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USE OF FORCE IN THE BLM ERA: HOW HIGH-PROFILE CITIZEN-KILLINGS BY POLICE OFFICERS

AFFECT USE OF FORCE RATES IN DALLAS, TEXAS

IS APPROVED BY ME AS FULFILLING THIS PART OF THE REQUIREMENTS FOR THE DEGREE OF

Bachelor of Arts in Liberal Arts and Sciences

APPROVED BY



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USE OF FORCE IN THE BLM ERA: HOW HIGH-PROFILE CITIZEN-KILLINGS BY POLICE  
OFFICERS AFFECT USE OF FORCE RATES IN DALLAS, TEXAS

BY

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## ABSTRACT

Little research currently documents the effects of high-profile citizen-killings by police officers on the behavior of police and citizens. Specifically, no paper to my knowledge studies high profile killings' effect on lesser-lethal use of force by police. In this study, I utilize use of force data from the Dallas Police Department to model force usage rates before and after eight major high-profile citizen-killings. I hypothesize an "Antagonism Effect" increases the stress of officers and force usage as a proportion of total incidents, following such killings. Using a regression discontinuity design, I find that high-profile killings do not significantly affect force rates. Moreover, when I restrict the models to Black, White, and other races respectively, I still do not find any change in force rates. Increasing the time-window, however, seems to increase significance levels of the results. Additionally, I find that like force rates, injury rates of citizens in force encounters did not change following the George Floyd killing.

*Keywords:* Police Use of Force, Black Lives Matter Movement, Citizen Injury Rates, High-Profile Killings by Police

Dedicated to my grandparents Mamie and Richard Laszlo for their endless support and kindness, and for taking care of me for so many years.

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## Introduction

American policing suffers a crisis of legitimacy. Through manifold media forms, citizens across the country routinely witness instances of police use of force in which death or severe injury occurs. After the death of George Floyd in June 2020, the country erupted in protests and police reform efforts. While the frequency of these encounters is rare relative to the number of annual police encounters, they damage the relationship between police departments and their respective communities everywhere. While few have explored how high-profile killings affect lethal force usage, none to my knowledge have explored how these killings affect lesser-lethal force usage like grappling, tasers, and pepper spray (Campbell 2018; Zimring 2017).

Do high-profile killings by police move the agenda of activists forward by creating a cultural atmosphere that inhibits the conditions of another shooting, in which police shy away from lesser-lethal use of force due to fear of another high profile incident? I will refer to this alleged phenomenon as an “Accountability Effect.” Besides descriptive studies of killings by police and a single longitudinal study looking at citizen killing rates by police before and after a high profile killing, the literature does not provide concrete answers to these questions (Campbell 2018). Yet these killings seem to be the stimulus for much recent national and local police reform (8 Can’t Wait Campaign, 2021). Hence, their causal effects seem bound tightly to the behavior of the public and police agencies alike.

Understanding how this behavior manifests in the day-to-day interactions of police officers could open a window into measuring the cultural effect of nationally controversial policing events. This has major implications for how we should respond to these events as a collective as well as whether they are causally tied to the worsening or betterment of the same conditions that caused them. For example, if we did find an “Accountability Effect” on lesser-lethal use of force by police, we must then ask if this should be seen as a victory in its own, symbolic of a cultural shift towards non-aggression, or does it worsen crime in the community and signal a weakening of police to legitimately perform their jobs? An empirical study of use of force rates can help answer this question.

Moreover, despite widespread claims of increased crime and demoralized police resulting from major citizen-killings by police, or the “Ferguson Effect,” little scholarship has documented these suggested departmental effects (Pyrooz, et al. 2016). While limited research has claimed a statistically significant decrease in citizen-killings by police correlated with BLM protests, other studies indicate no change in these killings following the Ferguson,

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Missouri killing of Michael Brown in 2014 (Skoy 2021; Campbell 2018). However, this unit of analysis may miss the effect to be gathered from citizen-killings by police. While these events nationally may represent hundreds of deaths per year, on a per-city basis, they are extremely rare. For example, comparing Washington Post and Dallas Police Department data, I find that during the BLM era in Dallas, there were more than 875,000 documented police interactions, 19,000 use of force incidents, but only 18 killings by police officers. Hence, lesser-lethal force usage may serve as a better catalyst of study. Major police departments alone may produce thousands of lesser-lethal use of force cases every year. Furthermore, many major cities have strict use of force policies that mandate officers only use deadly force when protecting the lives of others or themselves. Hence, using lesser-lethal force to capture behavioral change yields a parameter in which police have much more personal discretion and where a larger sample size is available. Less-lethal situations are also less apt to feature split-second decision-making and may reflect more reasoned and less instinctual reactions.

Because lesser-lethal force as an outcome variable seems more likely to capture a treatment effect and there is a lack of existing literature on the topic, it seems that understanding the relationship between high-profile citizen-killings and lesser-lethal force would be a valuable contribution to the literature. In this paper, I use a regression discontinuity scheme on Dallas Police Department “Response to Resistance” and “Incident” data to model the frequency of use of force before and after several major killings by police, expecting that increased stress levels amongst police and antagonism by suspects will increase use of force rates.

