# Weapon Prevalence and Police Use-of-Force[1]

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This analysis studies the impact of weapon prevalence and perceived weapon prevalence in New York City precincts on police use-of-force and shows that greater weapon prevalence is associated with higher use-of-force. We contribute to the literature through providing a bridge between the impact of firearm prevalence on public health and crime and research regarding police use-of-force. We show that as weapon prevalence increases police use-of-force rises alongside it, and further, the increased use-of-force is correlated with perceptions of firearm prevalence regardless of whether a firearm is actually present. Using various treatment effect models, we show that precincts with higher weapon prevalence had more adverse responses to the 2020 (COVID-19 era) jump in NYC gun prevalence than those with lower weapon prevalence.

[1] This analysis reference Suicide and Child Fatalities statistics. These elements are an undeniable reality of firearm prevalence but are not the subject of this analysis. This analysis also discusses racial disparities in police use-of-force. We allow for an impact of race in the model, but we make no claims about why race plays a role in police use-of-force. This analysis does not discuss whether use-of-force was justified or excessive.

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# 1. Introduction

The principal question answered in this analysis is the following: *does increased weapon prevalence in New York Police Department (NYPD) precincts lead to increased police use-of-force*? Firearms are incredibly commonplace in the United States and their prevalence has consequences that touch every part of American life. This analysis explores one particular consequence of firearm prevalence: police use-of-force.

Figure 1: Correlation between Use of Force Incidents and Weapons Arrests in New York City Precincts, 2017-2024

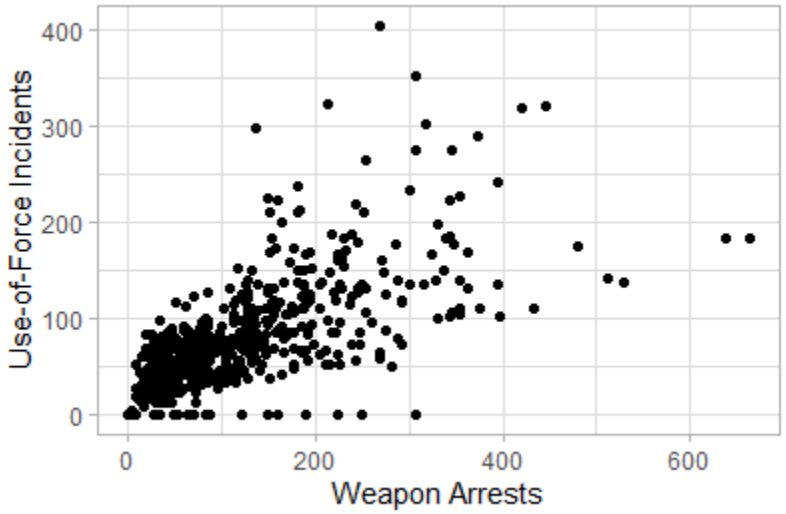



*Figure notes:* This figure shows the raw correlations between use-of-force incidents and weapons arrests at the precinct level between 2017 and 2024. Each point represents once precinct-year observation, A weapons arrest constitutes an arrest in a precinct under New York Penal Code Article 265 Firearms and Other Dangerous Weapons (New York Penal Law Ch. 40, Part 3, Title P). Police use-of-force are incidents of force used by NYPD Members of Service including both physical force and firearms discharges. These concepts are described in greater detail in Appendix A. New York City has 77 precincts

Figure 1 shows that NYPD precinct level weapon arrests are positively correlated with police use-of-force between the years 2017-2024. How precincts differ from each other in characteristics and across time is used to paint a fuller picture of the relationship between weapons prevalence and use-of-force. We show throughout this paper that there is a clear correlation between different measures of weapons prevalence (often measured by weapons arrests and use-of-force. We use various econometric tools and models to show that this relationship is statistically robust and causal. These conclusions are drawn from the preponderance of evidence rather than any one model or piece of analysis. Each model has weaknesses exacerbated by the public, and therefore limited, nature of the

data. However, between these model's overlapping assumptions and concurring results, we believe that these conclusions are compelling and statistically sound.

After a discussion of the literature and an examination of correlations we turn to econometrics. We use OLS models to show that the correlation holds even when accounting for potential omitted variables. Difference-in-Difference (DiD) and Two-Way-Fixed-Effects (TWFE) models are also used to take advantage of the non-uniform distribution of 2020 changes in weapons prevalence across New York City to craft a continuous treatment experiment and isolate the causal effects of weapon prevalence on use-of-force from other trends in the data.

We draw almost exclusively from New York City data; statewide statistics, when used, provide a comparison to trends present within New York City. The data sources used in this analysis include panel data generated from NYPD reported incident level data, precinct level data from the U.S. census and statewide data from the Federal Bureau of Investigation (FBI) (FBI, 2025) and Bureau of Alcohol, Tobacco, Firearms and Explosives (ATF) (ATF, 2025). Incident level data include arrest data (NYC Opendata – Arrests[4]), stop-question-and-frisk (SQF) data (NYPD, 2017), firearm report data (NYPD, 2024) and shooting data (NYC Opendata – Shooting Incidents) compiled by the author.

Using only New York data has the advantage of consistency in the law across the data, however, it introduces limitations on the ability to thoroughly study the impact of laws as treatments or to draw strong conclusions from statewide data. New York City may not be the actual location of the firearms surveyed statewide. That said, New York City is one of the largest and most diverse cities, economically, socially, and demographically, and arguably provides for a nationally representative cross section of America. Over eight million people live within New York, and another 10 million in the outside metro area, of which several million commute into New York regularly, and are present in NYPD data when they are arrested, stopped, or even shot.

This analysis provides a bridge between the research on the impact of firearm prevalence on public health and crime and the research on police use-of-force. This analysis supports previous research that has found links between statewide firearm prevalence and the use of lethal force. However, we go a step further and narrower than these prior studies by looking at all instances of force and incident level correlations, but for only one city, New York. The explanatory model tested in this analysis avoids the endogeneity issues that plague much of crime and firearm prevalence research as we are focused on police response to increasing prevalence rather than gun-owner responses to crime. We also

[4] Incident level arrest data is drawn from two, annually updated, NYC Opendata datasets: *Historic*, which ranges from 2006 - early 2024 and *Year to Date,* which includes the whole of 2024.

demonstrate that police *perceptions* of firearm prevalence can shape their use-of-force regardless of the actual presence of a firearm in that incident.

## 2. Background and Literature Review

There are 77 precincts across five boroughs included in this analysis.[5] The population density of New York City is far from uniform – Staten Island is relatively suburban with a population dwarfed by every other borough. Though three precincts have similar population sizes – around 20 precincts each in Manhattan, Brooklyn (a.k.a Kings County)[6], and Queens – there are only 12 precincts in the Bronx and four precincts in Staten Island. Manhattan also includes Time Square which has a considerable but relatively small population and Central Park which has almost no population; both Time Square and Central Park have plenty of arrests.

Of New York City's 8.2 million resident population, just over 31 percent are non-Hispanic White, a bit over 20 percent are Black. 30 percent of New Yorkers identify as Hispanic (U.S. Census, 2024). Non-Hispanic White New Yorkers make up the plurality of most boroughs, and the majority of the Staten Island population. These statistics are shown by borough in Figure 2 below.

Figure 2: Racial and Ethnic Breakdown of the City of New York by Borough, 2020

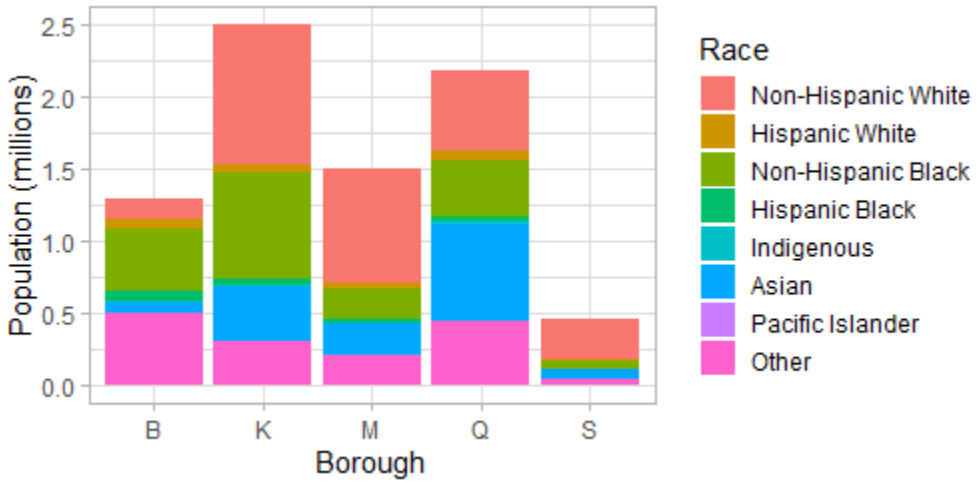



*Figure Notes:* This figure is drawn from 2020 Census Borough statistics aggregated by borough. Each bar represents the total population of each borough while the bands show the population for each borough by race. The variable shown is *Total Population of One Race*. The U.S. census defines Hispanic as an ethnicity and is included in a separate section that delineates between Hispanic and non-Hispanic respondents. Many New Yorkers identify

[5] The 116th Precinct is not included in this 77 as it only opened at the end of 2024

[6] The borough of Brooklyn and Kings County are coextensive and for this reason the data in this analysis uses "K" to indicate Brooklyn rather than "B", which is already used to indicate the Bronx.

solely as Hispanic. ”Other” includes those whose identities are not separately specified in the census data and those who identify as multi-racial.

The racial distribution of the population shown in Figure 2 is not reflected in arrest Data, SQF data, nor shooting incident data[7]. Nearly half of those arrested (roughly 45 percent) in 2019 were Black, followed by Hispanic at 30 percent and White at 15 percent. Black subjects make up 60 percent of stops; Hispanic and White subjects make up 30 and 10 percent of stops respectively. The lack of demographic proportionality across measures of weapon prevalence is also reflected in shooting rates – for both victims and suspects. A significant majority of shooting victims and SQF stops are Black. These data are shown in more detail in appendix A Figures A1 through A4.[8]

Figure 3: Primary Reason for an Arrest by Borough, 2019

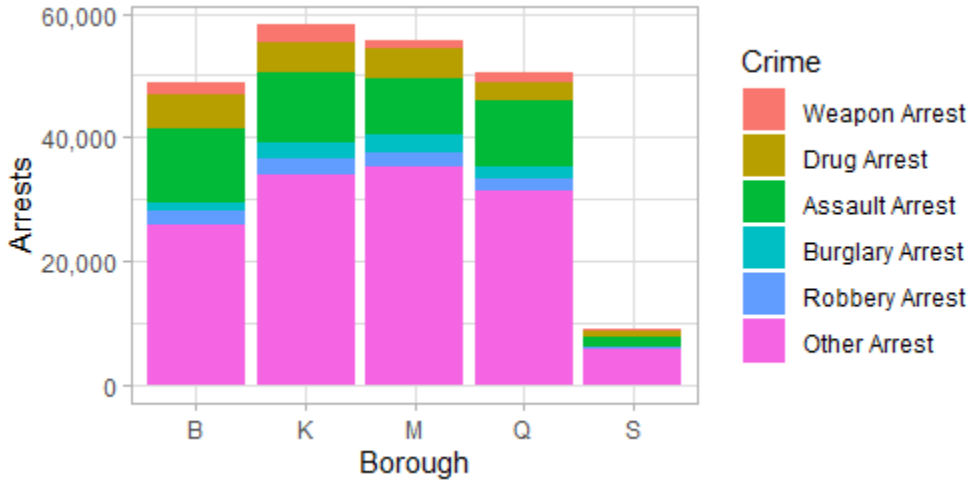



*Figure Notes:* This figure is drawn from 2019 arrest data aggregated by borough. Each bar represents the total arrests in each borough while each band represents the total arrests of a common category of arrests within said boroughs, while “Other arrests” include all other arrests. Only the primary alleged crime is reported in the NYPD data used in the figure even if the subject is being arrested for multiple crimes.

Figure 3 shows the number of arrests for a range of common crimes.[9] Weapon arrests, used in this analysis as a direct measure of firearm prevalence, only make up a fraction of all arrests across New York. In 2019, less than half of all New York City arrests were for weapons, drugs, assaults, burglary, or

[7] The processing of this data is discussed in Appendix B: Data Aggregation.
[8] An observation in these data does not mean the subject or victim resides in the precinct or borough in which they appear in the data; they may not even reside in New York. The publicly available NYPD data used in this analysis does not include residential origin and therefore cannot answer questions about mobility and crime.
[9] This is drawn from arrest data but does not show the additional crimes for which the subject may have been charged.

robbery, though these arrests do make up a sizable proportion of total arrests. Weapons arrests are often the sole charge in cases where there is a weapons arrest. However, violent crimes constitute the plurality of secondary charges. Furthermore, suspicion of criminal possession of a weapon (CPW) is the provided justification for the plurality of stops.

This study supports previous research that has found links between statewide firearm prevalence and the use of lethal force. For example, in *Firearm Availability and Fatal Police Shootings* (Nagin, 2020), the author shows a positive correlation between state firearm availability and police use of lethal force. In the meta-analysis, *A Decade of Police Use of Deadly Force Research (2011–2020)* (Mora et al., 2022), the presence of a firearm was consistently found to be a significant contributing factor to the use of lethal force across most of the studies included.

