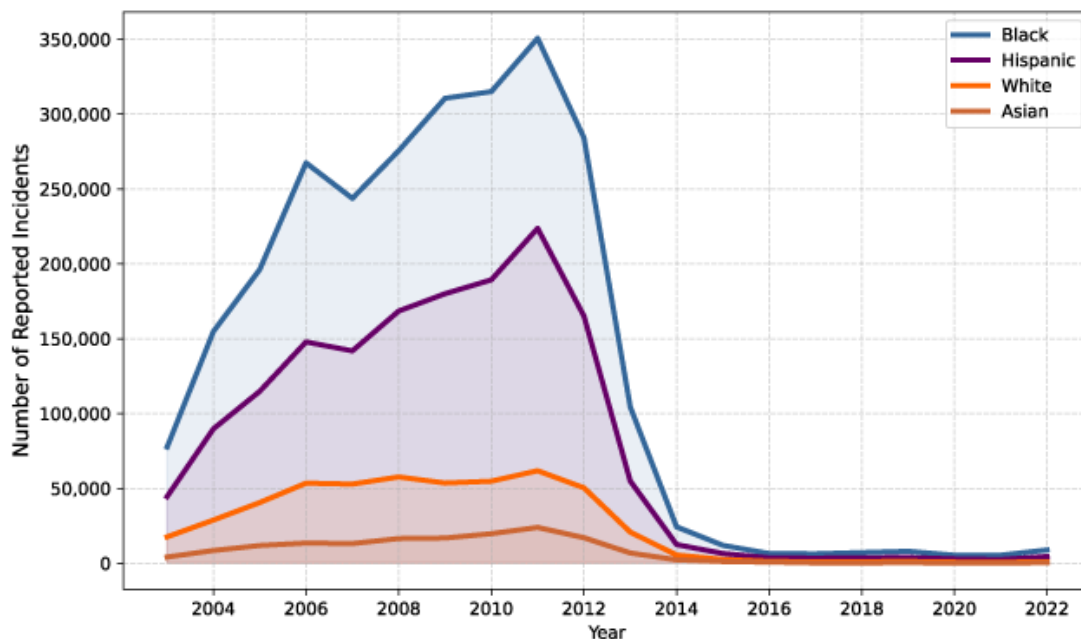
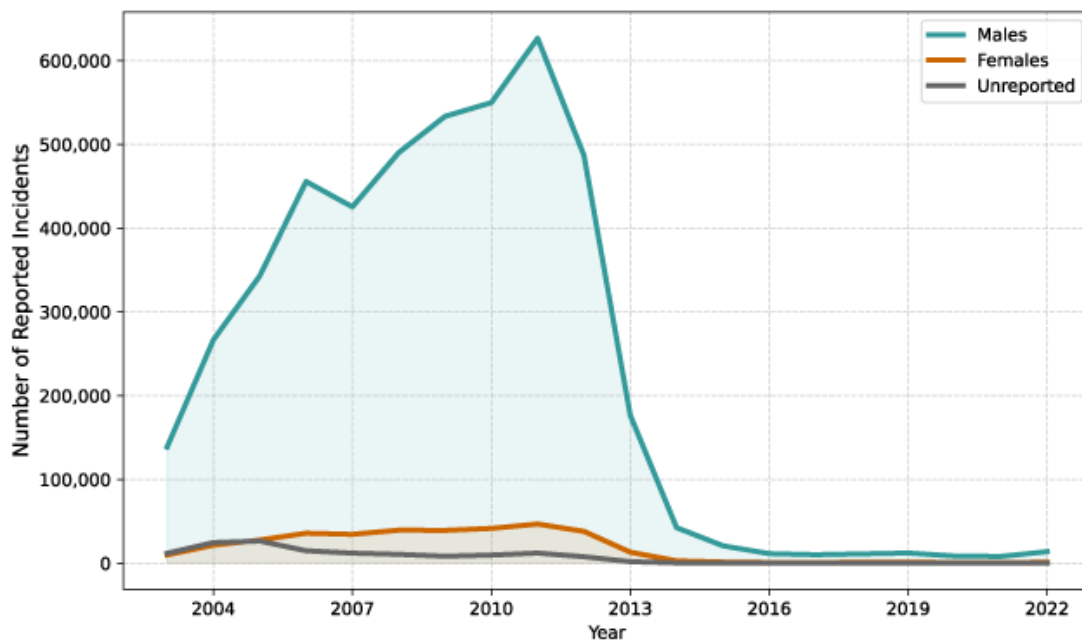


Chart omits categories below minimum threshold to display, including American Indian/Alaskan Native, Middle Eastern, and incidents where no race was listed.
Source: NYC.gov NYPD Stop, Question and Frisk Data

A study by Stanford University, Microsoft Research, and New York University traced the racial disparity to two factors: Impact Zones being set up in predominately Black and Hispanic housing areas, and "discriminatory enforcement" by those officers tasked with choosing who to stop. Since Impact Zones were selected based on crime rates, "a consequence of the tactic is that individuals who live in high-crime areas, but who are not themselves engaged in criminal activity, bear the costs associated with being stopped." [11]