## **Background**

### *Use of Force*

Use of force can be defined as the “amount of effort required by police to compel compliance by an unwilling subject” (International Association of Chiefs of Police 2001). Essentially, it is comprised of the coercive measures that police use, whether physical or verbal, to achieve suspect compliance. Policing happens mostly at the local level, and often police agencies use a “force continuum” in which variable levels of force are used in response to suspect resistance, with the highest response level being lethal force and the lowest often being verbal warning. Over 83 of the largest 100 police departments require a use of force continuum (8 Can’t Wait Campaign, 2021).

In the US, lethal force is very rare but relative to other developed countries, is exceedingly high. For example, in recent years, the US killed 100 times more civilians per capita than England and Wales, 40 times more

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than Germany, and around 6 times more than Canada (Zimring 2017). Over 95% of the victims are men, and Blacks and Native Americans are more than twice as likely as non-hispanic White males to be killed by the police (Zimring 2017). Since the start of the BLM movement in July 2013, around 7,800 civilians have been killed by police with around 90% of those being attributable to police gunfire, although this is likely a moderate underestimate (Washington Post 2022).

Interestingly, police deaths by assault are also comparatively much higher in the US. For example, per capita police deaths by assault are around 25 times higher in the US than in England and Wales (Zimring 2017). These high assault rates may be partially responsible for the high killing rates, as the overwhelming majority of killings by police were responses to threats to the safety of the police, and 91.8% of police fatalities from 2008 to 2013 were due to firearms (Zimring 2017). Furthermore, of the civilians killed by police during a six month period in 2015, 55.7% possessed firearms, 16.5% possessed knives, 15% possessed no weapon or the weapon only looked like a gun, and the rest had other weapons or armed status was unknown (Zimring 2017).

### *Use of Force Predictors*

Substantive work has been done on analyzing what causes police to use force, the level of force they use, as well as whether the suspect uses force. Both individual and situational factors play a role.

Situational factors that strongly predict use of force by police include chemical impairment of the suspect, whether suspect attempts to flee, suspect possession of a weapon, whether bystanders were present, suspect use of force, and an increased number of police officers (Johnson and Garner 1999; Crawford and Burns 1998). Individual factors that strongly predict police use of force were whether both the officer and suspect were male, suspect race, time on the force, and whether suspect has violent history or gang involvement (Garner 1996; Crawford and Burns 1998). Meanwhile, suspect use of force on police officers was consistently predicted by young age, gang involvement, previous violent crimes, the presence of bystanders, impairment by alcohol, and being non-Hispanic (Johnson and Garner 1999). These factors mostly seem intuitive – violent history, being male, being a gang member, and having a weapon are all indicators of potential danger; suspect use of force is a direct response to actual danger, and other demographic characteristics like length on force and race may be deeper indicators of biases or behavioral patterns.

One major potential causal pathway for these indicators in the literature is General Strain Theory, which is a criminology theory that suggests “deviant” behavior (deviating from accepted standards) becomes more violent and frequent as stressors increase and manifest as a form of deviation (Agnew 1992). Police may be susceptible to this behavior too. For example, a study of more than 450 police officers found that being a victim of violence on the job or expressing high levels of stress increased use of force usage by 57% and 48% respectively, both with a high level of significance (Manzoni and Eisner 2006). Continuous intense negative interactions with the public also predicted higher rates of force usage (Manzoni and Eisner 2006). Another study that used both survey methods and interviews showed that Belgian police officers were almost all affected to some degree by stress and fear during police encounters, substantiating the idea that stress levels are relevant to force usage (Verhage, et al. 2018).

### *Changes in Use of Force from Exogenous Stimulus*

Furthermore, major exogenous changes in the world may alter the mindsets of the actors or situations in which force is being used. Yet, despite the apparent social impact of high-profile killings by police, little research has been done to examine their effects on future instances of force usage. Of the studies that do, many attempt to establish the existence of a “Ferguson Effect,” which theorizes that crime rates increase after high-profile shootings by police due to a chilling effect on police use of force (Pyrooz, et al. 2016). This theory hypothesizes that officers exposed to the treatment of a high-profile citizen-killing by police will be less likely to enforce laws in fear of “being held accountable” for using force, whether that force is appropriate or not.

Studies henceforth show the effect to hold little weight. For example, using a regression discontinuity analysis of FBI crime data suggests that amongst major US cities, most crimes did not change in frequency after a high-profile killing incident at a notable level of significance, except for robbery rates, which went up (Pyrooz, et al. 2016). Nor did any study find a significant change in the rate of fatal police shootings using the protests in Ferguson Missouri in August 2014 as treatment (Campbell 2018). This could indicate either that a single instance alone may be insufficient to produce an aggregated effect, or perhaps the treatment was more localized and hence an aggregate analysis cannot capture a “Ferguson Effect.” Alternatively, the theory may simply be false.