Discussions of weapon prevalence and crime must navigate an endogeneity problem. People buy guns to commit crime, but they also buy guns for self-defense or as a hobby. There are many papers that try to disentangle this endogeneity; these papers have led to a plethora of conflicting results and a paper for every combination of the words "more," "less," "guns," and "crime." John Lotts's *More Guns, Less Crime* (Lott, 2010) argues that the introduction of legal concealed carry licenses in a state is correlated with a drop in violent crimes. *More Guns, More Crime* (Duggan, 2001) on the other hand, argues that higher weapon prevalence is correlated with higher homicide rates, although weapon prevalence does not have as strong a correlation with other crimes. The RAND corporation's fourth edition of *The Science of Gun Policy: A Critical Synthesis of Research Evidence on the Effects of Gun Policies in the United States* (Smart et. al., 2024), finds in general, that the methodologies of many firearm research papers is lacking. However, they do find that there is evidence that specific forms of gun control, such as waiting periods and "red flag" laws[10], do decrease violent crime, suicides, and homicides. This meta-analysis did not find papers with comparably good methodologies that suggest an opposite correlation. (ibid)

The main limitations that these various analyses face are twofold. First, state laws are inconsistent across time, and second, any treatment analysis is tainted by the legal grey area that is the movement of firearms between states. Supreme Court decisions are difficult to apply to time series data because of inconsistencies between the apparent nature of the decisions and the actual application to state law. *District of Columbia (DC) v Heller* (554 U.S. 570 2008), for example, overturned a DC law governing

[10] Waiting period laws require a person who acquires a gun permit to wait a set amount of time before making the purchase. Red flag laws allow certain individuals to petition the local court to deny another individual a gun permit. The laws vary across jurisdictions.

handgun possession and trigger locks,[11] but at the same time reinforced the State's right to legislate gun control. Many years later, in the case *New York State Rifle & Pistol Association v. Bruen* (597 U.S. __ 2022), the Supreme Court found unconstitutional New York's law requiring justification for a concealed carry license, and New York quickly responded with the *Concealed Carry Improvement Act* which requires proof of "Good Moral Character," which has been largely upheld. In summary, the enactment or overturning of various gun control laws, and the implementation or undoing of the law is not instantaneous.

National studies of gun control laws must also address that most guns are legally purchased, and when moved across state lines, often do so legally prior to their use in crime. A 2022 ATF gun trace study, the *National Firearms Commerce and Trafficking Assessment (NFCTA): Crime Guns - Volume Two*, found that New York had one of the longest average times between a firearm's sale and its recovery from a crime (time-to-crime, or TTC), but that 72 percent of recovered firearms were recovered from a different person than the purchaser. While we try in this paper to avoid getting entangled by the endogeneity of gun purchase and crime, New York State TTC data is used to investigate the kinds of weapons NYPD officers encountered in 2020 and the impacts of these weapons on use-of-force.

While the literature on weapons prevalence, gun-control and crime is conflicting and often inconclusive, many studies on firearms and public health have shown fairly consistent detrimental impacts on communities from firearm prevalence, particularly on suicides and youth fatalities. RAND's meta-analysis, *How Gun Policies Affect Suicide* found consistent results linking the two, and the positive impact of gun control on addressing this public health crisis (RAND, 2024). The Center for Disease Control (CDC) found that in 2022, 30 percent of firearm deaths were youth between 15-17 years old (Villarreal et al., 2024). Firearm fatalities are now the leading cause of youth fatalities. Many youth firearm fatalities are suicides, the percentage of which has been growing steadily, particularly among Black and Hispanic youth (ibid). Over half of all firearm deaths in total are suicides, however a significant portion of youth fatalities are from unintentional discharges. Further analysis of the CDC's National Violent Death Reporting System found that unintentional injuries were the leading cause of fatalities for those 17 and younger; among such injuries, the leading cause of injury was firearms (Wilson, 2023). Half of all youth who died from unintentional firearm fatalities were shot by others; 36 percent of the deaths were from self-inflicted wounds. 74 percent of firearms used in these incidents were stored loaded, and 76 percent were stored unlocked. These studies also found a disproportionate impact of firearms on

[11] Trigger locks are devices attached to firearms preventing the trigger from being pulled and rendering the firearm nonfunctional for self defense.

Black and Hispanic youth. For example, the homicide rate for Black youth was 18 times higher than the homicide rate of their White peers in 2022. (Villarreal et al., 2024)

Firearm prevalence also poses a risk to police officers. *Firearm Prevalence and Homicides of Law Enforcement Officers in the United States* (Swedler et al., 2015) found that 90 percent of Law Enforcement Officer (LEO) Homicides were carried out with a firearm, and they further found a positive correlation between high statewide firearm ownership rates and LEO occupational homicide rates.

Firearms also have significant impacts on the nature of intimate partner violence (IPV). Seven in 10 IPV deaths involve a firearm, 1.6 percent of all incidents of IPV involve a firearm (Sorenson, 2017). The 2024 RAND meta-analysis found moderate evidence across several studies indicating a positive correlation between the implementation of domestic violence related restrictions to gun ownership and lower IPV rates (Smart, et al., 2024). Domestic disturbance calls are considered one of the more dangerous calls on which police officers are sent; the nature of the call means that officers are not responding with the tactical support they might have for other incidents. However domestic disturbances can quickly turn violent with drastic consequences for everyone involved. An analysis of nation-wide line of duty officer fatalities from 2010-2014, found that 22 percent of call-responding officer fatalities were for domestic disputes and 18 percent for other domestic disturbances. Of these officers, more than a third were dispatched alone (Breul & Keith, 2016).

Firearms are commonplace in the United States. National surveys of gun ownership found that 32 percent of Americans 18 and older, owned at least one firearm. Survey data shows that 56 percent of those gun owners bought the firearm for self-defense, and 26 percent carry their firearm in public with a concealed carry license (English, 2022). The average gun owner has 5 guns, however only ⅔ of gun owners own multiple firearms (Ibid). A third of gun owners report having used firearms in self-defense, 1.67 million per year, however in 80 percent of those cases, no shot was fired (ibid). An oft cited National Self-Defense Survey (NSDS) issued in 1992 calculated that there are approximately 2.5 million incidents of defensive-gun-use (DGU) (Kleck & Gertz, 1995). The *Trends and Patterns in Firearm Violence, 1993–2018* (Kena, Truman, 2022) analysis of the National Crime Victimization Survey (NCVS) on the other hand found that there were only approximately 70,040 incidents of defensive gun use in 2018, a number dwarfed by the estimated 484,800 firearm victimizations, though the NCVS acknowledges that the nature of the survey would lead to an under-reporting of defensive gun use. In all crime victimization, firearms were only used in self-defense two percent of the time. There were also an estimated 125,400 incidents of firearm theft (Ibid). Both the NSDS and National Firearm Study have considerable methodological issues, The NSDS was a phone study that polled less than 5,000 gun

owners; the National Firearm surveyed 16 thousand gun owners. Assuming that nearly a third of the people in the U.S. own firearms, the NCVS, which polled 240 thousand people, would have polled considerably more gun owners, yet the NCVS calculates millions less DGUs. Furthermore, misrepresentation, including cases where someone reports an incident of self-defense that might be considered an aggressive act by others, would lead to an overestimate of DGUs. Lastly, the 2.5 million incidents of DGUs calculated by Kleck and Gertze imply a staggering amount of unreported firearm injuries and severe miscalculations of crime rates (RAND, 2018).

This analysis is primarily focused on incidents involving alleged or suspected criminal activity, and therefore conclusions must be qualified by this selection bias. However, police aren't exclusively interacting with criminals, even when their experiences and decision-making is shaped by those interactions. In short, merely because the data is primarily related to criminal activity, it does not mean any given subject in the data is committing a crime or has a criminal history. Importantly, not every gun related interaction with police is criminal. At the same time, many legally owned guns are used criminally. Amongst those who are currently serving time in federal prison, a Bureau of Justice Statistics Report found that one in five were carrying a gun while committing the offense for which they were indicted. Handguns were the primary type of gun carried and/or used (Alper & Glaze, 2019). Of those who possessed a firearm, 1.6 percent acquired their firearm from a retail source (Ibid).

We make no claims about use-of-force being justified or excessive, but we do allow for discrimination to play *a* role in any given interaction between police and subjects. *A Simple, Statistically Robust Test of Discrimination* (Gaebler & Goel, 2025) proposes a twofold test for the presence of discrimination: first a "Benchmark" test – disproportionality of observations – is applied, followed by an "Outcome" test – disproportionality of success rates. They argue that failing these two tests is a clear indication of discrimination. Their paper uses stop data from across California police Jurisdictions to measure how often Black Subjects are searched compared to White Subjects and how often the search successfully turns up contraband. If the search rate for Black subjects is higher yet the success rate is lower, the authors argue that Black subjects are searched under a *discriminatory standard of evidence* (Ibid). The results of that paper show that many California police Jurisdictions failed this robust test. In other words, many jurisdictions recorded disproportionate higher rates of searches of Black subjects coinciding with lower search success rates (Ibid). Furthermore, prior analysis that seemed to contradict studies of discrimination should at most be deemed inconclusive as even though a precinct might pass the benchmark test, they might still fail the outcome test or vice versa. We performed a similar robustness test on NYPD SQF data and found over half of NYPD precincts failed this robust test for

discrimination on stops in any given year. These results are in addition to the vastly disproportionate arrests and stops in NYC.

The literature of firearm epidemiology includes a series of dose-response studies on firearms and health outcomes. In these studies, the presence of firearms is dependent on the treatment. For example, *Adverse Childhood Experiences and Adolescent Handgun Carrying* (Jones, et al., 2023) demonstrated that increased Adverse Childhood Experience increased the likelihood of handgun carrying and the *Association Between Acute Alcohol Use and Firearm-Involved Suicide in the United States* (Lange, et al., 2023) concluded that increased alcohol consumption was linked to higher probability of firearm-suicide. We instead define the level of firearm prevalence as the treatment or *dose*. We rely on multiple econometric models to measure dose response, in particular Continuous Treatment DiD and Weighted TWFE models supplemented by Inverse Propensity Weighting (IPW) and Propensity Matching respectively.

While the treatment of firearms prevalence is a continuous variable, binary treatment models have an advantage of simplicity. We use the Differences-In-Differences model described in *Minimum Wages and Employment: A Case Study of the Fast Food Industry in New Jersey and Pennsylvania* (Card & Krueger, 1993) as a first pass analysis of the impact of the COVID-19 era jump in gun prevalence on police use-of-force. Card and Krueger designed this difference model to account for unknowns by taking advantage of the similarities between the "treated" and "untreated" fast-food stores. We apply the DiD model to NYC precincts, which share some similarities, as every precinct in New York is subject to the same laws and COVID-19 pandemic measures. The main distinction is between the model defined by Card and Kreuger and the application here is that the continuous treatment variable must be artificially bisected as "treated" and "untreated."

To address the pitfalls of artificially coercing the data into a binary treatment, we take inspiration from *Differences-In-Differences with A Continuous Treatment* (Calloway, et al., 2024) which suggests that the DiD model can be practically applied to atypical scenarios, such as non-binary treatment effects. In a similar approach to Two-way-fixed-effect models of continuous treatments, DiD uses a weighted binary variable to account for the difference between the dose and the average treatment dose. However, assuming a normal distribution of dose within the treatment group around the ingroup mean and a linear relationship between treatment and effect, the effect of the weighting itself should washout in aggregate. This application of DiD to continuous treatments relies on a few key assumptions, some shared with traditional DiD applications and some unique. First, a random, independent sampling and the parallel trend assumption are core assumptions to both the traditional DiD model and the

application to continuous treatments, the efficacy of those assumptions are discussed in the discussion section. We assume that the increase in weapons prevalence post 2020 is a continuous treatment, which is consistent with the distribution of weapons arrest rates across New York. However, as there are no "untreated" precincts, the power of the conclusions is limited. Calloway shows that, with a stronger reliance on the parallel trend assumption, the DiD model can still be applied to continuous treatments. Any conclusion, however, is limited to the effects of a *higher* dose vs a *lower* dose, not *no* dose (Ibid), or in the case of this analysis, the treated precincts received a higher "dose" of firearm prevalence in 2020 than the "untreated" precincts.

The effects of selection bias can be differenced out (Calloway, et al., 2024) if one makes a strong parallel trend assumption; if that assumption does not hold, at least in the aggregate, a DiD model supplemented by Propensity Score Matching only assumes parallel trends between *like* treated and untreated observations and can be used in its place. Geography and demographics contribute to the likelihood of a precinct receiving treatment. Precincts in the Bronx, for example, are much more likely to be treated than precincts in Staten Island, coinciding with the significant differences in arrests rates and population sizes in the two boroughs. In *Using propensity scores in difference-in-differences models to estimate the effects of a policy change* (Stuart, et al., 2015), the authors used propensity scores to weigh each observation according to the likelihood of being treated or untreated and applied these weights to a DiD model. To account for demographic and geographic effects on weapon prevalence and police use-of-force, we use propensity scores drawn from precinct level demographic and arrest data and apply those scores to the now weighted treatments of Firearm Prevalence in the DiD model.