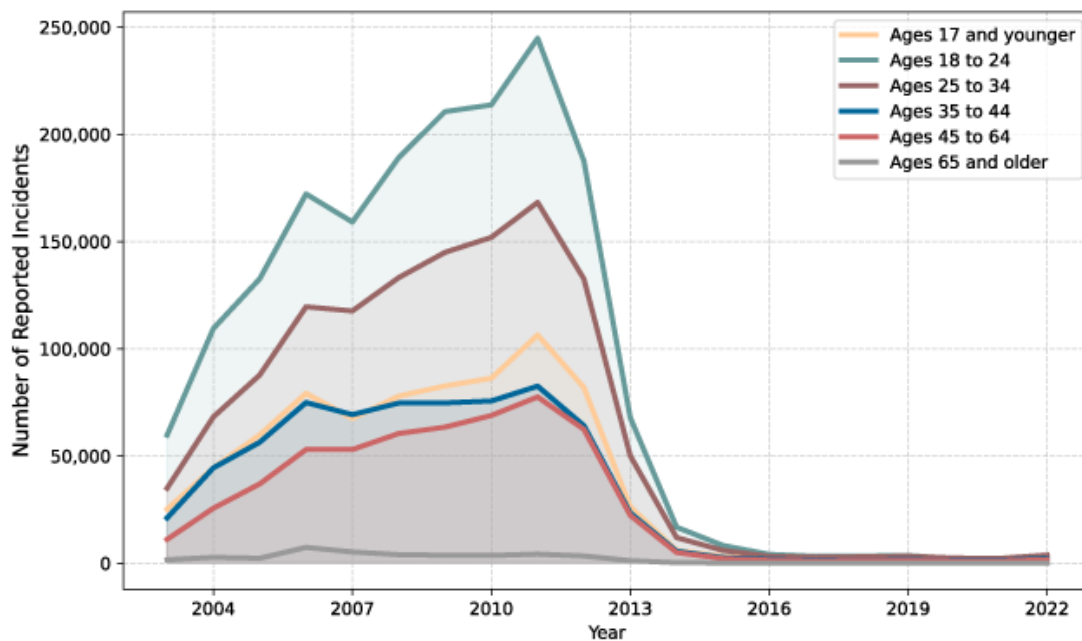
In addition to disparities by race, the program overwhelmingly targeted males over females by 13-to-1, and especially targeted men between the ages of 18 to 24.

Figure 2: NYPD Stop-And-Frisk Targeting By Reported Sex



Source: NYC.gov NYPD Stop, Question and Frisk Data

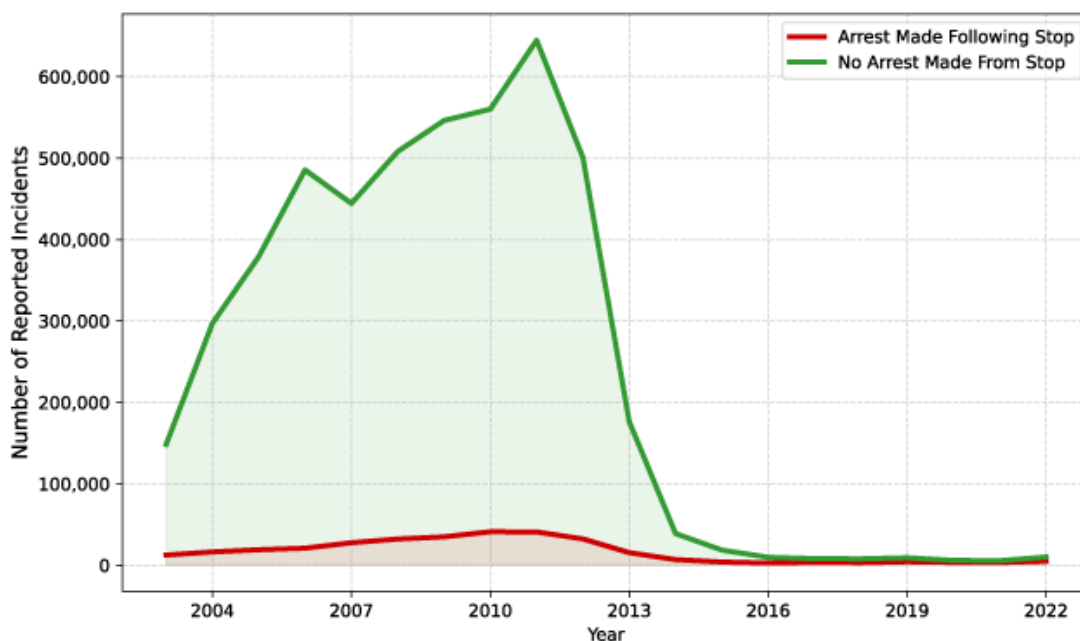
Figure 3: NYPD Stop-And-Frisk Targeting By Age



Source: NYC.gov NYPD Stop, Question and Frisk Data

Official records further illustrate how often stops came to nothing. The year 2011 saw 685,700 stop-and-frisk encounters logged by police officers, the most of any year, but only 5.96 percent of stops led to some form of criminal charge (possession of marijuana, prior outstanding warrants, or possession of a weapon). The remaining 94 percent of police stop encounters that year involved people completely innocent of any wrongdoing. This stop-to-arrest ratio went as low 25-to-1 in 2006.

Figure 4: NYPD Arrests Following Stop-And-Frisk Stops



Source: NYC.gov NYPD Stop, Question and Frisk Data

The skew toward stop-and-frisk encounters ending without evidence of criminality was not an anomaly in law enforcement, but rather part of what Vitale characterizes as one of several core tactics in quality-of-life policing:

"Officers in New York City were told to use any pretext to stop young men on the streets who they believed might be carrying illegal drugs or weapons and to search them. The legalities of the search were sometimes questionable, but consistent with the 'broken windows' theory, the emphasis was on establishing a new standard of behavior rather than making arrests that would necessarily end in successful prosecutions." [12]