However, through using protests as an exogenous input to police departments, research has posited a negative effect on deadly use of force. A 2021 study using [elephrame.com](https://elephrame.com) and the Fatal Encounters database found using an interrupted time-series design that on average, each BLM protest in the US lowered the fatalities of Blacks



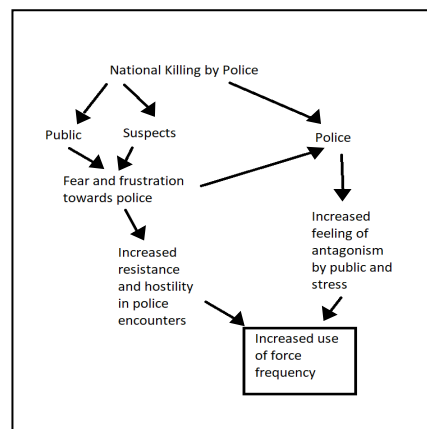
per protest by 0.25 but also found no effect on crime after BLM protests (Skoy 2021). Hence, the literature points towards criminal activity staying consistent despite protests and notable citizen-killings by police. However, besides the limited support that suggest protests lower black fatalities by police, there is little to be gathered about how officers seem to react or change behavior at a more microscopic level.

Amongst other empirical studies that exist on high-profile citizen-killings by police, a 2020 study sought to determine if police departments attempted to portray a more positive image following major killings, conceivably, to improve community trust. Using more than 350,000 police agency social media posts, this study found that on average, agency posts were “decidedly neutral” in tone and positive content did not increase or decrease following a shooting, although public comments were slightly more negative (Hand 2020). This suggests that if we expect citizen-killings to affect use of force, it may not result from organizational messaging but instead from individual or collective behavior.

## Theoretical Framework

While running contrary to the narrative of de-policing and the “Ferguson Effect,” I suggest that an “Antagonism Effect” occurs after a killing in which police officers are treated with stress and a feeling of disapproval by the public, which prompts them to use discretionary force more often, while simultaneously, suspects act more belligerently when encountering police officers, increasing suspect resistance, and creating a similar upwards effect on force frequency. This may be moderated by an “Accountability Effect” that I discuss later. The hypothesis is stated below and illustrated with Figure 1:

H1: *High-Profile Citizen-Killings by police will increase force frequency as a proportion of total police-citizen interactions.*



**Figure 1.** Theoretical Causal Pathway

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### *Support for Antagonism Effect on Police*

The central questions in this theory are “are police more stressed due to high-profile killings by police?” and “does increased stress lead to more frequent and more severe use of force?” If the answer to both is yes, then it must be true that there is at least a positive effect on use of force rates by police when treated by high-profile citizen-killings, whether there are other variables pushing the outcome upwards or downwards. What does the literature say about these questions?

To the first question, the answer seems to be yes, although there is little direct literature on the subject. Supporting evidence stems from first, public reaction – public opinion was shown to be decidedly more negative towards the police after the George Floyd police killing (Reny and Newman 2021). If when people encounter police, at least some act upon this negative disposition, or that officers feel this way regardless of whether people actually treat them with a greater negative disposition, continuous negative interactions with the public have been shown to predict higher rates of force usage (Manzoni and Eisner 2006). Moreover, public opinion surveys of thousands of police officers indicated that 86% of officers say the public does not understand the challenges police face, opposed to less than 50% of the public who say the public does not understand these challenges (Pew Research 2016). This perception asymmetry seems to suggest a heightened potential for negative interaction, as officers feel that their job is highly misunderstood, and citizens seem to lack an understanding of challenges police face. High-profile killings likely exacerbate this lack of understanding.

Additionally, police may feel directly more stressed from other effects. Reportedly, 86% of officers say policing is harder now than before and 70% of the public views it as more dangerous, while 42% of officers say they have serious concerns about their physical safety while on the job (Pew Research 2016). Overall, data suggest officers feel that their job is increasingly difficult and that the public view the job as increasingly dangerous. These sentiments are likely in response to the BLM movement, which was provoked primarily by citizen-killings. Further, because police officers ranked other officers being killed in the line of duty as the most stressful occurrence in their job and having to kill a civilian as the second most stressful, it seems likely that an increasing association of their job with danger and difficult decisions is increasing their stress on the job (Spielberger, et al. 1981).

Having affirmed with a few assumptions that killings by police and the ongoing BLM movement seem to be contributing to officer stress, we must ask our second question – does it matter? Data have shown that

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experiencing high levels of stress greatly increases force usage by officers (Manzoni and Eisner 2006). Moreover, General Strain Theory points towards increased deviancy across people generally because of increased “stressors” from their environment. Hence, when an officer has the discretion legally to use force, it seems that when he or she is frustrated or fearful (i.e., two stressors), he or she would be apt to use more force as an expression of that frustration or fearfulness, whereas frustration may be gratified through hurting or anger, and fearfulness through neutralization of a potential threat through force. Why stress causes increases use of force may represent an abstract psychological or neurological concept that may be beyond the scope of the paper to say.