Like the DiD model used in this analysis, some firearm studies have used Two-Way-Fixed Effects (TWFE) to investigate the intersection of firearms and public health. The paper *Neighbors Do Matter: Between-State Firearm Laws and State Firearm-Related Deaths in the U.S., 2000–2017* (Liu et al., 2020) which similarly analyzes treatment groups of significant population disparities and across several years applies a TWFE model to measure the impact of neighboring state gun laws on firearm deaths. Treatment in this study was defined as a high or low difference between the number of state gun laws of neighboring states. This study uses the contiguous 48 states and year as fixed effects to account for the changing nature of the state and the country as a whole. This study supports prior research concluding that lax gun laws were linked to higher gun fatalities, and further, that neighboring state gun laws affect firearm fatalities, in line with ATF gun trace data that shows disproportionate recovery of firearms in strict gun control states originating in looser gun control states. We differ from Liu et al. as we apply the

treatment instantaneously in 2020, as opposed to staggered impacts due to changing laws across the country.

The TWFE model has a few weaknesses that the nature of this analysis exposes. First, as discussed before, treatment is artificially conformed to a binary variable. The TWFE model can suffer from contamination issues when applied to staggered and heterogeneous treatments but applying an artificial uniformity in treatment may only conceal these issues. Calloway et. al. propose application of DiD models to continuous treatment to address the difficulties parsing causal inferences from similarly applied TWFE models. That said, both the TWFE model and the DiD model rely on a strong parallel trend assumption, and both use weighted treatment effects to measure the ”causal response” to a “dose.” The TWFE model has advantages over the DiD model, as the year-to-year changes in the precincts independent of the treatment is accounted for. However, presuming little variation in year-to-year changes in the precinct outside of the treatment, the effects measured in these models should both come out to approximately the same.

## 3. Data

We rely on multiple measures of weapon prevalence drawn from NYPD produced and publicly available incident level arrest data, stop-question-and-frisk (SQF) data, firearm report data and shooting data and statewide firearm purchase data and TTC data collected by the FBI and ATF. Use-of-force data is drawn from NYPD reports from 2017-2024. (NYPD, 2020) SQF data provides insights into perceptions held by officers prior to making a stop. Incident level data are all broadly similar in structure and include demographic information about the subject (and/or victim), the time, location and precinct of the incident, and for SQF and arrest data, details about the offense alleged or for which the subject was arrested. SQF data also includes data about use-of-force during the incident. This incident level data was aggregated at either the precinct or borough level and then merged to create the precinct and borough panel data used in this analysis. Census data compiled at the precinct level (Keefe, 2022) is used to place this research into demographic contexts. The data are further detailed in Appendix B: Data Aggregation.

Across many measures of weapons prevalence, between 2017-2024 there is a correlation between increased weapon prevalence and use-of-force.

Table 1: Simple Correlation Matrix between Weapons Prevalence and Use of Force in New York City, 2017 through 2024

| | Year | Stops | Suspicion of CPW | Susp. of CPW (Weight) | Weapon Arrest | SQF Arrests | Tossed |
|---|---|---|---|---|---|---|---|
| Year | 1.00 | 0.28 | 0.29 | 0.30 | -0.01 | 0.40 | 0.27 |
| Stops | 0.28 | 1.00 | 0.96 | 0.64 | 0.52 | 0.74 | 0.99 |
| Suspected CPW | 0.29 | 0.96 | 1.00 | 0.71 | 0.48 | 0.59 | 0.98 |
| Suspected CPW Weight | 0.30 | 0.64 | 0.71 | 1.00 | 0.64 | 0.46 | 0.68 |
| Weapon Arrest | -0.01 | 0.52 | 0.48 | 0.64 | 1.00 | 0.47 | 0.52 |
| SQF Arrests | 0.40 | 0.74 | 0.59 | 0.46 | 0.47 | 1.00 | 0.70 |
| Tossed | 0.27 | 0.99 | 0.98 | 0.68 | 0.52 | 0.70 | 1.00 |
| Weapon Found | 0.33 | 0.93 | 0.96 | 0.74 | 0.54 | 0.67 | 0.95 |
| Weapon Found Rate | 0.32 | 0.17 | 0.23 | 0.49 | 0.28 | 0.23 | 0.19 |
| SQF Draw and Point | 0.14 | 0.57 | 0.52 | 0.52 | 0.49 | 0.51 | 0.57 |
| SQF Verbal Commands | 0.28 | 1.00 | 0.96 | 0.64 | 0.51 | 0.73 | 0.99 |
| SQF Use-of-Force | 0.09 | 0.46 | 0.49 | 0.69 | 0.66 | 0.37 | 0.49 |
| Use of Force | 0.19 | 0.70 | 0.68 | 0.65 | 0.67 | 0.58 | 0.71 |

| | Weapon Found | Weapon Found Rate | SQF Draw & Point | SQF Verbal Commands | SQF Use-of-Force | Use of Force |
|---|---|---|---|---|---|---|
| Year | 0.33 | 0.32 | 0.14 | 0.28 | 0.09 | 0.19 |
| Stops | 0.93 | 0.17 | 0.57 | 1.00 | 0.46 | 0.70 |
| Suspected CPW | 0.96 | 0.23 | 0.52 | 0.96 | 0.49 | 0.68 |
| Suspected CPW Weight | 0.74 | 0.49 | 0.52 | 0.64 | 0.69 | 0.65 |
| Weapon Arrest | 0.54 | 0.28 | 0.49 | 0.51 | 0.66 | 0.67 |
| SQF Arrests | 0.67 | 0.23 | 0.51 | 0.73 | 0.37 | 0.58 |
| Tossed | 0.95 | 0.19 | 0.57 | 0.99 | 0.49 | 0.71 |
| Weapon Found | 1.00 | 0.41 | 0.55 | 0.94 | 0.57 | 0.71 |
| Weapon Found Rate | 0.41 | 1.00 | 0.19 | 0.17 | 0.44 | 0.25 |
| SQF Draw and Point | 0.55 | 0.19 | 1.00 | 0.57 | 0.51 | 0.58 |
| SQF Verbal Commands | 0.94 | 0.17 | 0.57 | 1.00 | 0.46 | 0.70 |
| SQF Use-of-Force | 0.57 | 0.44 | 0.51 | 0.46 | 1.00 | 0.61 |
| Use of Force | 0.71 | 0.25 | 0.58 | 0.70 | 0.61 | 1.00 |

*Table Notes:* The matrix shows the simple correlations among a variety of measures of force and related terms from 2017 to 2024 by precinct. Year is the year the stops occurred. Stops – aggregate reported SQF stops. Suspicion of CPW – SQF stop where the police believe the suspect may be in criminal possession of a weapon. Suspicion CPW (Weighted) – rate of suspected CPW stops over total arrests. Tossed – number of incidents a subject is searched, either their person, or their bag. Find rate – percentage of *tosses* where a weapon is found. Draw flags and Verbal flags are two of the various ways the SQF data reports incidents of force use, drawing and pointing a firearm, and verbal commands respectively. Use-of-force – number of reported use-of-force incidents.

Weapons arrests, shootings, and suspected CPWs all have high individual correlations with use-of-force (.67 and .61 respectively). Suspicion of CPW is also only vaguely correlated to the rate at which weapons are found (.23), a rate which is also only weakly correlated use-of-force (.25) even while both the level of suspected CPW stops and actually finding a firearm during a stop are very correlated

with use-of-force (.68 and .71 respectively), indicative of the important role perception plays in use-of-force. These measures are not solely correlated with use-of-force nor is use-of-force solely correlated with weapons prevalence.

Table 2: Correlation Matrix for Arrest Types and Use of Force, 2017-2024

| | Arrest Type | | | | | | Other Characteristics | | |
|---|---|---|---|---|---|---|---|---|---|
| Arrest/Characteristic | Weapon | Drug | Robbery | Burglary | Assault | Total | Shooting Incidents | Use-of-Force | Black |
| Weapon Arrest | 1.00 | 0.55 | 0.62 | 0.34 | 0.76 | 0.75 | 0.66 | 0.67 | 0.80 |
| Drug Arrest | 0.55 | 1.00 | 0.51 | 0.45 | 0.55 | 0.74 | 0.26 | 0.43 | 0.60 |
| Robbery Arrest | 0.62 | 0.51 | 1.00 | 0.54 | 0.84 | 0.77 | 0.51 | 0.65 | 0.65 |
| Burglary Arrest | 0.34 | 0.45 | 0.54 | 1.00 | 0.40 | 0.66 | 0.10 | 0.21 | 0.54 |
| Assault Arrest | 0.76 | 0.55 | 0.84 | 0.40 | 1.00 | 0.84 | 0.59 | 0.80 | 0.70 |
| Total Arrests | 0.75 | 0.74 | 0.77 | 0.66 | 0.84 | 1.00 | 0.38 | 0.61 | 0.82 |
| Shooting Incidents | 0.66 | 0.26 | 0.51 | 0.10 | 0.59 | 0.38 | 1.00 | 0.61 | 0.54 |
| Use-of-Force | 0.67 | 0.43 | 0.65 | 0.21 | 0.80 | 0.61 | 0.61 | 1.00 | 0.61 |
| Black | 0.80 | 0.60 | 0.65 | 0.54 | 0.70 | 0.82 | 0.54 | 0.61 | 1.00 |

*Table Notes:* This correlation matrix is drawn from arrest, shooting incident and use-of-force data from 2017-2024 aggregated by precinct and year. This matrix includes 5 categories of arrests: weapon arrests, drug arrests, robbery arrests, burglary arrests, and assault arrests. The matrix also includes correlations with the total level of precinct arrests. Lastly, the correlation matrix measures the correlations with shooting incidents, use-of-force and the arrests of Black subjects.

Assault arrests and robbery arrests are both positively correlated with use-of-force and to a much greater degree than drug arrest or burglary arrests. Weapons arrests, robbery arrests and assault arrests are highly correlated. These arrests are all mechanically linked. Felony assaults, robbery, and murder are all often committed with presence of a firearm; nearly 30 percent of prisoners serving time for violent offenses possess a firearm at the time of the offense (Alper & Glaze, 2019). Eight in ten murders were committed with a firearm (Gramlich, 2025). Felony assault is also mechanically linked to weapon arrests as felony assault is by definition committed with a weapon. The FBI's Uniform Crime Reporting program found that 36 percent of robberies involved firearms, making up two thirds of robberies involving weapons. (FBI, 2020) This correlation between weapons arrests and other arrests is less present between weapons arrests and burglary arrests – burglary does not involve violence or threats – and consequently there is a low correlation between burglary arrest rates and use-of-force. The mechanical links between weapon arrests and other arrests poses an issue of collinearity when performing a regression analysis. Dangerous drug offenses, which are often secondary charges to Criminal Possession

of a Weapon charges are not mechanically linked to weapons prevalence: one does not possess a firearm for the intention of committing a drug offense even if weapons are present during the drug offense.

The correlation table also shows a positive correlation between race and weapon prevalence as well as race and use-of-force. The correlation matrix shows that race plays a role in police interactions. Demographic breakdowns of arrests, shootings and stops all show disproportionate amounts of Black subjects, however, *find rates* – the rate at which contraband is found on a searched subject – illustrates that discrimination acts beyond proportionality.

Figure 3: Outcome/Benchmark Difference in Search and Find rates among Black and White Subjects

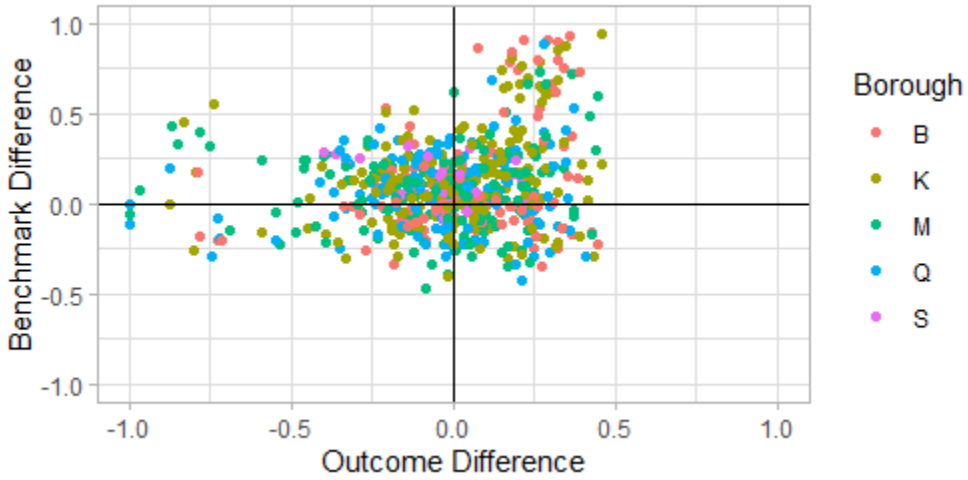



*Figure Notes:* This chart is drawn from SQF data from 2017-2024 aggregated by precinct and year and plots the results of twofold test for discrimination. "Benchmark Difference" measures the difference in the toss rates – number of searches per SQF stops – between Black and White subjects. A positive number indicates that black people are searched at a higher rate than white people in that precinct-year. "Outcome Difference" measures the difference in the find rates – percentage of searches that turn up contraband – between Black and White subjects. A negative number indicates a higher find rate for White subjects than Black subjects. Each axis measures a difference in rate and therefore range between [-1,1]. Each observation is color-coded by borough.