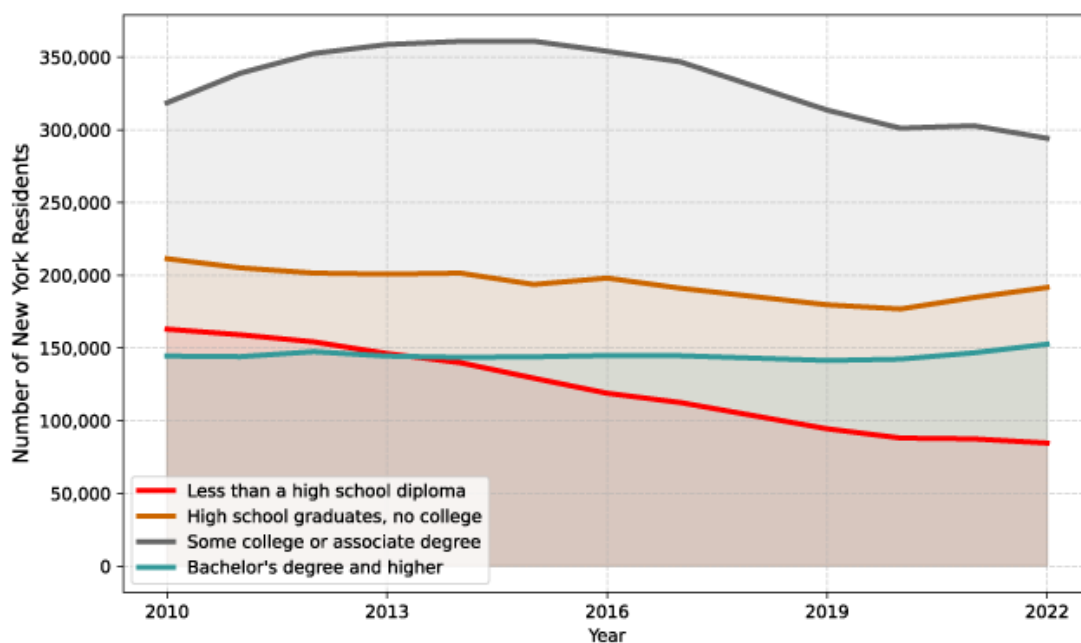
The institutional practice of high-frequency stops within these Impact Zones created a halo effect among the entire community. As researchers from the John Jay College of Criminal Justice and Center for Policing Equity in New York put it: "Indeed, even in the absence of an encounter, Black pedestrians and drivers live with the accumulated knowledge (acquired from both direct experience and observation) that investigative

stops are an ever-present threat; and one that cannot be reliably avoided simply by following the law." [13]

New York City Educational Attainment Benchmarks

Measurements on the highest levels of educational attainment were available from the American Community Survey's S1501 Educational Attainment 2010-2023 data. Since the suspension of most NYPD stop-and-frisk practices a decade ago, both the number and percentage of New York City residents between the ages of 18 to 25 with a top educational attainment level below a high school diploma has steadily decreased.

Figure 5: Highest Level of Educational Attainment, New Yorkers Ages 18 to 24



Source: American Community Survey

Educational attainment remains unevenly divided across New York City due to socioeconomic, cultural, environmental, and systemic factors. Using census tracts as a base for comparison, the map below illustrates areas where a significant number of local residents have less than a high school diploma (or equivalent).

Note that population density and demographic differences between neighborhoods confound the relationship between educational attainment and stop-and-frisk incidents, requiring further controls in the analysis.

In terms of experiencing a stop-and-frisk encounter before the age of 25, White and Asian young people of both sexes showed very weak or no correlation to their graduation from high school. The impacts are shown to be very different for Hispanic

and Black people under 25: For every two to three stops, trends show one Hispanic youth tends to not graduate high school, with about 5% greater chance among males over females. Among Blacks, the trend is closer to eight stops per person below a high school diploma, with both sexes affected equally.

As stated earlier, such correlations cannot be taken as an indication of causation, but the trend appears consistent.

Precincts with the most stop-and-frisk encounters also had among the lowest educational attainment levels.

Comparing Educational and Stop-And-Frisk Data

The focus of stop-and-frisk use on "impact zones" led to far more encounters in some neighborhoods than others, often at the discretion of the local precinct's commanding officer. In many cases, a change in precinct-level leadership drove a substantial change in the frequency of stop-and-frisk encounters. The map at right links to an illustration of differences regarding stops involving subjects between the ages of 18 and 25.

Of particular note is the case of Brooklyn's 75th Precinct under the command of Jeffrey Maddrey, under whose tenure the policy posted its highest number of stops between 2010 to 2012. Maddrey had previously driven stop-and-frisk numbers as the commanding officer of Brownsville's 73rd Precinct from January 2006 before moving to his post in East New York in January 2009. In each precinct, stops rose dramatically under Maddrey and dropped when he changed posts. The trend is not academic, as Mayor Eric Adams went on to appoint Maddrey as the NYPD Chief of Department in December of 2022, overseeing all of the city's policing policies at the end of a year that saw SQF use almost double.

Education data from census tracts (2010, 2020 boundaries) were grouped into precincts (defined by 2023 boundaries). As previously noted, this creates an inconsistency on Staten Island, where the 121st Precinct was created in 2013, but broad comparisons fit elsewhere. In cases where a census tract was split by a precinct boundary, data for the entire tract was grouped into the precinct of greatest area.

The top 10 precincts with the highest number of reported stop-and-frisk encounters between 2003 to 2022 also show high rates of 18- to 24-year-old individuals with lower educational attainment levels.