### *Support for Antagonism Effect in Civilians*

The next causal pathway we should consider is whether the treatment affects the suspect mindset in a way that increases their resistance to police officers, whereas suspect resistance is a pathway to overall use of force (Johnson and Garner 1999; Crawford and Burns 1998). To answer this question, which again has no direct answer in the literature, we can look to larger scale mental health data post-citizen-killings. For example, recent research seems to suggest a substantial negative effect on the mental health of Black Americans following unarmed police shootings of black men (Bor, et al. 2018). It seems to be a reasonable assumption that negative mental health effects can be seen as a stressor, and that this effect on stress is likely heightened during police encounters.

If we accept these premises as true, we can add to our previous findings that at least some individuals are experiencing added stress from the perception of increased danger from officers. General Strain Theory may then support the idea that higher stress or “strain” is liable to add to suspect deviance (likelihood to deviate from law) and hence in the context of a police encounter, produce physical resistance. Increased stress may also manifest in a negative disposition towards the officer, which could also increase the likelihood of force usage. For example, a recent randomized control trial study showed compelling evidence that when officers are exposed to disrespectful but compliant civilians versus compliant and non-disrespectful ones, that police officers felt an increased level of suspicion, perceived danger, and antagonistic emotions, as well as sometimes fear (Nix, et al. 2019). As expressed in the previous section, expected potential for danger and negative interactions with the public are direct predictors for use of force by police officers (Manzoni and Eisner 2006).

### *Understanding the Competing “De-policing” Theory*

The “De-policing” theory or the “Ferguson Effect,” which opposes our “Antagonism Effect,” lacks support for one of its necessary conditions. Part of the “Ferguson Effect” expects that if police take a more hands-off approach to suspects, there will be lower engagement with criminals and higher levels of crime. Yet, the current literature shows that crime levels do not change after killings by police (Pyrooz, et al. 2016). Hence the crucial outcome variable does not show signs of change. However, this may also suggest that another effect is moving the force usage in the other direction, and the other effect is more intense. Perhaps several effects exist simultaneously.

We might also theorize that crime rates may be unassociated with use of force rates, and the “Ferguson Effect” is looking at the wrong outcome variable. The literature also lends some support to the “Accountability Effect” which again is not identical to the “Ferguson Effect,” but uses the same causal mechanism – the desire of officers to avoid punishment. For example, evidence shows that Belgian officers from the study mentioned earlier almost all reported that they were anxious about the consequences of using force because they know that they are accountable for their actions (Verhage, et al. 2018). Additionally, a randomized control trial studying the introduction of body cameras into a police department also found that officers relied on less intrusive methods to resolve conflicts (Headley, et al. 2020).

How strong is this support? If we concede to the supporting evidence above, we accept that (1) increased anxiousness and (2) less intrusive methods may result from accountability measures. If we accept that high-profile citizen-killing represent an accountability measure or indirectly increase these measures, then high-profile citizen-killing may also increase anxiousness and spur use of less intrusive methods. Yet using “less-intrusive” methods does not mean using “less force” generally. Moreover, our intermediate variable “increased anxiousness” may be seen as a stressor and act in the same way as we predict all stressors will act – towards increased force usage. I have found no evidence that increased accountability measures lower force usage as a percentage of police interactions. Furthermore, direct public opinion data shows that other accountability mechanisms like body cameras are supported by two-thirds of police officers (Pew Research 2016). Hence, even if police feel increased accountability, it may not necessarily be unwelcomed, and its acceptance may not reflect lower levels of force. In fact, the case may be made that increased accountability measures may protect officers too.

### *Potential Implications of Findings and Ongoing Uncertainty*

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If we observe decreased force usage contrary to our “Antagonism Effect” and studies on police behavior, it may support an “Accountability Effect.” I believe the most probable scenario is that both an “Accountability” and “Antagonistic” effect are present and working in different directions on force usage rates, but one to a greater degree. Since the evidence above seems to show more support for an “Antagonistic Effect,” I theorize this effect will be larger. Because use of force studies as they relate to national events are so sparse, the extent of this study is not to validate the causal mechanism but simply to establish whether a relationship worth investigating further may exist.

## **Data**

To examine the effects of a high-profile citizen-killing on use of force rates, I use Dallas Police Department “Response to Resistance” data that includes every documented use of force instance from 2014 to 2020 in the city of Dallas, Texas. The data set contains 19,451 observations of officer-level force usage on suspects. Force usage ranges from verbal commands to fire-arm discharge. I do not restrict my observations to lesser-lethal force due to logistical constraints in the dataset, although most observations are lesser-lethal force usage. Lesser-lethal force, opposed to use of force generally, excludes the use of typically lethal force options, like guns and police vehicles. I also use a “Police Incident” dataset from the Dallas Police Department that contains about 875,973 observations from 2014 – 2021 of documented police-citizen interactions.