Figure 3 shows that discrimination is present in many NYPD precincts based on the Gaebler and Goel's methodology for exposing a *discriminatory standard of evidence* (Gaebler & Goel, 2025). This figure compares police SQF behavior by race. More precincts lie above the X axis than below, corresponding to disproportionately more searches of Black suspects. In precincts to the left of the Y axis, searches of Black suspects turned up contraband less often than searches of White suspects Many precincts land in the 2nd Quadrant (upper left) – these precincts have a higher search rate *and* a lower find rate of Black subjects relative to white subjects. In other words, the data suggests that Black subjects – across boroughs and precincts – are searched more often despite being less likely to possess

contraband and are therefore subject to a Gaebler and Goel's *discriminatory standard of evidence*. As stops are one of the main forms of police interaction, discriminatory SQFs would mechanically lead to disproportionate use-of-force even assuming the use-of-force itself was completely independent of discriminatory bias. Far from every precinct fails both tests; although many, in any given year, fail one test or the other. The robustness of this test is discussed in Appendix C: Validity of Robust Test for Discrimination.

OLS models, presented in the results section, show that the correlation between weapons prevalence and use-of-force holds even when accounting for potential omitted variables, such as race, other criminal activity, or changes in the boroughs. This correlation holds consistently from 2017-2024, despite changes to criminal and police activity and in particular, measures of weapons prevalence in 2020.

Figure 4: Weapon Prevalence and Use-of-Force across Time, 2017-2024

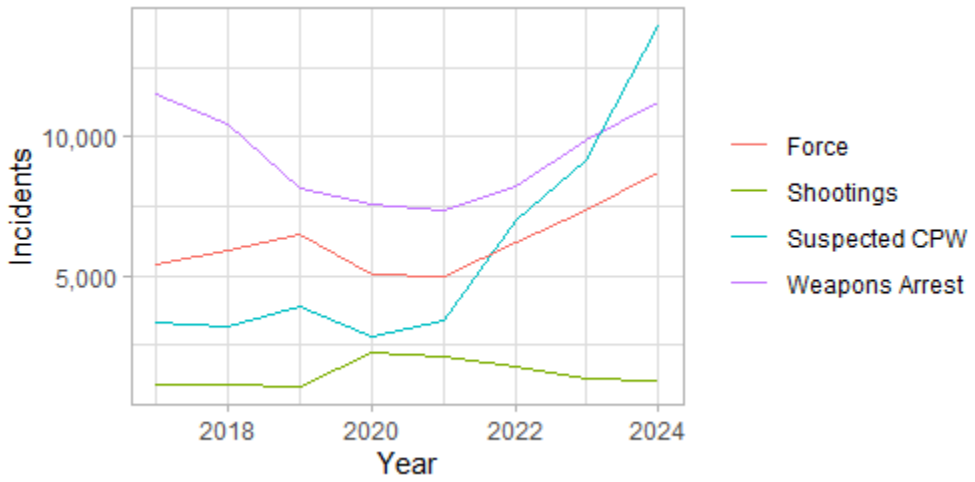



*Figure Notes:* This table is drawn from arrest, SQF, shooting incident and use-of-force data from 2017-2024. The figure shows, by year, the levels of incidents across the whole of New York City.

Prior to 2020, arrests – particularly weapon arrests – had been falling, while use-of-force had been on the rise. In 2020, shootings spiked preceding a significant rise in suspected-criminal-possession-of-weapons stops. Use-of-force and weapons arrests have been growing steadily since 2021 as well.

Statewide gun recovery data, shown in Figure 5, indicates that more recovered guns were recovered with low TTCs – indicative of higher likelihood of purchase with criminal intent, Levels peaked in 2020 and 2021 while remaining above pre-pandemic levels in 2023.

Figure 5: Firearms Recovered with TTC under 3 months, 2017-2024

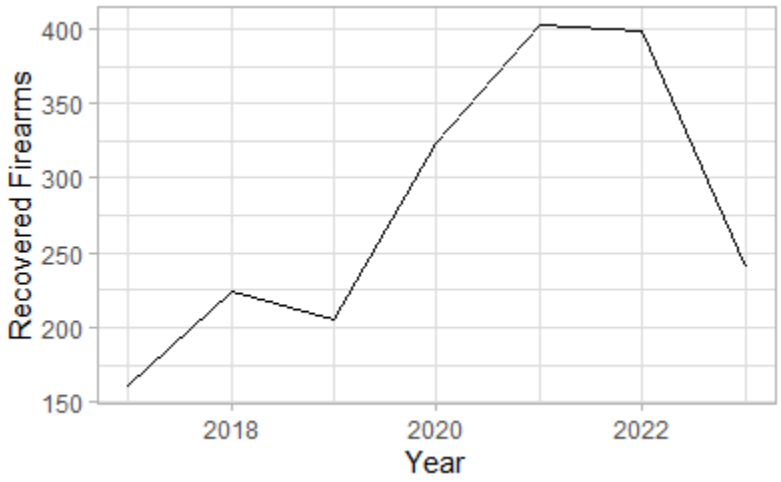



*Figure Notes:* This table is drawn from ATF gun recovery data. The line tracks the number of recovered firearms, across the whole of New York State with a less than 3-month time-to-crime.

# 4. Model Methodology

## Conceptual Framework

We rely on two models of police-subject interactions, the first, and underlying the whole of this analysis is the mechanical relationship between firearm arms and police behaviors. The decision to use force is determined by environmental conditions, time, location, resources, the implicit and explicit biases reinforced and evolved by experience, and the beliefs officers hold about a subject. The following excerpt from the NYPD patrol guide provides an explicit statement of the considerations for determining appropriate levels of force:

---

In determining whether the use of force is reasonable, members of service [MOS] should consider the following:

a. The nature and severity of crime/circumstances,
b. Actions taken by subject,
c. Duration of action,
d. Immediacy of perceived threat or harm to subject, members of the service, and/or bystanders,
e. Whether the subject is actively resisting custody,
f. Whether the subject is attempting to evade arrest by flight,
g. Number of subjects in comparison to number of MOS
h. Size, age, and condition of subject in comparison to MOS

i. Subject's violent history, if known,
j. Presence of hostile crowd or agitators, and/or
k. Subject apparently under influence of stimulant/narcotic which would affect pain tolerance or increase likelihood of violence.

---

NYPD Patrol Guide - Section: Tactical Operations, Procedure No: 221-01 , Subject: Force Guidelines, Page: 1 of 4

Figure 6 presents a Directional Acyclic Graph (DAG) where the presence of a firearm drastically increases the risk to officer and bystander safety and correspondingly increases likelihood of force being used. In this analysis, the arrest and environmental conditions are captured by the various descriptive statistics of a precinct. The typical arrests, number of shootings, and demographics of a precinct paint a picture of the environment officers are working in. Weapon prevalence in this model is measured using weapon arrests. Environmental conditions affect police use of force directly, since it is the environmental conditions that affect judgement, history, and the likelihood that circumstances meet one of the force criteria listed, such as the presence of a firearm. Environmental and arrest conditions also affect police use of force indirectly through their impact on weapons prevalence (and police perceptions of weapons prevalence). This model is tested in the next portions of the paper.

Figure 5: Directional Acyclic Graph

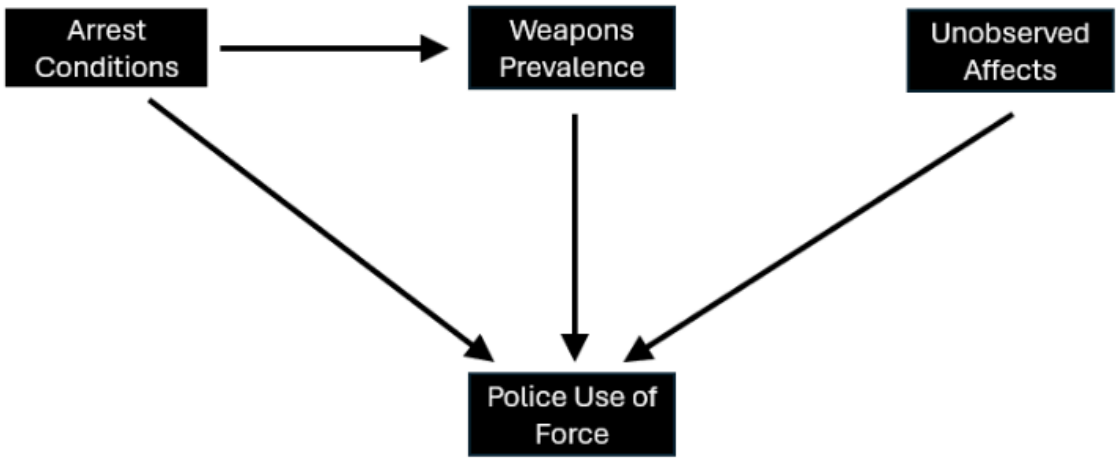



*Chart Notes:* This Directional Acyclic Graph (DAG) maps the underlying model tested in this paper. Arrest Conditions include every observable characteristic of an interaction between a subject and a member of service. Some of these conditions affect use-of-force, as well as perceptions of weapon prevalence. Weapons prevalence itself affects the likelihood of force being used. There are also unobservable factors that affect police use-of-force.

During a weapons arrest, the subject is arrested for illegally possessing a weapon. This may occur at the time of the incident, or the arrest may have taken place sometime after the alleged criminal incident. Either way, the officer would have believed the subject was armed or is likely to have been armed. The treatment of weapon prevalence in the experimental model is therefore measured as a quantity or rate of weapons arrests, as the actual number of firearms is unknown. While many other crimes are committed with weapons, such as robberies and assaults, more than three quarters of weapon arrests in 2024 were for just criminal possession of a weapon. The nature and effect of this measured treatment is dissected further in Appendix C: Validity of Measures of Weapon Prevalence/Perceived Prevalence.

The second pathway, overlaid upon the first, is the effect of *perceptions* of weapon prevalence on use-of-force. A firearm does not actually have to be present for officers to behave as if a firearm is present. Precincts with high numbers of shootings, likely have higher rates of gun prevalence, precincts that have more weapons arrests similarly have higher rates of weapon prevalence. The primary measure of perception is the "suspected crime" officers are investigating during a SQF encounter. In this model, the suspicion of a firearm can lead to greater use-of-force regardless of the actual presence of a firearm.

## Definition of Treatment

We use a change in weapon arrest rate – weapons arrests over total arrests – from 2019 to 2020 to define treatment. Of the 77 precincts in this data from those years, 21 precincts had a decrease in weapon arrest rates – considered untreated – and 56 had an increase – considered treated. Around a quarter of the precincts in each borough are untreated, except in Staten Island where two of the four precincts are untreated.

Weapon arrest rates are relative to total arrests in the precinct. A precinct may be considered treated even if the number of weapon arrests have fallen, as weapon arrests would still make up a larger percentage of police activity. Further analysis of the breakdown of arrests, shooting, and stops in precincts explores the distinction between weapon arrest rates and weapon arrest levels. Importantly, even if treated precincts did not in fact have a higher weapon prevalence, defined by gun ownership – we can still show that the *perception* of weapon prevalence and how often officers interact with firearms is still correlated with use-of-force. Despite this distinction, the measures for weapon prevalence are assumed to reflect true weapon prevalence in the precinct.

## Empirical Models

We assume that the empirical implications of this model are twofold. First, measured use-of-force would increase with the measured level of weapon prevalence. Second this trend would measurably hold even when accounting for other explanatory variables. OLS, DiD and TWFE models each have their own strengths and pitfalls, but taken together, they tell a compelling story. There is a measurable correlation between weapons prevalence and use-of-force and the OLS analysis shows that this correlation is distinct from race, level of arrest activity, and borough fixed effects. DiD analysis shows that the rise in weapons prevalence drives up use-of-force, however DiD relies on strong assumptions regarding the similarities between treated and untreated precincts and further, weapon prevalence may be endogenous to the precincts. TWFE matching should address some of the selection biases in the analysis and the OLS analysis suggests a positive relationship between weapons prevalence – including perception of prevalence – and use-of-force whether or not the precinct is "treated." The particularities of the assumptions relied on in this analysis are discussed in the Validity of Results section of the Appendix.

# 5. Results

## OLS Regression Tables

Regression Table 1: Arrests, Race, and Use of Force[12]

| | *Dependent variable: Use of Force* | | | | |
|---|---|---|---|---|---|
| | Specification (See Notes) | | | | |
| | (1) | (2) | (3) | (4) | (5) |
| Weapon Arrest | 0.385*** | 0.197*** | 0.106*** | 0.007 | |
| | (0.016) | (0.026) | (0.026) | (0.023) | |
| Black Suspect | | 0.022*** | 0.011*** | 0.016*** | |
| | | (0.003) | (0.003) | (0.002) | |
| Total Arrests | | | 0.016*** | -0.007*** | |
| | | | (0.002) | (0.002) | |
| Assault Arrest | | | | 0.125*** | 0.132*** |
| | | | | (0.008) | (0.004) |
| Constant | 35.922*** | 28.108*** | 9.332*** | 5.051** | 2.381 |
| | (2.439) | (2.461) | (3.037) | (2.548) | (2.446) |
| Observations | 619 | 619 | 619 | 619 | 619 |
| $R^2$ | 0.483 | 0.542 | 0.600 | 0.722 | 0.689 |
| Adjusted $R^2$ | 0.482 | 0.540 | 0.598 | 0.720 | 0.688 |
| Residual Std. Error | 38.974 (df = 617) | 36.727 (df = 616) | 34.337 (df = 615) | 28.659 (df = 614) | 30.245 (df = 617) |
| F Statistic | 577.115** (df=1;617) | 364.337*** (df=2;616) | 307.790*** (df=3; 615) | 398.595*** (df=4;614) | 1,365.821*** (df = 1;617) |
| *Note:* | | | | | *p<0.1; **p<0.05; ***p<0.01 |

*Table Notes:* This table is drawn from a series of standard OLS regressions on precinct panel data, where use-of-force is the dependent variable in all columns. Weapon Arrests is the main variable of interest, with additional explanatory variables added in columns 2, 3, and 4:Column 1 – Weapon Arrests, Column 2 – Weapon Arrests and number of Black subjects, Column 3 – Weapon Arrests, Black subjects, and overall arrest activity (Total Arrests), Column 4 – Weapon Arrests, Black subjects, Total Arrests, and Assault Arrests, Column 5 – Assault Arrests.