Top 10 Highest Stop-and-Frisk NYPD Precincts (2003-2022)

PRECINCT	NEIGHBORHOODS	NUM. SQF STOPS	LOW EDUC. ATTAINMENT
75th Precinct	Brooklyn: East New York and Cypress Hills	93,220	21%
73rd Precinct	Brooklyn: Brownsville and Ocean Hill	77,549	24%
40th Precinct	Bronx: Port Morris, Mott Haven, and Melrose	61,804	29%
120th Precinct	Staten Island: North Shore	55,329	17%
79th Precinct	Brooklyn: Bedford Stuyvesant	53,960	15%
103th Precinct	Queens: Hollis, Lakewood, and Jamaica	53,157	18%
23th Precinct	Manhattan: East Harlem/El Barrio	52,640	20%
44th Precinct	Bronx: Southwest, Yankee Stadium	51,908	27%
43rd Precinct	Bronx: Westchester Avenue, Castle Hill Avenue, White Plains Road, and Parkchester	45,032	26%
67th Precinct	Brooklyn: East Flatbush and Remsen Village	43,639	14%
AVERAGE	All precincts	28,009	15%

NUM. SQF STOPS: Total number of recorded Stop, Question, and Frisk encounters between 2003 to 2022.

LOW EDUC. ATTAINMENT: Percentage of residents age 18 to 25 with a maximum educational attainment level below a high school diploma (or equivalent).

Source: New York City Police, NYC.gov, ACS

The correlation may reflect a vicious circle: Limited opportunities due to lower educational attainment may increase crime rates, which in turn prompt "impact zone" policies such as stop-and-frisk, which in turn alienate communities from further pursuit of education.

Such broad visualizations are in line with conclusions made by Legewie and Fagan: "The findings show that Operation Impact lowered the educational performance of African-American boys, with implications for child development, economic mobility and racial inequality." [14]

Furthermore, they note "direct police contact such as pedestrian stops, police harassment or arrests can erode trust in state institutions, lead to system avoidance and induce stress or other health problems, which in turn reduce educational performance." [15]

In a later paper by Fagan, working with Dr. Amanda Geller of the University of California, Irvine, the pair characterized resulting distrust of institutions such as police and schools as "legal cynicism." [16] The pair used data from Princeton University's Fragile Families & Child Wellbeing Study tracking children born between 1998 to 2000 from nearly 5,000 couples in 20 major cities, including youth coming of age as teens in New York City under the era of "stop-and-frisk" policing. [17]

Regardless of ever having been personally stopped by police, the overall message to this generation was clearly shared: "Minority (specifically, black, Hispanic, and multiracial) teens report significantly more legal cynicism than their white counterparts,

net of racial differences in their reported personal and vicarious police experiences." [18]

Projected Impacts On Educational Attainment Levels and Lifetime Household Earnings

In 2019, Harvard University's Joscha Legewie and Columbia Law School's Jeffery Fagan built statistical regression models to compare New York State's English Language Arts (ELA) and Mathematics test scores from students grades 3 through 8 who lived in neighborhoods designated for Operation Impact enforcements. "The findings were striking," they wrote, noting Black boys became increasingly negatively affected as they grew older from age 9 to age 15. Their analysis showed exposure to Impact Zones for one school year accounted for one-fifth of the Black-White test score gap and also contributed to reducing school attendance by Black boys. "The findings show that Operation Impact lowered the educational performance of African-American boys, with implications for child development, economic mobility and racial inequality." [19]

A similar analysis performed the following year by Harvard's Andrew Bacher-Hicks and Elijah de la Campa found that those exposed to "stop-and-frisk" interactions - even indirectly through friends, family members, or teachers who were stopped - became inclined to suffer educational setbacks. The researchers found that stops among Black students "increases high school dropout likelihood by 6 percent, reduces college enrollment by 5 percent, and reduces college persistence after four semesters by 8 percent." [20]

A working paper titled "School Finance Reform and the Distribution of Student Achievement" posted online by the Washington Center for Equitable Growth in 2016 found that increases in funding gradually raised the relative achievement of students in low-income school districts. [21] As Bacher-Hicks and de la Campa conclude in their analysis of New York City's "stop-and-frisk" effects, "because educational attainment is highly predictive of future earnings, these results imply that the racial disparities in police have broad implications for inequality in labor market outcomes and lifetime earnings." [22]

According to nationwide U.S. Bureau of Labor Statistics, college-educated workers' median earnings for bachelor's degrees in the third quarter of 2024 were higher by \$50,000, or 130 percent, than those whose highest educational attainment below a high school diploma. [23]

Weekly Earnings by Educational Attainment (Q3 2024)

EDUCATIONAL ATTAINMENT	First decile	First quartile	Median	Third quartile	Ninth decile
Less than a high school diploma	\$465	\$601	\$734	\$920	\$1,257
High school graduates, no college	\$580	\$710	\$946	\$1,331	\$1,891
Some college or associate degree	\$615	\$780	\$1,053	\$1,537	\$2,096
Bachelor's degree and higher	\$832	\$1,149	\$1,697	\$2,556	\$3,844

Source: U.S. Bureau of Labor Statistics

Of the millions of people who were detained during the stop-and-frisk era, if only 1 in 100 of those experienced lower educational attainment due to this experience, that would leave 52,000 people earning less per year for their families. Even ignoring inflation and speaking only in nominal dollars, it is easy to see how quickly the difference of just one tier of educational attainment matters, comparing high school graduates to those without a diploma.

Beyond educational and economic impacts, stop-and-frisk encounters created an unwarranted legal legacy for many individuals.

Despite innocence, personally identifiable information resulting from such stops could and did remain in the police records of individuals, and these records stayed available for use in any future prosecutions. [24] This systematic disadvantage to those "with a stop record" created a new kind of legal binary - the targeted "stopped" and the privileged "not stopped" - and codified "the usual suspects" of mostly Black and Hispanic men into the NYPD's method of "predictive guilt."