Using this data is ideal because of the large time window in which data is collected – throughout the entire modern policing reform movement. The dataset is also a suitable candidate because it contains a large sample size, Dallas is a large American city and is therefore representative of locations in which killings by police typically happen, and because the Dallas Police Department collects data on both force-incident and non-force-incidents, allowing use of force to be measured as a proportion of incidents, rather than raw frequency. Such a large dataset on force usage is rare. Smaller police departments very rarely appear to manage public databases with incident or use of force data, and no national database yet exists which contains individual-level data on local police department use of force, although the FBI is currently working on such a project.

The “Response to Resistance” dataset consists of individual instances of use of force, as well as the time of incident, officer and suspect race and gender, resultant injuries to officer and suspect, type of force used, and location. The “Police Incident” dataset contains all police-citizen interactions, meaning the “Response to

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Resistance” data is a subset of it. The date variables from both datasets are manipulated in R to count the frequency of use of force incidents and total incidents per date for the entire time window.

## Methods

### Defining “High-profile”

To identify the causal effect of high-profile killings by police on use of force rates, I use eight instances of high-profile killings by police as natural experiments that “treat” police officers with the theorized “Antagonism Effect.” While the literature does not explicitly quantify which instances of killings by police are “high-profile,” I use news coverage as a proxy for being treated. To do this, I combed through news articles to find lists of high-profile citizen-killings. I compiled these individuals into a list of 30 unique killings and used the University of Illinois Archer query system to find the number of articles published containing the citizens’ names within one month of their death. Articles were both national and local in nature. Eight subjects featured more than 1,000 published articles within the first month, while the remaining 22 did not. I considered these eight cases to be “treated” by coverage, whereas news articles are an indicator of how many people are aware of the high-profile killing. To be aware of the killing is to receive “treatment.” The eight subjects in the treatment group are George Floyd, Alton Sterling, Philando Castile, Stephon Clark, Michael Brown, Rayshard Brooks, Botham Jean, and Terence Clutcher. Because Alton Sterling and Philando Castile were killed a day apart, their cutoff point is essentially identical, and they are treated as one “individual” in the regression.

### Identification Assumption

Furthermore, I argue that because the “Response to Resistance” data contains data both directly prior to and directly after such killings, differences in use of force rates can be attributed to the treatment of officers and suspects through knowledge of the killing. This knowledge may manifest as direct behavioral changes, changes in policy, or changes in other contextual factors relevant to use of force rates, like for example, if certain officers retired early after a high-profile killing. Some evidence supports this idea – a 2021 synthetic control study found that relative to the synthetic control, during a 60-month period in a major police department, retirement rates were 280% higher (Mourtgos, et al. 2021). Furthermore, while officers and suspects may receive information through different avenues and conceivably not every individual is necessarily treated right away, I believe that it is reasonable to infer that most officers are treated with this information due to the saliency of police-killings in officers’ day-to-day interactions. Likewise, the

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average American seems to be aware of high-profile killings by police, so suspects are likely treated too. For example, a May 2020 survey by Yahoo and YouGov found that in a 1050 person sample of Yahoo users, 85% had heard of the name George Floyd within five days of his death in May 2020 (YouGov 2020).

Assuming treatment has occurred, we must also make the case that the sample of officers and suspects from directly before and after the national police killing are not fundamentally different in characteristics unrelated to behavioral changes from the treatment. Unless a large influx of migration occurred between Dallas and other cities within the small time periods surrounding the killings, we should not expect that the demographics of people in Dallas differed significantly. Yet could the type of person who is being arrested or that force is being used against differ? Possibly, but such an effect would likely be attributed to the event itself and would relate to its causal implications. Unless some external factor like a new law or other significant local or national event occurred simultaneously, variation should be mostly attributable to the police killing within a short time span. However, the case for officer demographics being unchanged may be harder to make if significant changes in resignations or attendance occur. Additionally, the possibility of prior treatment should be evaluated. A threat to validity would involve another major killing happening soon before or after the incident of interest. I address this issue by using several killings over several years. Moreover, residual effects from similar killings further from the incident at study could be present but should not affect seeing a variation from a current incident unless subjects have a maximum capacity for treatment. These internal threats will be evaluated in depth in the results section.