Regression Table 1 shows that weapon arrests are positively correlated with use-of-force even when accounting for subject race, and overall arrest activity (Total Arrests). Notably, however, the inclusion of

[12] OLS regression tables were produced using the Stargazer package (Hlavac, 2022) in R Studio.

assault arrests in Column 4 practically subsumes the measured impact of weapon arrests. This coincides with the tight correlation between weapon arrests and assault arrests found in the correlation matrix.

Regression Table 2: Arrest Rates, Force Rates and Borough Fixed Effects

| *Dependent Variable: Force Rate* | | | |
|---|---|---|---|
| | Specification (See Notes) | | |
| | (1) | (2) | (3) |
| Weapons Arrests Rate | 0.162*** | 0.087*** | 0.076*** |
| | (0.020) | (0.023) | (0.025) |
| Black Arrests Rate | | 0.014*** | 0.015*** |
| | | (0.002) | (0.002) |
| Kings | | | -0.003*** |
| | | | (0.001) |
| Manhattan | | | -0.004*** |
| | | | (0.001) |
| Queens | | | -0.004*** |
| | | | (0.001) |
| Staten Island | | | -0.0003 |
| | | | (0.002) |
| Constant | 0.023*** | 0.020*** | 0.023*** |
| | (0.001) | (0.001) | (0.001) |
| Observations | 619 | 619 | 619 |
| $R^2$ | 0.095 | 0.144 | 0.162 |
| Adjusted $R^2$ | 0.093 | 0.142 | 0.154 |
| Residual Std. Error | 0.011 (df = 617) | 0.01 (df = 616) | 0.01 (df = 612) |
| F Statistic | 64.435*** (df = 1; 617) | 51.956*** (df = 2; 616) | 19.784*** (df = 6; 612) |
| *Note:* | | | *p<0.1; **p<0.05; ***p<0.01 |

*Table Notes:* This table is drawn from a series of standard OLS regressions with borough fixed effects. This also uses arrest rates – number of arrests over total arrests. Force rate – incidents of force over number of arrests – is the dependent variable. The columns and the included explanatory variables are as follows: Column 1 – weapon arrests rate, Column 2 – weapon arrests rate and black arrest rate, Column 3 – weapon arrests, black arrest rate and borough fixed effects.

Regression Table 2 is similar to Table 1 using rates instead of levels. Use-of-force, weapon arrests, and arrests of black subjects are divided by the total amount of arrests in that precinct to calculate rates. In the case of Force Rate, this is not a count of instances of use-of-force in any given arrest but rather a measure of use-of-force relative to the arrest activity in the precinct. This table also uses borough fixed effects and shows that even across boroughs, weapon arrests rates are correlated with use-of-force rates. Use-of-force is similarly correlated with other measures of weapon prevalence.

Regression Table 3: Weapons Prevalence and Use-of-Force

*Dependent Variable: Force Rate*

| | Specification (See Notes) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Suspected CPW Rate | 0.069*** | 0.053*** | 0.039*** | |
| | (0.001) | (0.002) | (0.002) | |
| Find Rate | | 0.033*** | 0.029*** | |
| | | (0.002) | (0.002) | |
| Stop Rate | | | 0.099*** | |
| | | | (0.007) | |
| Shooting Incident Rate | | | | 1.212*** |
| | | | | (0.071) |
| Constant | 0.003*** | 0.002*** | 0.002*** | 0.006*** |
| | (0.0003) | (0.0003) | (0.0003) | (0.0010) |
| Observations | 1,522 | 1,522 | 1,522 | 1,522 |
| $R^2$ | 0.645 | 0.692 | 0.732 | 0.161 |
| Adjusted $R^2$ | 0.645 | 0.691 | 0.731 | 0.16 |
| Residual Std. Error | 0.01 (df = 1520) | 0.009 (df = 1519) | 0.008 (df = 1518) | 0.015 (df = 1520) |
| F Statistic | 2,760.572*** (df = 1;1520) | 1,703.244*** (df = 2; 1519) | 1,381.398*** (df = 3; 1518) | 291.111*** (df = 1; 1520) |
| *Note:* | | | | *p<0.10; **p<0.05; ***p<0.01 |

*Table Notes:* This table is drawn from SQF and shooting incident data, as well as use-of-force data. Suspected CPW rate measures the percentage of SQF stops for *suspected CPW*, Find rate measures the percentage of searches that turn up contraband. Stop Rate, Shoot Rate, and Force rate measures number of incidents over number of arrests. Force rate is the dependent variable. The columns and the included explanatory variables are as follows: Column 1 – suspected CPW rate, Column 2 – suspected CPW rate and find rate, Column 3 – suspected CPW rate, find rate and stop rate, Column 4 - shooting incident rate.

The results of Regression Table 3 are consistent with the correlation matrix in Table 1; the actual find rate of a stop is less correlated with use-of-force than suspicion of CPW. The number of stops is correlated with force as they are mechanically linked, however adding this variable doesn't drastically take away from the explanatory power of suspected CPWs.

## Treated vs Untreated Weapons Prevalence

We define treatment as an increased weapons arrest rate between 2019-2020 in the precinct. Of the 77 precincts in this data from those years, 21 precincts had a decrease in weapon arrest rates – considered untreated – and 56 had an increase – considered treated. Weapon arrest rates are relative to total arrests in the precinct. A precinct may be considered treated even if the number of weapon arrests have fallen, as weapon arrests would still make up a larger percentage of police activity. While treatment is defined by weapon arrests, the distinctions between treated and untreated precincts are present in other measures of weapon prevalence.

Figure 6: Treated/Untreated Weapons Rate, 2017 - 2024

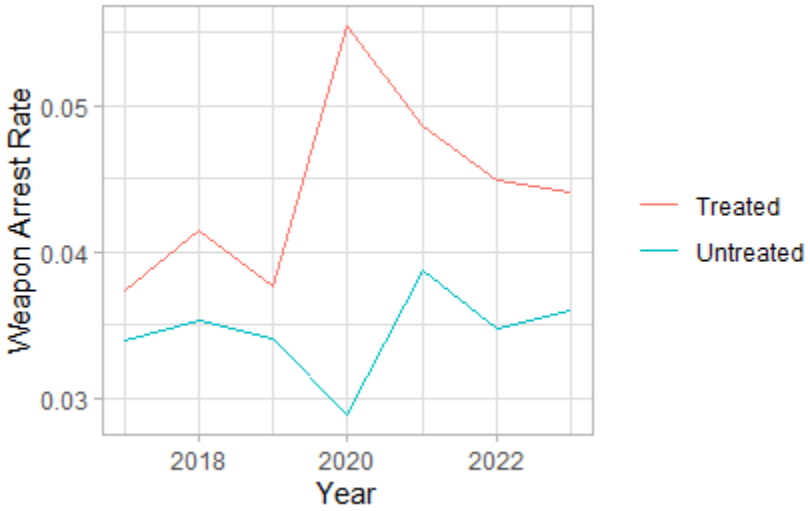



*Figure Notes:* This figure is drawn from arrest data from 2017 -2024. Weapons rate is the number of weapons arrests over the total arrests aggregated at the treatment group level.

Figure 6 shows that weapon arrest rates of "treated" precincts grew in 2020, where the rate for untreated fell. They moved closer together in later years but did not converge. Figure 7 shows that shootings spiked in 2020 for both groups, but to a greater extent for "treated" precincts.

Figure 7: Shooting Incident Precinct Average, 2017-2024

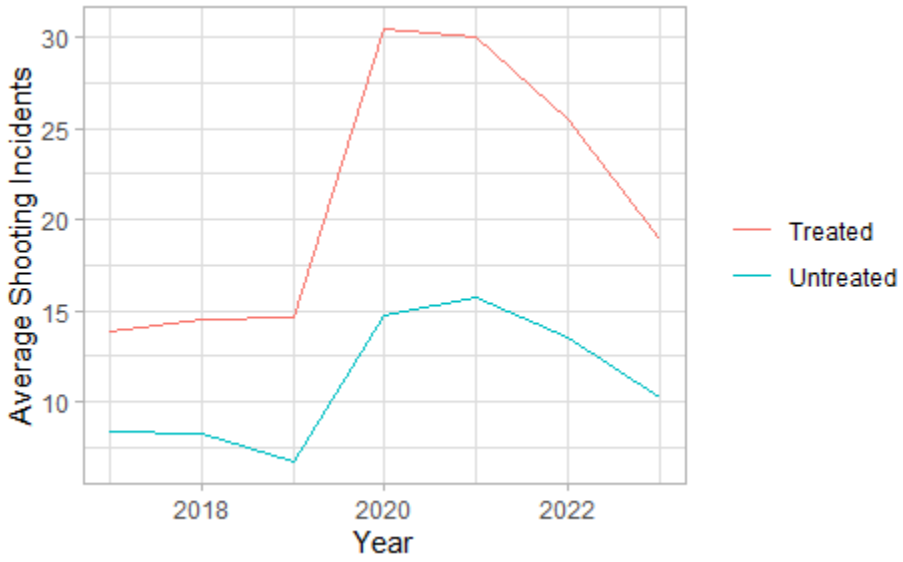



*Figure Notes:* This figure is drawn from shooting incident data from 2017 -2024. Shoot average is the number of shooting incidents in a precinct averaged across treatment groups.

Figure 8: Average Suspected CPW Stops Per Precinct, 2017-2024

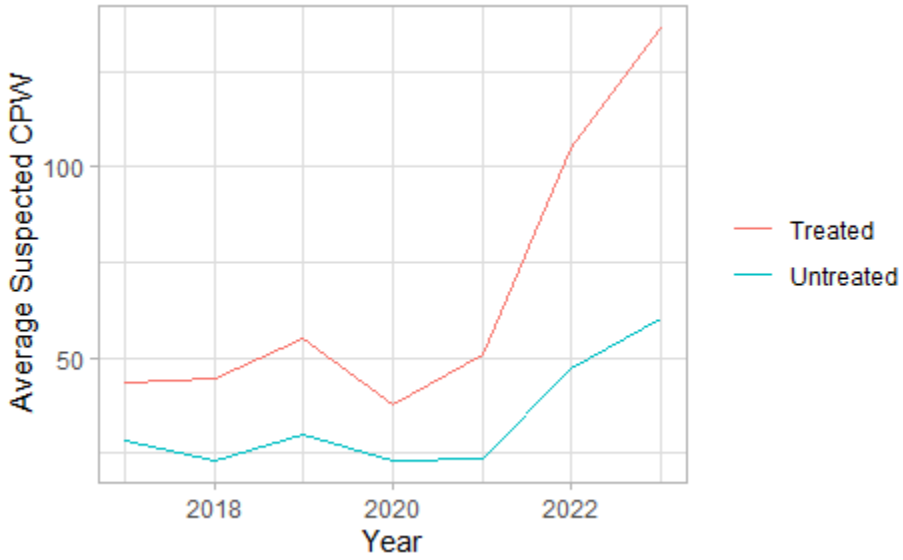


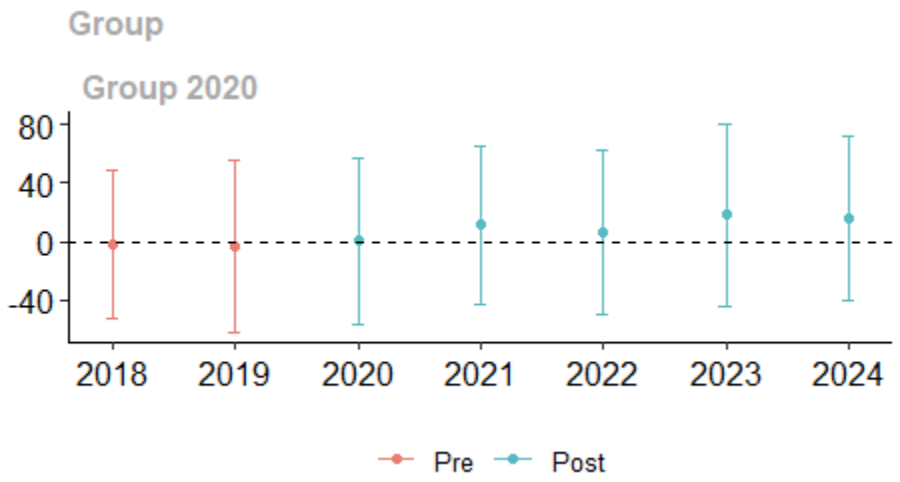

*Figure Notes:* This figure is drawn from SQF data from 2017 -2024. Suspected CPW average is the average number of stops for suspected CPW in a precinct across treatment groups.