Jenn Rolnick Borchetta, a lawyer with The Bronx Defenders legal firm, led the move for a class-action lawsuit against the city over such "stop-and-frisk" records being used to track individuals. "It's not just Facebook and Google that have big data, it's also police departments around the country using it to train the spotlight of their suspicion," she said in 2019. "They're running their algorithms and their facial-recognition software on arrest records and mugshots that were supposed to have been destroyed." [25]

These arguments halted broad SQF use by the NYPD on Sept. 5, 2019, after Judge Lyle E. Frank noted "likely tens of thousands" of people were being affected by their unwarranted stop records, adding that number might be "a conservative estimate." [26]

Toward a Framework for Further Study

Did the stop-and-frisk program directly contribute to reduced educational attainment among affected demographics? If so, how best can the Stop, Question, and Frisk impact on household earnings and lifetime incomes be quantified? How can policymakers ensure that similar programs are implemented equitably in the future?

As stated earlier, these various correlations do not prove causation. Examining the direct consequences of the Stop, Question and Frisk program would require tracking individuals' stories at scale, something along the lines of how Jan Haldipur approached narratives in his book *No Place on the Corner: The Costs of Aggressive Policing*.

To establish a causal relationship between NYPD stop-and-frisk practices and educational attainment, the following steps will be necessary:

1. Identify and control for potential confounding variables (e.g., income levels, employment rates, school funding, neighborhood crime rates).
2. Use statistical methods (e.g., regression models) to account for confounding factors that might influence both policing practices and education.
3. Gather longitudinal data on educational outcomes for individuals or communities affected by stop-and-frisk policies. This step would require case study analysis involving personally identifiable information, a feature outside the scope of this paper.
4. Study the direct impacts of stop-and-frisk on individuals (e.g., stress, criminal records, school attendance) using surveys or interviews.
5. Compare areas before and after policy changes against unaffected areas. Show that changes in stop-and-frisk practices occurred before any observed changes in educational attainment to establish temporal precedence.
6. Use natural experiments, such as changes in policing policies or practices in specific neighborhoods, to observe impacts on educational outcomes.
7. Identify variables correlated with stop-and-frisk practices but not directly with education (e.g., shifts in police leadership or policy mandates) to isolate causal effects. (See the case of NYPD Chief Jeffrey Maddrey mentioned above).
8. Compare data and correlations with other urban municipalities where police have implemented aggressive stop-and-frisk policies (Philadelphia, Chicago, Los Angeles).
9. Submit findings to rigorous peer review and replicate studies in other settings to confirm causality across contexts.

There is already precedence for pursuing community remediation. Judge Scheindlin, in addition to ruling that the NYPD's use of stop-and-frisk had been unconstitutional, also granted *Davis v. City of New York* class-action status in challenging the use of discriminatory stops in Housing Authority buildings. [27]

In future study, should a more clear casual link be demonstrated, it would also be possible to quantify harms and affect corrective policies. Whether this action took the form of compensation or community reinvestment initiatives in neighborhoods disproportionately targeted by the program, or simply legal assistance to help expunge individuals' records tied to stop-and-frisk encounters - especially when no crime was committed - it would represent a tangible step toward addressing the systemic inequities and restoring trust between affected communities and law enforcement institutions.

Appendix: NYPD Precincts Snapshot

PRECINCT	NEIGHBORHOODS	NUM. SQF STOPS	LOW EDUC. ATTAINMENT
1st Precinct	Manhattan: World Trade Center, SOHO, Tribeca, Wall Street	11,099	3%
5th Precinct	Manhattan: Chinatown, Little Italy, the Bowery	10,956	10%
6th Precinct	Manhattan: Midtown South, Times Square, Penn Station	12,134	1%
7th Precinct	Manhattan: Lower East Side	13,264	15%
9th Precinct	Manhattan: East Village, Tompkins Square Park	19,838	4%
10th Precinct	Manhattan: Chelsea, Clinton/Hell's Kitchen South, Hudson Yards	10,195	5%
13th Precinct	Manhattan: Midtown, Peter Cooper Village/Stuyvesant Town, Union Square	16,515	3%
14th Precinct	Manhattan: Midtown South, Times Square, Penn Station.	37,250	6%
17th Precinct	Manhattan: Sutton Area, Beekman Place, Kipps Bay, Turtle Bay, Murray Hill, Rose Hill	6,314	1%
18th Precinct	Manhattan: Midtown North, Diamond District, Theatre District, Rockefeller Plaza	11,732	4%
19th Precinct	Manhattan: Upper East Side	17,399	5%
20th Precinct	Manhattan: Upper West Side	15,423	4%
22nd Precinct	Manhattan: Central Park	3,701	**
23rd Precinct	Manhattan: East Harlem/El Barrio	52,640	20%
24th Precinct	Manhattan: Upper West Side, Manhattan Valley, Riverside Park	15,532	9%
25th Precinct	Manhattan: East Harlem	31,993	25%
26th Precinct	Manhattan: Upper West Side	17,400	4%
28th Precinct	Manhattan: Central Harlem	26,052	20%
30th Precinct	Manhattan: West Harlem, Hamilton Heights, Suger Hill	22,490	17%
32nd Precinct	Manhattan: Northeastern Harlem	39,382	24%
33rd Precinct	Manhattan: Washington Heights	18,378	20%
34th Precinct	Manhattan: Washington Heights and Inwood	33,789	18%
40th Precinct	Bronx: Port Morris, Mott Haven, Melrose	61,804	29%
41st Precinct	Bronx: Hunts Point, Longwood	31,620	31%
42nd Precinct	Bronx: Morrisania	36,918	30%
43rd Precinct	Bronx: Southeast	45,032	26%
44th Precinct	Bronx: Southwest, Yankee Stadium	51,908	27%
45th Precinct	Bronx: Northeast, Co-Op City	16,614	12%
46th Precinct	Bronx: Hunts Point, Longwood	35,396	28%
47th Precinct	Bronx: Woodlawn, Wakefield, Williamsbridge, Baychester, Edenwald, Olinville, Fishbay, Woodlawn Cemetery	34,158	19%
48th Precinct	Bronx: Belmont, East Tremont, West Farms	16,910	28%
49th Precinct	Bronx: Allerton, Morris Park, Van Nest, Pelham Parkway, Eastchester Gardens, Pelham Gardens	26,970	17%
50th Precinct	Bronx: Riverdale, Fieldston, Kingsbridge, Marble Hill, Spuyten Duyvil	9,267	11%
52nd Precinct	Bronx: Bedford Park, Fordham, Kingsbridge, Norwood, Bronx Park, University Heights	37,496	22%
60th Precinct	Brooklyn: Coney Island, Brighton Beach, West Brighton Beach, Sea Gate	33,933	18%