## Outcome Variable

Because no “use of force rate” variable exists naturally in the data set, I use R to merge the “Response to Resistance” and “Incidents” datasets. Then, as described earlier, I back out “force usage,” which I define as the proportion of police interactions on a given day that involve use of force. This entails finding the frequency of force incidents on a given day from “Response to Resistance” data and dividing it by the total police interactions on a given day, from the “incident” dataset. Hence, the former dataset is a subset of the incidents in the latter set. The outcome variable can be represented numerically as such:

$$Y_i = \frac{\text{Number of Force Incidents}_i}{\text{Number of Total Incidents}_i}$$

## Empirical Model

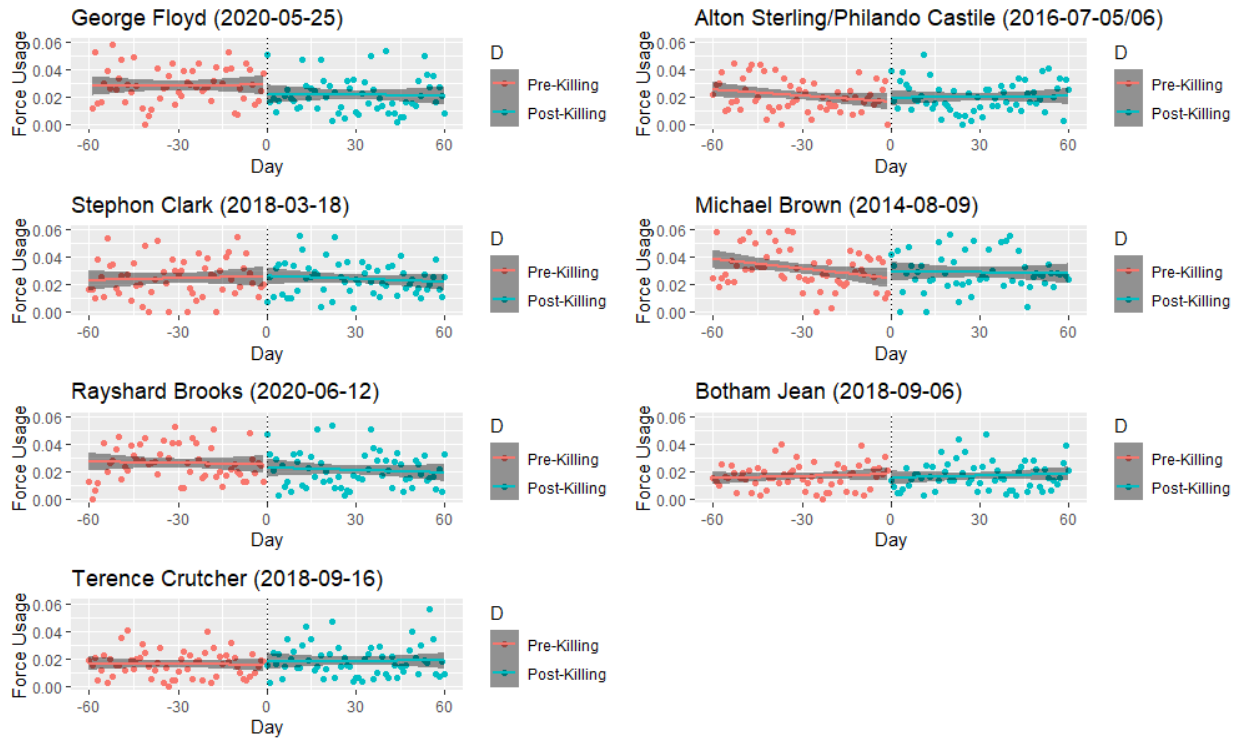
Using this variable and the corresponding dates relative to the day of death of the citizen, I perform a regression discontinuity analysis, regressing use of force incident proportion over time over two months before and after treatment. A regression discontinuity model is preferred to other models because it avoids the difficulty of finding a control group when the proxy for treatment is news coverage, and much coverage is national. It is also easy to interpret and is somewhat descriptive – I have found no literature using a similar outcome variable in response to high-profile citizen killings either, so a more basic model may be more informative for future research. I use this time window before and after because within two months, each case received over one thousand articles of news coverage, and this offers at least 120 data points for the regression. Using a smaller time window like this may also ensure that if the effect is temporary and only associated with the news coverage, as news coverage tapers off after a month or two, I am not capturing extra time in the regression, devoid of the treatment. Variable timeframes are explored later. I model the regression using the following equation:

$$y_i = B_0 + B_1 * Treat + B_2 * (Day - Day\ of\ Treatment) + B_3 * Treat * (Day - Day\ of\ Treatment)$$

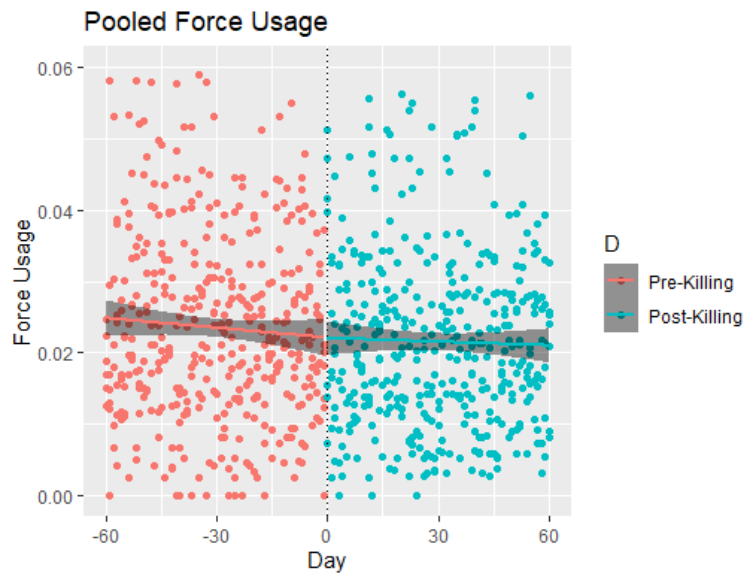
Whereas  $y_i$  predicts force usage on a given day  $i$ ,  $B_0$  represents the y-intercept at the left-side end of the time window.  $B_1$  provides our treatment effect, which is interpreted as the gap between the end of the first regression line and beginning of the second regression line, or the difference in the outcome variable at the inflection point.  $B_2$  represents the slope of the pre-treatment regression line, and  $B_3$  represents the difference between the post-treatment regression line and pre-treatment regression line, whereas the treatment point is at day 0.