In 2021, suspected CPWs began to grow significantly, particularly for treated precincts. In conjunction with the increased shootings, these results, (shown in Table 8) are indicative of a rising perception of firearm prevalence, if not actual weapon prevalence, and further that this growth is greater in “treated” precincts following 2020.

## Differences-in-Differences

The results of the DiD analysis, Figure 9 and 10, suggest a causal relationship between weapon prevalence and use-of-force. However, there is little statistical confidence in the effect.

Figure 9: Differences in Differences




[13]

*Figure notes:* This figure is drawn from precinct-year aggregated weapon arrest and use-of-force data. 2020 marks the beginning of treatment.

Figure 9 shows that there is a measurable effect of increased Weapons Prevalence on police Use-of-force, yet the error bars are extensive and inclusive. When Inverse Propensity Score Weighting (IPW) is used on the DiD model, shown in Figure 10, the measured effect falls even further, though is not eliminated entirely.

[13]DiD analysis was performed using the did package (Callaway, Sant'Anna, 2021) in R Studio.

Figure 10: Differences in Differences, Inverse Propensity Weighting

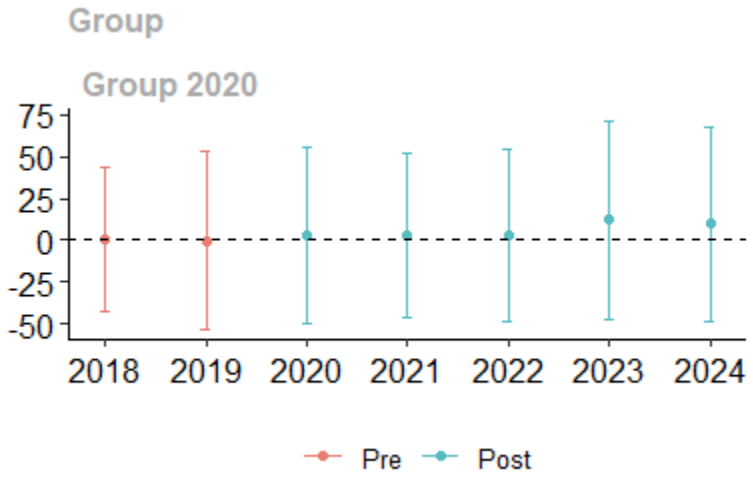



*Figure notes:* This figure is drawn from precinct-year aggregated weapon arrest and use-of-force data. 2020 marks the beginning of treatment. Precinct differences are weighted using IPW. Treatment begins in 2020.

## Two-Way-Fixed-Effects

TWFE Table 1: Treatment and Race[14]

| | *Dependent Variable: Use of Force* | | |
|---|---|---|---|
| | Specification (See Notes) | | |
| | (1) | (2) | (3) |
| Treated | 6.613 | 10.437*** | 12.116*** |
| | (4.158) | (3.967) | (4.488) |
| Black Suspect | | 0.023*** | 0.025*** |
| | | (0.003) | (0.003) |
| Observations | 616 | 616 | 616 |
| $R^2$ | 0.005 | 0.109 | 0.109 |
| Adjusted $R^2$ | (0.153) | (0.034) | (0.034) |
| F Statistic | 2.529 | 32.494*** | 41.096*** |
| | (df = 1; 531) | (df = 2; 530) | (df = 2; 530) |
| *Note:* | | | *p<0.10; **p<0.05; ***p<0.01 |

*TWFE Table 1:* Year and Precinct are treated as fixed effects. Columns 1 and 2 are unweighted effects of treatment and race on use-of-force. Column 3 is weighted by weapon arrest rates.

[14] TWFE analysis was performed using the plm package (Croissant, Millo, 2008) in R Studio.

The results of the TWFE on the other hand give us more confidence. The effect of treatment is greater when treatment is weighted. Interestingly, we find not accounting for Race leads to greater statistical uncertainty.

TWFE Table 2: Treatment, Race, and Propensity[15]

*Dependent Variable: Use of Force*

| | Specification (See Notes) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Treatment | 10.446*** | 11.443*** | 13.561** |
| | (3.985) | (3.330) | (5.478) |
| Black Suspect | 0.023*** | 0.020*** | 0.023*** |
| | (0.003) | (0.003) | (0.004) |
| Propensity Score | -0.189 | | |
| | -7.059 | | |
| Observations | 616 | 616 | 336 |
| $R^2$ | 0.109 | 0.108 | 0.108 |
| Adjusted $R^2$ | -0.036 | -0.035 | -0.067 |
| F Statistic | 21.622*** | 23.851*** | 17.028*** |
| | (df = 3; 529) | (df = 2; 530) | (df = 2; 280) |
| *Note:* | | | *p<0.10; **p<0.05; ***p<0.01 |

*TWFE Table 2:* Year and Precinct are treated as fixed effects. Column 1 uses Propensity Scores from a Binomial regression (treated or untreated). Column 2 uses Inverse Probability Treatment Weighting. Column 3 uses Propensity Score Matching

Binomial regression propensity score covariates result in a rather large, but statistically dubious, negative relationship between likelihood of treatment and use of force. On the other hand, Inverse Probability Treatment Weighting shows a positive correlation between treatment and use-of-force, though again statistically dubious. As does Propensity Score Matching, however as there are more treated precincts than untreated, not every treated precinct receives a match. These results were also consistent with previous results of a positive effect of weapons prevalence on police use-of-force.

[15] Propensity Matching was performed using the MatchIt package (Ho, Imai, King, Stuart, 2011)

# 6. Discussion

This analysis asks a yes or no question: does increased weapon prevalence in NYPD police precincts lead to increased use-of-force. It does not try to quantify that result. Many firearm epidemiology papers have shown with varying degrees of confidence that weapons prevalence is correlated with negative medical and sociological outcomes, however the problem of small numbers limits the ability to measure the magnitude of the impacts. We have to navigate this issue as well. While there are many arrests across NYC, there are significantly less instances of use-of-force, and many precincts have very few, – some years zero – suspected CPW stops and searches. There is also a lot of statistical noise in the data, driven by the nature of New York, the world, and mere random chance, not to mention the COVID-19 pandemic.

The COVID-19 pandemic in New York sent many people into isolation, and many mental health and economic consequences followed the initial outbreak. Criminal activity also shifted. 2020 was the low point in many precincts for arrest levels, and 2021 wasn't much higher, however shootings skyrocketed. We treat the impacts of COVID-19 as relatively universal, with few but still important differences across New York City. The change in New York City weapon prevalence was not uniform across precincts however we assume that the change in weapon prevalence is practically random and not the result of some unknown factor that also leads to greater police Use-of-force. In other words, while COVID-19 had impacted the level of criminal activity – suppressing it in 2020 and exacerbating in the years that followed – we attribute the changes in police use-of-force to the rise in weapon prevalence, or at least perception of weapon prevalence.

There is evidence that we underestimate the non-weapon connection between weapon prevalence and police use-of-force. Man-power shortages due to COVID-19 would have led to lower levels of arrests and higher stress for officers, both factors would lead to higher measured rates of use-of-force, as police would be spared for more serious calls. In other words, COVID-19 is a confounding variable even while being an effective treatment effect. Notably the correlation between weapons prevalence and use-of-force held before, during, and after COVID-19 policy measures.

There is a possibility that weapons prevalence is a symptom or merely coincidental to the true driver of use-of-force, however there are many reasons to suggest that this is not the case. The greatest indication that there may be some other driver is the measured correlations after the inclusion of other violent crimes in the OLS analysis. These results showed that when violent crimes are included, the correlation between weapons arrests and use-of-force is subsumed by the correlation between the

violent crimes and use-of-force. Police activity also fell during the pandemic due to policy, independent of falling crime rates. We use arrests as an indicator of police and criminal activity, these indicators may not be accurate reflections of activity. In some departments, traffic enforcement fell, while violent crime response rose (Nielsons, 2022). Police were considered *essential* front-line workers during the pandemic and therefore were still active – policing is not work-from-home compatible, yet their activities and priorities during the pandemic would have changed. Many crimes may have also gone unreported.

Despite these shortcomings, there are key elements of this analysis that suggest that even if there is some unmeasured driver of use-of-force, weapons prevalence still has an independent effect. First, the OLS model, while not accounting for every possible variable, includes borough fixed effects which should capture hidden geographic drivers. Second, violent crimes are mechanically linked to weapons, while not all violent crimes are committed with weapons, many are, and the presence of a weapon is a major element of use-of-force justification. Third, shootings are likely correlated to overall rises in otherwise unreported violent crime but are considered a measure of weapon prevalence in their own right. Essentially, even if this analysis was capturing the effects of rising violence, a claim for which we do not find a preponderance of evidence, then the results of this analysis would still show that weapons are inextricably linked to use-of-force. Lastly, SQF correlations show that perception of weapons prevalence has a strong correlation with use-of-force independent of the rate of finding a weapon, which has clear implications regarding the role weapons play in use-of-force decision making. A hidden explanatory variable would have to justify the disparity between these correlations – suspicion rates and find rates – as well as the coincident relationship between other measures of weapon prevalence and use-of-force.

# 7. Conclusions

Between NYPD statements of policy, correlation analysis of weapon arrests and stops, OLS analysis, and the Causal Experiments, the results in this paper support the conclusion that increased weapons prevalence has a measurable, positive, and independent effect on use-of-force by the members of the NYPD. While the DiD models did not present a clearly identified effect, there is a visible, if not statistically confident effect supported by a statistically confident TWFE result. These findings hold even when propensity scoring and treatment weighting are used to adjust for geographic and demographic impacts.

There is also compelling evidence from this analysis suggesting that perception of weapon prevalence is a key factor in the decision to use force, as suspicion of criminal possession of a weapon was positively correlated with the rate at which officers draw weapons during a stop, as well as the rate

of use-of-force more generally, while the percentage of weapons stop searches that actually produced a weapon was at most loosely correlated to use-of-force. The increase in use-of-force driven by COVID-19 era gun demand reinforces these conclusions. They also illustrate that this spike in gun demand marked a jump in the flow rate of guns into NYC and that many of those guns remained in NYC in the years that followed, contributing to the higher rates of police use-of-force even after COVID-19-related economic and social constraints diminished. These conclusions are drawn from the preponderance of evidence rather than any one model or piece of analysis. Between these model's overlapping assumptions and concurring results, we believe that these conclusions are compelling and statistically sound.

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# 9. Appendices

## Appendix A: Additional Figures

Figure A1: Arrests by Borough and Race, 2019

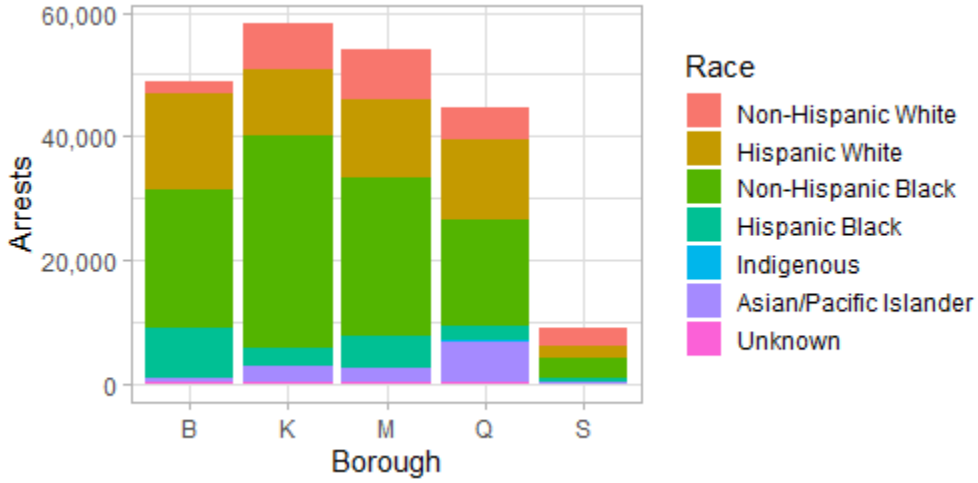



*Figure notes:* Drawn from arrest reports in 2019 aggregated by borough and race of subject.

Non-Hispanic Black subjects make up the plurality of arrests in all boroughs, even though Black New Yorkers are only a plurality of the population in one borough, the Bronx. The number of arrests is not as proportional to borough population as expected. Brooklyn has close to 60 percent more people than Manhattan but only a marginally greater number of arrests.