61st Precinct	Brooklyn: Kings Bay, Gravesend, Sheepshead Bay, Manhattan Beach	22,857	10%
62nd Precinct	Brooklyn: Bensonhurst, Mapleton, Bath Beach	18,567	13%
63rd Precinct	Brooklyn: Marshlands near Floyd Bennett Field	14,687	10%
66th Precinct	Brooklyn: Borough Park, Midwood, Kensington	13,972	18%
67th Precinct	Brooklyn: East Flatbush, Remsen Village	43,639	14%
68th Precinct	Brooklyn: Bay Ridge, Dyker Heights	10,308	13%
69th Precinct	Brooklyn: Canarsie	22,838	13%
70th Precinct	Brooklyn: Midwood, Fiske Terrace, Ditmas Park, Prospect Park South	39,767	13%
71st Precinct	Brooklyn: Crown Heights, Wingate, Prospect Lefferts	22,665	14%
72nd Precinct	Brooklyn: Sunset Park, Windsor Terrace	20,113	23%
73rd Precinct	Brooklyn: Brownsville, Ocean Hill	77,549	24%
75th Precinct	Brooklyn: East New York, Cypress Hills	93,220	21%
76th Precinct	Brooklyn: Carroll Gardens, Red Hook, Cobble Hill, Gowanus	18,320	16%
77th Precinct	Brooklyn: Crown Heights, Prospect Heights	37,527	16%
78th Precinct	Brooklyn: Park Slope, Prospect Park	12,529	9%
79th Precinct	Brooklyn: Bedford Stuyvesant	53,960	15%
81st Precinct	Brooklyn: Bedford Stuyvesant, Stuyvesant Heights	37,955	20%
83rd Precinct	Brooklyn: Bushwick	41,840	20%
84th Precinct	Brooklyn: Brooklyn Heights, Boerum Hill, Vinegar Hill	18,072	4%
88th Precinct	Brooklyn: Clinton Hill, Fort Green Park, Commodore Barry Park	23,881	11%
90th Precinct	Brooklyn: Williamsburg	41,922	18%
94th Precinct	Brooklyn: Greenpoint	7,401	8%
100th Precinct	Queens: Rockaway Peninsula	15,320	13%
101st Precinct	Queens: Far Rockaway, Bayswater	40,290	23%
102nd Precinct	Queens: Kew Gardens, Richmond Hill East, Richmond Hill, Woodhaven, Ozone Park	29,395	14%
103rd Precinct	Queens: Hollis, Lakewood, Jamaica	53,157	18%
104th Precinct	Queens: Ridgewood, Glendale, Middle Village, Maspeth	22,213	11%
105th Precinct	Queens: Queens Village, Cambria Heights, Bellerose, Glen Oaks, Floral Park, Bellaire	36,139	12%
106th Precinct	Queens: Ozone Park, South Ozone Park, Lindenwood, Howard Beach, Old Howard Beach	30,704	14%
107th Precinct	Queens: Fresh Meadows, Cunningham Heights, Hilltop Village	21,236	7%
108th Precinct	Queens: Long Island City, Sunnyside, Woodside	18,237	13%
109th Precinct	Queens: Downtown Flushing, East Flushing, Queensboro Hill, College Point, Malba, Whitestone, Beechhurst, Bay Terrace	38,612	11%
110th Precinct	Queens: Corona, Elmhurst	38,275	21%
111th Precinct	Queens: Bayside, Douglaston, Little Neck, Auburndale, Hollis Hills, Fresh Meadows	16,107	6%
112th Precinct	Queens: Forest Hills, Rego Park	12,978	8%
113th Precinct	Queens: Jamaica, St. Albans, Hollis, S. Ozone Park, Rochdale	35,262	16%
114th Precinct	Queens: Astoria, Long Island City, Woodside, Jackson Heights	36,262	18%

115th Precinct	Queens: Jackson Heights, East Elmhurst, North Corona, LaGuardia Airport	42,659	19%
120th Precinct	Staten Island: North Shore	55,329	17%
121st Precinct	Staten Island: Northwestern Shore	4,191	12%
122nd Precinct	Staten Island: South Shore	26,988	9%
123rd Precinct	Staten Island: South Shore	8,242	6%

NUM. SQF STOPS: Total number of recorded Stop, Question, and Frisk encounters between 2003 to 2022.

LOW EDUC. ATTAINMENT: Percentage of residents age 18 to 25 with a maximum educational attainment level below a high school diploma (or equivalent).

** Educational data for the 22nd Precinct (Central Park) have been omitted due to its lack of residential census.

Source: New York City Police, NYC.gov, ACS

Citations

[1] New York Civil Liberties Union (2022), "Stop-And-Frisk Data," <https://www.nyclu.org/en/stop-and-frisk-data>.