## Results



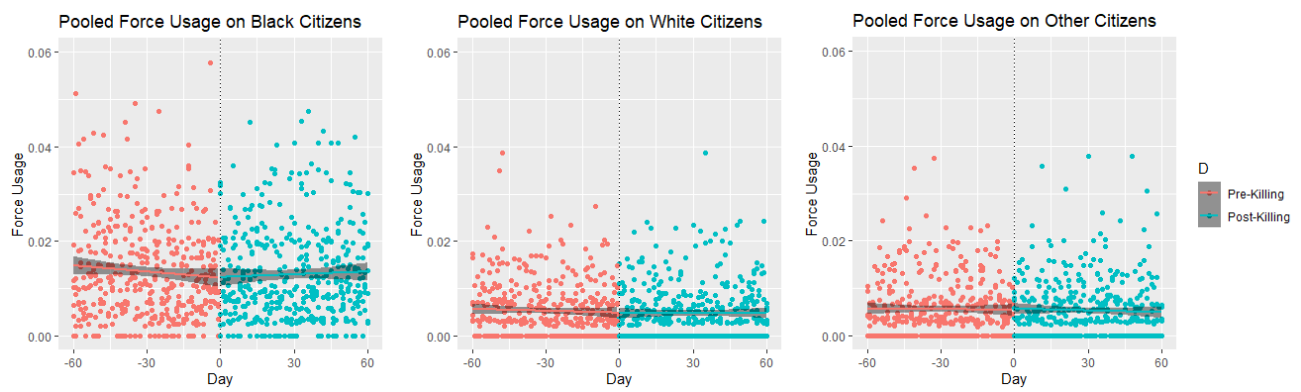


**Model 1.** Force usage regression plots from seven distinct citizen-killings, using DPD data. Each killing generated more than 1,000 news articles within one month, according to UIUC Cline Center Archer System (N=120 per killing). Regression summaries contained in Table 1 of Appendix.



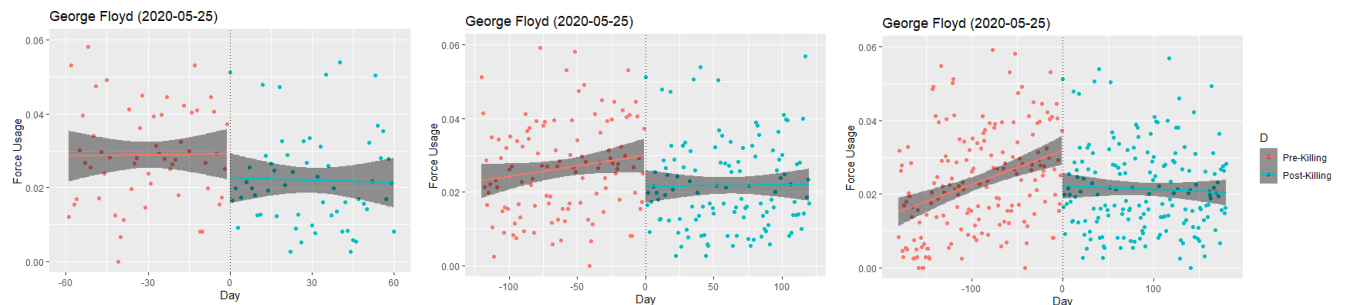
**Model 2.** Pooled Force model combines individual plots in Model 1 onto a single regression plot (N=840). Regression summary contained in Table 2 of Appendix.

Models 1 and 2 explore our primary variable of interest. Model 1 explores regression outputs of individual citizen-killings using all races of citizens to compute force usage. 60-day time windows are used before and after. Both models report no significant treatment effect at the  $p < 0.10$  level. Neither model reports regression lines that are significant either, except for the Michael Brown killing – both before and after treatment periods have slope values significant at the  $p < 0.10$  level. The pooled force usage model sees less visual variation at the inflection point than individual models, suggesting that these models seem to be more sensitive to change and a pooled model may eliminate random variation.