Figure A2: Suspected Shooting Perpetrators by Race, 2019

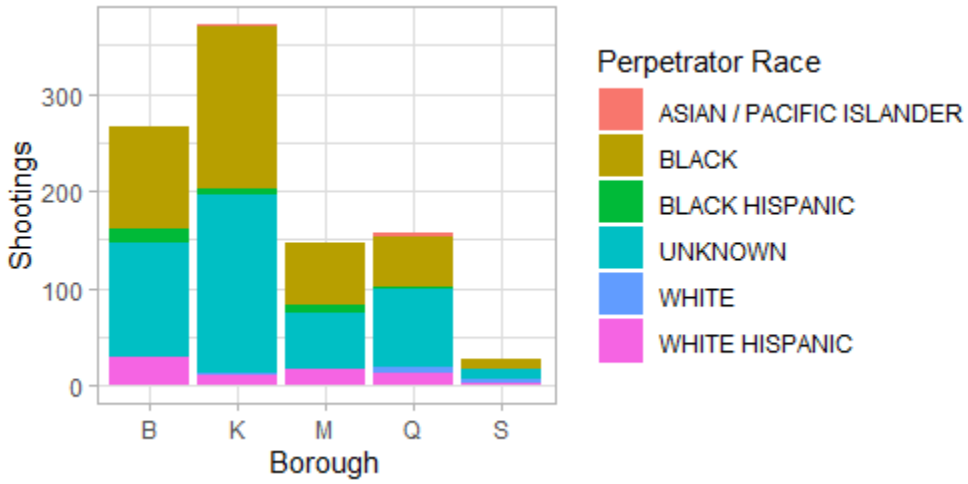



*Figure notes:* Drawn from shooting incident data in 2019 aggregated by borough and reported race of suspected perpetrator. Unknown indicates the race of the suspected perpetrator is unknown, or otherwise unreported.

The majority of suspected shooters where race is reported are Black. However, the race of the majority of suspected shooting perpetrators is unknown or unreported.

Figure A3: Shooting Victim by Race, 2019

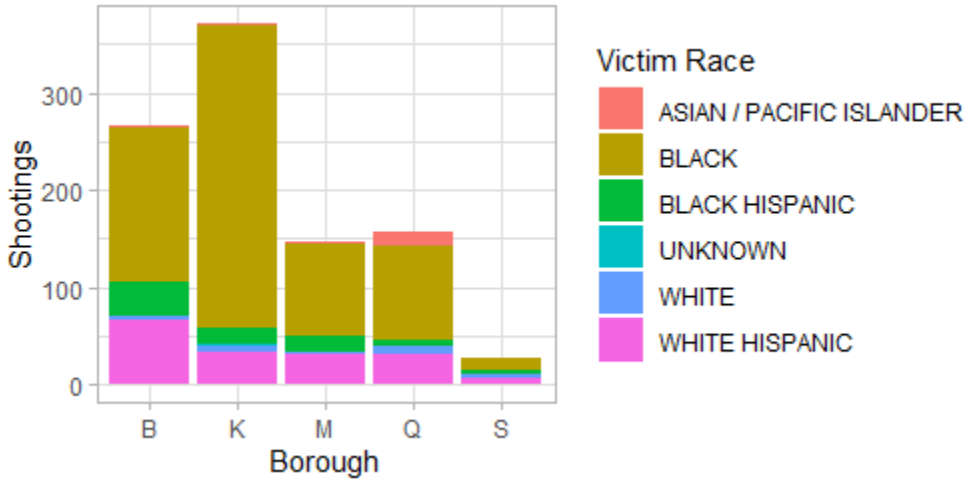



*Figure notes:* Drawn from shooting incident data in 2019 aggregated by borough and race of shooting victim. This chart does not make any indication of whether the shooting was fatal, however there is a murder flag in the shooting incident data.

The overwhelming majority of shooting victims in 2019 were Black. This is in line with prior research on the disparate impacts of firearms by race. The majority of suspected shooters have the same race as their victim conditional on the race of both being known.

Figure A4: SQF stops by Race, 2019

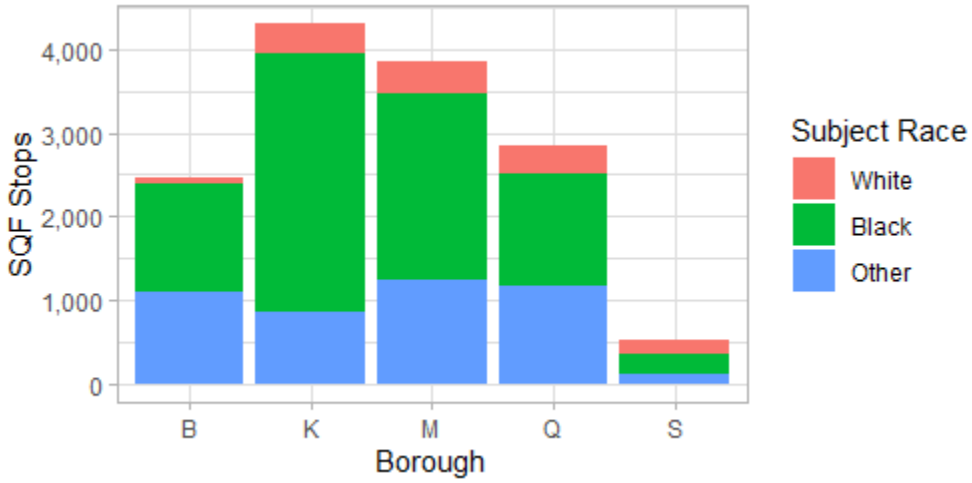



*Figure notes:* Drawn from SQF data in 2019 aggregated by borough and race of subject. Others include White/Black Hispanics as well as every other racial identifier besides White and Black.

In 2019, Black subjects were stopped the most often. White subjects made up only a small fraction of police stops.

Figure A5: SQF stops by Suspected Crime, 2019

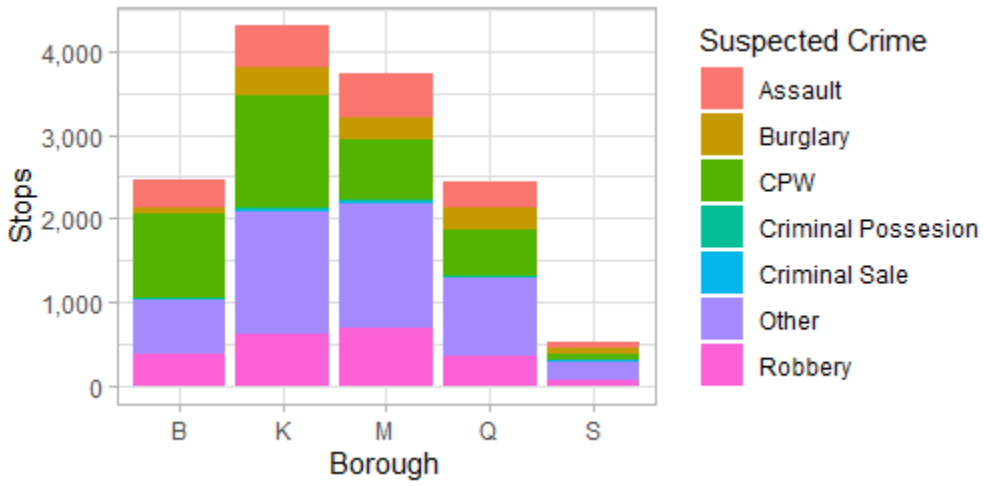



*Figure notes:* Drawn from 2019 SQF data aggregated by borough and suspected crime.

*Suspected criminal possession of a weapon* makes up the plurality of stops. Stop levels are approximately proportional to arrests. Arrests and stops are mechanically linked as many stops turn into arrests. This information is drawn from 2019 SQF data.

Figure A6: SQF suspected CPW stop rates by borough, 2017-2024

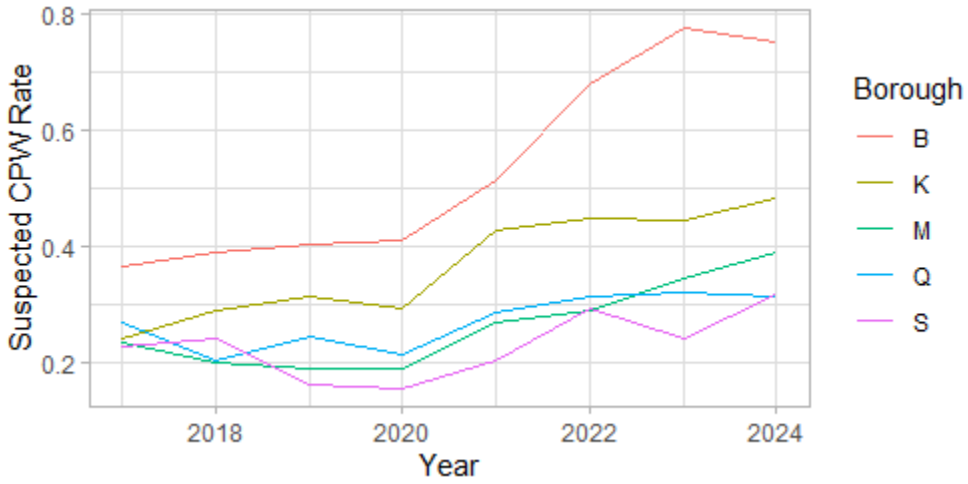



*Figure notes:* Drawn from SQF data aggregated by borough from 2017-2024. Each line represents the borough's suspected CPW rate – percentage of SQF stops that are for suspected CPW.

The rate of suspected CPWs – the percentage of stops that are suspected CPWs – has been growing across New York City since 2020, with the most drastic increase in the Bronx. The higher rate of suspected CPWs has persisted even after COVID-19 era policies and restrictions ended.

Figure A7: Top Charges With Firearm Charge, 2024 Q4

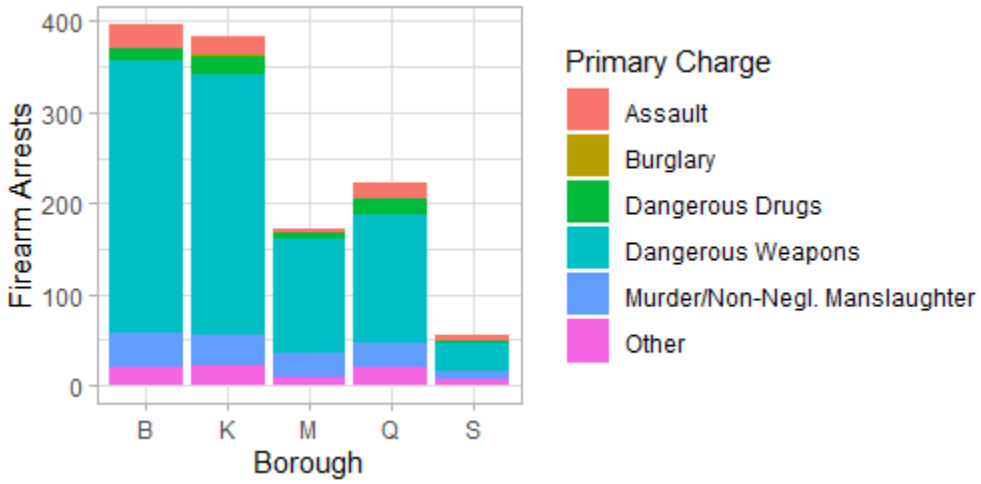



*Figure notes:* Drawn from 2024 Q4 NYPD Firearm Report data aggregated by borough. Each band represents the number of arrests where a particular offense was the top charge additional to a firearms charge.

This chart is drawn from firearm arrest reports, a newly published data set as of 2024. It shows that in the last quarter of 2024, Dangerous Weapons (possession of) were overwhelming the top charge in any given firearm charges, however a sizable portion of additional charges were for felony assault and robbery. This holds true across precincts and boroughs.

## Appendix B: Data Aggregation

The data used in this analysis includes panel data generated from NYPD reported incident level data, precinct level data from the U.S. census and statewide data from the FBI and ATF. Incident level data includes shooting incident data, Stop, Question, and Frisk (SQF) data, arrest incident data, and firearm report data. Years for arrest and shooting data range from 2006 through 2024. SQF data is available from 2003 to 2024. As data reporting rules changed in 2016, this analysis draws only from 2017 through 2024. Use-of-force data are published at the precinct level going as far back as 2007. Due to similar 2016 changes to arrest and shooting data reporting, this analysis only uses data from 2017 through 2024. In 2024, the NYPD began publishing a Firearm Recovery Report. Firearm recovery data has also been reported in various forms and detail by the NYPD in earlier years, including within SQF data. These firearm recovery reports only cover the 4th quarter of 2024. 2020 Census data at the block level was compiled at the NYPD precinct level by John Keefe (Keefe, 2022). The 2020 Census implemented data anonymization – artificial fuzziness – at the block level; John Keefe notes that as the blocks are

compiled at the precinct level, this fuzziness should wash out. ATF and FBI data from 2003 to 2024 were used to measure gun purchases state-wide and changes in TTCs.

Precinct level aggregation of arrests, shootings, and stops are drawn from incident level data from 2006-2017. This precinct level data was then joined with precinct level use-of-force data. From these aggregations, a few calculations are drawn. Shootings Per Arrest, is a measure of the number of shootings in a precinct over the number of arrests made in the precinct. This number does not imply that the arrests are actually related to the shooting, though they could be, rather this ratio is an indication of the extent that shootings are a part of precinct-wide trends in crime. This ratio is also an indication of shifts in weapon prevalence beyond ebbs and flows of criminal activity in a precinct. This analysis aggregates all incidents of use-of-force, regardless of form. However what constitutes use-of-force in the police use-of-force data is different from what is deemed use-of-force in the SQF data. For this reason, draw-and-point data are used as an indicator of use-of-force rates amongst SQF stops. Also drawn from the SQF data is the "suspected criminal possession of a weapon (CPW) rate" and "weapon find rate", the first is calculated from the amount of stops where CPW is the suspected crime, and weapon find rate measures how often a weapon is found when a subject is searched. Not every stop results in a search but most do.