[2] *Floyd v. City of New York*, 959 F. Supp. 2d 540 - Dist. Court, SD New York 2013. <https://law.justia.com/cases/federal/appellate-courts/ca2/13-3088/13-3088-2014-10-31.html>

[3] *Terry v. Ohio*, 392 U.S. 1 (1968). <https://supreme.justia.com/cases/federal/us/392/1/#20>

[4] Priar, L. L.; Martin, T. F. (1955). "Searching and Disarming Criminals," *Journal of Criminal Law & Criminology*, Vol. 45, Issue 4, p. 481. <https://scholarlycommons.law.northwestern.edu/cgi/viewcontent.cgi?article=4291&context=jclc>

[5] Geller, Amanda; Fagan, Jeffery; Tyler, Tom; Link, Bruce G. (2014), "Aggressive Policing and the Mental Health of Young Urban Men," *The American Journal of Public Health*, December 2014, Vol. 104, No. 12, p. 2321.

[6] Vitale, Alex. *City of Disorder: How the Quality of Life Campaign Transformed New York Politics*. New York University Press, p. 47.

[7] Haldipur, Jan (2019). *No Place on the Corner: The Costs of Aggressive Policing*. New York University Press, p. 17.

[8] NYC.gov, "NYC Safety and Security Operation Impact" (2008), https://www.nyc.gov/html/unccp/gprb/downloads/pdf/NYC_Safety%20and%20Security_Operation%20Impact.pdf

[9] *Daniels v. City of New York*, 138 F. Supp. 2d 562 (S.D.N.Y. 2001). <https://law.justia.com/cases/federal/district-courts/FSupp2/138/562/2462331/>

[10] Legewie, Joscha; Fagan, Jeffery (2019). "Aggressive Policing and the Educational Performance of Minority Youth," *American Sociological Review*, p. 9; <https://osf.io/preprints/socarxiv/rdchf/>.

[11] Goel, Sharad; Rao, Justin M.; Shroff, Ravi (2016), "Precinct or Prejudice? Understanding Racial Disparities in New York City's Stop-and-Frisk Policy," *The Annals of Applied Statistics* Vol. 10, No. 1, p. 377.

[12] Vitale, p. 123.

[13] Bandes, Susan A.; Pryor, Marie; Kerrison, Erin; Atiba Goff, Phillip (2019), "The mismeasure of Terry stops: Assessing the psychological and emotional harms of stop and frisk to individuals and communities," *Behavioral Sciences & the Law*, Volume 37, Issue 2, p. 176.

[14] Legewie and Fagan, p. 2.

[15] Bandes, Susan A.; Pryor, Marie; Kerrison, Erin; Atiba Goff, Phillip (2019), "The mismeasure of Terry stops: Assessing the psychological and emotional harms of stop and frisk to individuals and communities," *Behavioral Sciences & the Law*, Volume 37, Issue 2, p. 176.

[16] Geller, Amanda; Fagan, Jeffery (2019). "Police Contact and the Legal Socialization of Urban Teens," RSF: The Russell Sage Foundation Journal of the Social Sciences, Vol. 5, No. 1, January 2019, p. 35. Project MUSE: <https://muse.jhu.edu/article/720074>.

[13] Geller and Fagan, p. 30.

[14] Geller and Fagan, p. 35.

[15] Legewie and Fagan, p. 2, 9, 16, 19, 24.

[16] Bacher-Hicks, Andrew; de la Campa, Elijah (2020), "Social Costs of Proactive Policing: The Impact of NYC's Stop and Frisk Program on Educational Attainment" (working paper), p. 27.

[17] Lafortune, Julien; Rothstein, Jesse; Schanzenbach, Diane (2016), "School Finance Reform and the Distribution of Student Achievement," Washington Center for Equitable Growth (working paper), p. 1; <https://equitablegrowth.org/working-papers/school-finance-reform-and-the-distribution-of-student-achievement/>.

[18] Bacher-Hicks, Andrew; de la Campa, Elijah (2020), "Social Costs of Proactive Policing: The Impact of NYC's Stop and Frisk Program on Educational Attainment" (working paper), p. 27.

[23] U.S. Bureau of Labor Statistics, "Quartiles and selected deciles of usual weekly earnings by educational attainment" for 3rd quarter 2024. <https://www.bls.gov/charts/usual-weekly-earnings/usual-weekly-earnings-by-quartiles-and-selected-deciles-by-education.htm>.

[20] Benjamin, Ruha (2019). *Race After Technology: Abolitionist Tools for the New Jim Code*, p. 121.

[21] Hager, Eli (2019). "Your Arrest Was Dismissed. But It's Still In A Police Database," The Marshall Project; <https://www.themarshallproject.org/2019/07/18/your-arrest-was-dismissed-but-it-s-still-in-a-police-database>.

[22] Hager.

[27] *Davis v City of New York*. <https://law.justia.com/cases/new-york/other-courts/2005/2005-25407.html>.

Data Repository

Github: <https://github.com/pingstanton/nypdsqf>

Dropbox: <https://www.dropbox.com/scl/fo/4j5bvlgnsvkeim2ipt2r8/AL4buYDMJ4FmeZTTpvk1Rk4?rlkey=f87shv0msi436viwg8oe3t8fo&st=rzn5ewsq&dl=0>

First sources

NYPD Stop, Question and Frisk Data: <https://www.nyc.gov/site/nypd/stats/reports-analysis/stopfrisk.page>

American Community Survey S1501 | Educational Attainment: <https://data.census.gov/all?q=Educational%20Attainment>

Special thank you

John Keefe (Census to Precinct Mapping): <https://github.com/jkeefe/census-by-precincts/tree/master/data/nyc>

Bibliography

Alexander, Michelle (2020). *The New Jim Crow: Mass Incarceration in the Age of Colorblindness*. New York: The New Press.