The correlation tables are drawn from precinct-level statistics on a series of variables using a *Pearson* correlation. The Robustness Test of Discrimination uses coincidental flags to track rates of searches, and search success by race, and is aggregated at the precinct and borough levels. The OLS analysis uses a few different sets of instrumental variable strategies against use-of-force. The primary explanatory variable used in this analysis is weapon arrest rates. Demographic effects are measured by the rate of arrests of Black subjects, and overall police activity is measured by total arrests in a precinct. Various other explanatory variables are included as well, including drug arrests, assaults, and Shootings, however as some of these variables are mechanically linked and collinear, the results can be difficult to disentangle.

## Appendix C: Validity of Results

### Validity of Measures of Weapon Prevalence / Perceived Prevalence.

This model uses weapon arrest data as the primary measure of weapon prevalence. The strength of this measure is that: a) every weapons arrest is by definition an instance where police officers are encountering a weapon, or a subject known to criminally possess weapons; and b) the distribution of weapon arrests is not uniform across precincts. This analysis uses weapon prevalence and gun

prevalence interchangeably; while not all weapons arrests are for firearms, the overwhelming number of them are. Firearms are also the most common weapon used in an assortment of crimes including and importantly, the homicides of on-duty police officers. Firearms play an outsized role in force determination, as they, even when legally possessed, can pose a risk to both officers and the public. Furthermore, weapons arrests are not the only indicator of firearm prevalence used in this analysis; SQF data specifically denotes when a firearm is found at a stop, and shootings (by definition) are always committed with a firearm.

This analysis also uses statewide firearm purchase data which has the obvious issue of not actually being the number of guns legally or illegally purchased in New York City. Statewide TTC data is an indication of the number of criminal firearms recovered in the State, but again, not just in New York City, nor is there any real indication of the number of guns currently in use, or will be in use, for criminal activity but have yet to be recovered. Weapons arrests furthermore do not indicate whether the firearm was possessed by someone who lived in the precinct. Subjects who travel across precincts may have an effect on use-of-force in every precinct they have visited but will only show up in the one precinct where they are arrested or stopped.

Despite this barrier to accurately measure actual firearm prevalence in NYC, this analysis relies on data that does reflect the amount of times police officers arrest someone with a gun or stop someone who they believe possesses a firearm. In short, assuming these measures of weapon prevalence accurately reflect weapon prevalence as some notable percentage of the total guns in the precinct, the conclusion that the COVID-19 era increase in gun demand led to an increase in use-of-force will be supported. Regardless of whether these measures for weapons prevalence accurately reflect weapons prevalence city-wide, this analysis does show that the increased police interactions with armed, or suspected-to-be armed, of the COVID-19 era is positively and causally related to increased use-of-force.

## Validity of DiD/TWFE assumptions

The DiD model rests on a few key assumptions, first, the parallel trend assumption. The data in this analysis does show that there is a parallel trend in the years prior to 2020 between the two different treatment groups however there is some volatility that undermines this assumption. Propensity scoring did not lead to radical changes in the results, indicating that if the parallel trend assumption does not hold, it is likely due to some unmeasured variable, rather than improperly accounting for the variables that are measured. A second assumption, more particular to this analysis, is that there is a linear

continuous treatment. Chart C5, shows a linear (for the most part), and continuous relationship between ordinal ranking and weapons rate.

Figure C5: Above/Below 50th Percentile Average Weapon Arrest Rate, 2017-2024

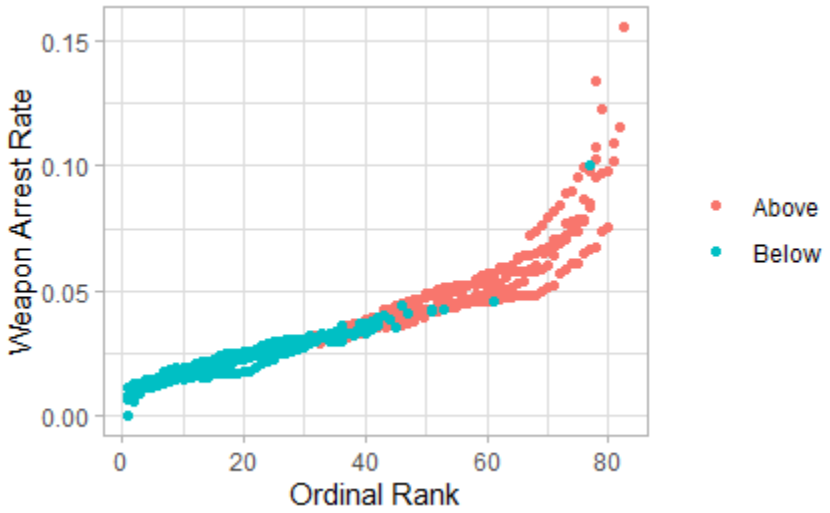



*Figure Notes:* This figure is drawn from arrest data from 2017 -2024, though this chart does not plot across time. The y-axis represents the weapon arrest rate, where the x-axis is the weapon arrest rate ordinal ranking. The precincts are grouped by average ordinal ranking post-COVID-19.

A third core assumption, illustrated in Figure C6, is a parametric relationship between weapons rate and use-of-force, particularly as this is a continuous treatment experiment with no truly untreated precincts. The positive correlation between weapon prevalence and police use-of-force within the treated and untreated precincts is still present and, when modeled linearly, consistent across treatment groups.

Figure C6: Treated/Untreated Correlation between Use of Force Incidents and Weapons Arrests in New York City Precincts, 2017-2024

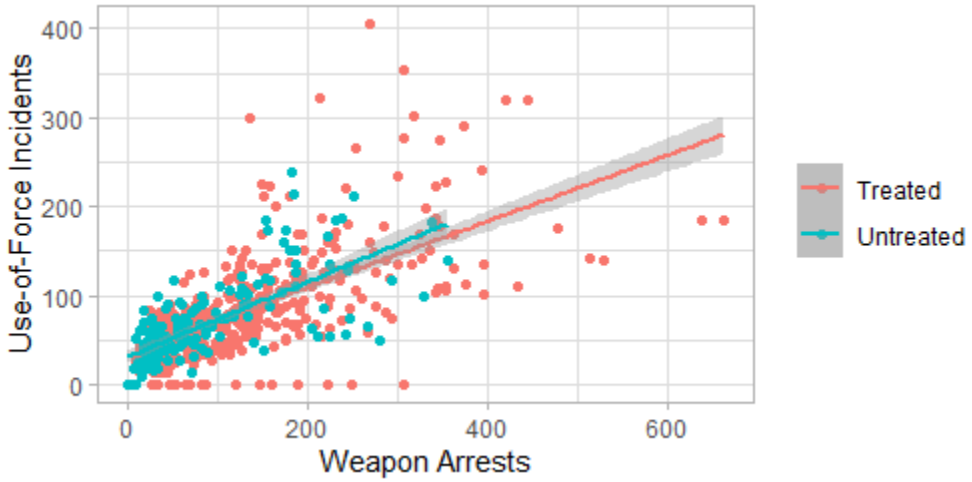



*Figure Notes:* This figure is drawn from arrest data from 2017 -2024, though this chart does not plot across time. Weapons Rate is the percentage of precinct wide arrests that are weapons arrests. Use-of-force is the number of incidents of use-of-force. The precincts are grouped by treatment and a linear fit model is mapped to each group.

While this analysis refers to spikes in gun demand, shootings and arrest rates, the actual number of arrests, and in particular weapon arrests had been falling prior to 2020, and continued to fall in 2020 for both the treated and untreated precincts, although rates rose again in both groups post-2020. This is shown in Figure C7.

Figure C7: Treated/Untreated Precinct Weapon Arrest Average, 2017-2024

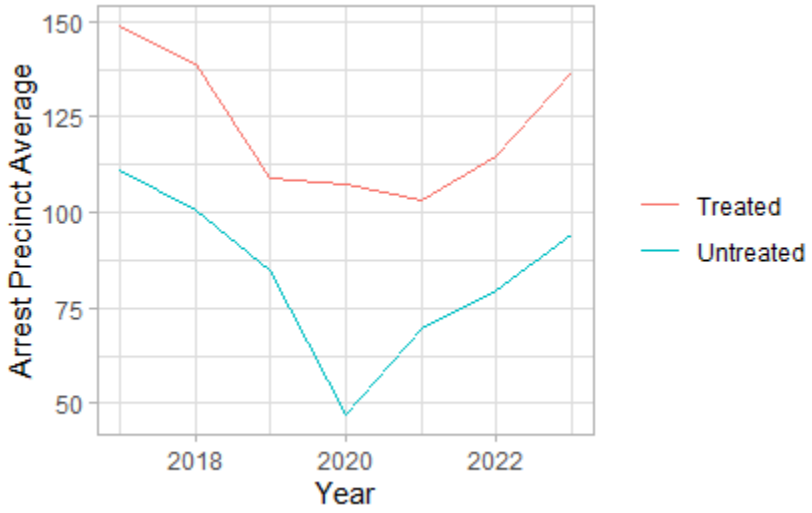



*Figure Notes:* This figure is drawn from arrest data from 2017 -2024. Weapon Arrest average is the average number of weapon arrests across precincts by treatment group.

There are other indications of higher weapon prevalence and perception of weapon prevalence for treated precincts than untreated precincts. The number of shootings per precinct spiked in 2020, for both treated and untreated precincts. In short, while this analysis shows strong evidence that weapon prevalence is positively correlated to police use-of-force, this conclusion must be taken in the context of city-wide rates of criminal activity.

## Validity of Simple, Robust Test for Discrimination

The results of this test suggest discriminatory behavior in police stops in many, though not all New York City precincts. In about half of the precincts in any given year, Black subjects are searched at a higher rate while the search success rate of White subjects is higher. There are two important caveats to this analysis. First, this test suffers from small numbers, there are some precincts in which no white people are searched, and therefore there is no evidence that white subjects are held to a higher evidentiary standard. Furthermore, t-tests of the benchmark test and the outcome test found no statistical difference between precinct averages of Black and White subjects even when filtering for precincts that fail both tests. In a perfect, nondiscriminatory world, where each test is independent, only around 25 percent of precincts would be expected to fail both tests, as just random chance would mean that half of the precincts fail the Benchmark test, and a statistically independent half would fail the Outcome test. The chart itself would look like a circular cluster around 0,0. However, the tests are not independent. Even if discrimination is present, the likelihood of having contraband conditional on being searched is probably higher than conditional on not being searched assuming the officer is at all able to discern who is likely to have contraband. In short, even while more than half of the precincts fail the Robust Test of Discrimination in any given year, and the results in line with most studies finding discriminatory patterns in policing, this analysis cannot conclusively separate every result from statistical noise. Importantly, the results of this analysis do not in any way suggest discrimination is not present in NYC stops.

## Appendix D: Beyond

The model used in this analysis focuses greatly on the mechanical relationship between weapons and use-of-force. The correlations and causal analysis demonstrate that weapons prevalence can act independently from Race, and other precinct dependent effects. While the extent of the effect is clearly dependent on preexisting conditions, whether weapons prevalence impacts use-of-force has implications that can extend beyond New York City. The NYPD patrol guide was not crafted in a vacuum. Many other police departments have similar use-of-force guidelines, including Washington DC's Metropolitan Police Department (MPD). The MPD's general orders to officers include the following factors for deciding when and if force is appropriate:

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Use of Force Factors:

a) The risk of harm presented by the subject
b) The risk of harm to the member or innocent subject by using force.
c) The seriousness of the law enforcement objective.
d) Whether further de-escalation techniques are feasible, including the time available to a member to decide, and whether additional time could be gained through tactical means.
e) The mental or physical disability, medical condition, and other physical and mental characteristics.
f) Whether there are other exigent or emergency circumstances.

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(MPD Written Directives: General Orders – USE OF FORCE (GO-RAR-901.07) page 3 of 24.)

There are many nationwide studies that show that firearms can pose a danger to police officers, and if those dangers affect police response to weapons through use-of-force in NYC, other police departments would likely respond in a similar fashion to NYPD officers, though guided by their own procedures. There are data limitations to exploring the relationship between weapons prevalence and use-of-force in other departments, though those limitations are not insurmountable. The MPD publishes similar arrest reports to the NYPD, and use-of-force reports, as do many other police departments. This analysis relies on publicly available data. Further analysis would seek to expand this analysis to other cities and departments, as well as explore restricted data sources and other models, such as Synthetic Controls, to get a more detailed picture of how weapons prevalence shapes use-of-force nationwide.

There is also interesting analysis to be done on off/on duty use-of-force, as off-duty shootings are disproportionate to other off-duty use-of-force incidents. In 2024, there were 50 reported NYPD instances of Member of Service (MOS) firearm use-of-force, of which 41 were on-duty and 9 were off

duty (18 percent of shootings and 5 percent of all instances of off-duty force). At the same time, there were over 9,627 instances of on-duty physical force and only 166 off-duty (1.7 percent of all instances of MOS physical force), a disproportionality that has held since use-of-force data was first published. In 2017 off-duty instances made up 28 percent of MOS Firearm use-of-force where off-duty instances of physical force made up only .7 percent of all instances of MOS physical force incidents (NYPD, 2020). This disproportionality gets to the heart of self-defense, off-duty police obligations, and the generalized notion of a “good-guy-with-a-gun.”