Bacher-Hicks, Andrew; de la Campa, Elijah (2020), "Social Costs of Proactive Policing: The Impact of NYC's Stop and Frisk Program on Educational Attainment" (working paper).

Bandes, Susan A.; Pryor, Marie; Kerrison, Erin; Atiba Goff, Phillip (2019), "The mismeasure of Terry stops: Assessing the psychological and emotional harms of stop and frisk to individuals and communities," *Behavioral Sciences & the Law*, Volume 37, Issue 2.

Benjamin, Ruha (2019). *Race After Technology: Abolitionist Tools for the New Jim Code*. Polity.

Correia, David, and Wall, Tyler (2022). *Police: A Field Guide (Second Edition)*. Brooklyn: Verso.

D'Ignazio, Catherine, and Klein, Lauren F. (2020). *Data Feminism*. Cambridge, MA: The MIT Press.

Floyd v. City of New York, 959 F. Supp. 2d 540 - Dist. Court, SD New York 2013.

Geller, Amanda; Fagan, Jeffery (2019). "Police Contact and the Legal Socialization of Urban Teens," *RSF: The Russell Sage Foundation Journal of the Social Sciences*, Vol. 5, No. 1, January 2019. Project MUSE: <https://muse.jhu.edu/article/720074>

Geller, Amanda; Fagan, Jeffery; Tyler, Tom; Link, Bruce G. (2014), "Aggressive Policing and the Mental Health of Young Urban Men," *The American Journal of Public Health*, December 2014, Vol. 104, No. 12.

Goel, Sharad; Rao, Justin M.; Shroff, Ravi (2016), "Precinct or Prejudice? Understanding Racial Disparities in New York City's Stop-and-Frisk Policy," *The Annals of Applied Statistics* Vol. 10, No. 1.

Hager, Eli (2019). "Your Arrest Was Dismissed. But It's Still In A Police Database," The Marshall Project; <https://www.themarshallproject.org/2019/07/18/your-arrest-was-dismissed-but-it-s-still-in-a-police-database>.

Haldipur, Jan (2019). *No Place On The Corner: The Costs of Aggressive Policing*. New York: New York University Press.

Hood, Quinn (2008). "Stop, Question, and Frisk Visualized," NYC OpenData. <https://opendata.cityofnewyork.us/projects/stop-question-and-frisk-visualized/> | <https://qhood01.github.io/nycSQF/>.

International Monetary Fund World Economic Outlook Database, <https://www.imf.org/en/Publications/WEO/weo-database/2022/October/weo-report>

IPUMS USA U.S. Census Data for Social, Economics, and Health Research, <https://usa.ipums.org/usa/>.

Keefe, John (2022). "Sharing NYC Police Precinct Data." <https://johnkeefe.net/nyc-police-precinct-and-census-data>

Lafortune, Julien; Rothstein, Jesse; Schanzenbach, Diane (2016), "School Finance Reform and the Distribution of Student Achievement," Washington Center for Equitable Growth (working paper). <https://equitablegrowth.org/working-papers/school-finance-reform-and-the-distribution-of-student-achievement/>.

Legewie, Joscha; Fagan, Jeffery (2019). "Aggressive Policing and the Educational Performance of Minority Youth," *American Sociological Review*. <https://osf.io/preprints/socarxiv/rdchf/>.

New York Civil Liberties Union (2022), "Stop-And-Frisk Data." <https://www.nyclu.org/en/stop-and-frisk-data>.

NYC Department of City Planning | Population Division (2021). "2020 Census Reconfiguration of Statistical Geographies: A Guide for New York City." <https://storymaps.arcgis.com/stories/d30850ba28944619b94e8ee4f746d5c4>

NYC.gov, "NYC Safety and Security Operation Impact" (2008). https://www.nyc.gov/html/unccp/gprb/downloads/pdf/NYC_Safety%20and%20Security_Operation%20Impact.pdf.

Maher, Geo (2021). *A World Without Police: How Strong Communities Make Cops Obsolete*. Brooklyn: Verso.

Packard, Samuel; Verzani, Zoe; Finsaas, Megan; Levy, Natalie S.; Shefner, Ruth; Planey, Arrianna M; Boehme, Amelia K.; Prins, Seth J. (2024). "Maintaining disorder: estimating the association between policing and psychiatric hospitalization among youth in New York City by neighborhood racial composition, 2006-2014," *Social Psychiatry and Psychiatric Epidemiology*. <https://doi.org/10.1007/s00127-024-02738-7>.

Priar, L. L.; Martin, T. F. (1955). "Searching and Disarming Criminals," *Journal of Criminal Law & Criminology*, Vol. 45, Issue 4. <https://scholarlycommons.law.northwestern.edu/cgi/viewcontent.cgi?article=4291&context=jclc>

Vitale, Alex S (2021). *The End of Policing (Updated Edition)*. Brooklyn: Verso.

Vitale, Alex S (2008). *City Of Disorder: How the Quality of Life Campaign Transformed New York Politics*. New York: New York University Press.

Terry v. Ohio, 392 U.S. 1
(1968). <https://supreme.justia.com/cases/federal/us/392/1/#20>.

U.S. Bureau of Labor Statistics, "Quartiles and selected deciles of usual weekly earnings by educational attainment" for 3rd quarter 2024. <https://www.bls.gov/charts/usual-weekly-earnings/usual-weekly-earnings-by-quartiles-and-selected-deciles-by-education.htm>