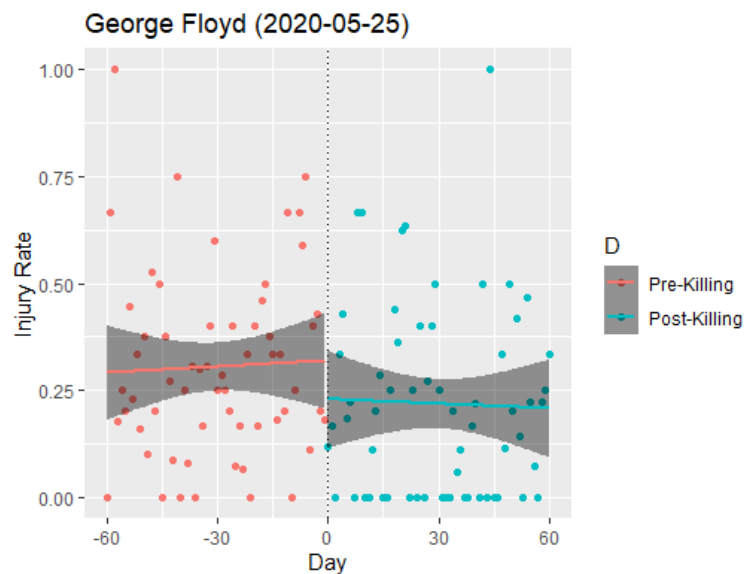
**Models 3 - 5.** Pooled Force Usage model similar to Model 2 except citizens that force is used on is restricted to black, white, and other (N=840 each model). Regression summaries contained in Table 2 of Appendix.

Models 3 – 5 explore possible racial differences in treatment effect. If a certain type of citizen is more greatly treated, we may expect to see differential treatment by race. For example, if an accountability or antagonism effect only applies when officers are interacting with black citizens, Model 2 may not show a treatment effect because blacks represent only a proportion of total cases. While the average force usage on black citizens appears to be about three times higher than on white or other citizens, none of the regressions observe a significant treatment effect at  $p < 0.10$ .



**Models 6 - 8.** Force Usage model using George Floyd’s death as treatment point, varied across 60, 120, and 180 day treatment windows ((Model 6):N=120, (Model 7) N=240, (Model 8) N=360).

Models 6 – 8 explore the George Floyd regression with variable time windows. The George Floyd case was used because it received the most news exposure at about 72,000 news articles within one month, whereas the next most was around 3,000. If we are to see a treatment effect and accept news as a good proxy for this, we should expect that the George Floyd regression would have the best chance of demonstrating the effect. Here, we observe that by changing the time window, the gap at the inflection point becomes very large. Both models 7 and 8 feature treatment effects significant at the  $p < 0.01$  level. Interestingly, force usage appears to be increasing steadily in Model 8 for the 180 days prior to the George Floyd killing.



**Model 9.** This model measures the proportion of force incidents where citizens were injured on a given day using “Response to Resistance” data from Dallas Police Department Open Data source.

Model 9 explores an additional outcome variable relevant to force usage – the proportion of force incidents on a given day in which citizens were injured. This can serve as a proxy for force intensity. Summarily, separate from the rate of force usage, when a force incident occurs, what kind of quality does it take? Is it more severe or less severe after a high-profile killing? This model uses a 60-day time window both before and after treatment, and a clear visual drop in injury rates is apparent. This drop mirrors the force usage drop in the 60-day force usage regression in

Model 6. However, the treatment effect is not significant at the  $p < 0.10$  level. The regression line seems to drop because there are many days in the post-treatment period with no injuries reported.

## Discussion

### Hypothesis

The null hypothesis of *HI*, which hypothesized that use of force rates would increase following a high-profile killing, is not rejected. While force rates do not seem to increase, they do not necessarily decrease either. This may suggest that neither the “Accountability Effect” or “Antagonism Effect” are taking place, or perhaps that both are occurring but “cancel” each other out because they are running in opposite directions. Some other major confounders may also explain our results.

Firstly, the treatment effect may not work how we may think. Rather than a “shock” through exposure to new information, the behavior of citizens and suspects may have a “capacity” for treatment, and hence by the later killings no effect was to be had at all, regardless of media coverage. However, I have shown that killings through several years, even as early as 2014, do not produce a significant increase or decrease in force rates. It may instead be the case that treatment occurs rapidly and dissipates rapidly. Hence, a tight time window is needed around the exposure date to truly capture any effect. Because the time-window is very small already, this seems not to be the case. Moreover, effects became more significant as the time-window increased, suggesting a possible more long-term effect. On an individual level, we may also note that some of the killings appear in close proximity to one another. It seems that this could result in a “double treatment” or simply a null effect. Current evidence does not support one way or the other.

Two additional threats which are not evaluated include 1) officer resignation and 2) BLM protests. If officer resignation was significant in Dallas during any of these regression time windows, it may signify that the police officers before and after the treatment are different, and hence bias the treatment upwards or downwards. Although this could itself be thought of as “treatment,” it may preclude causal implications. BLM protests may also bias the post-treatment force usage upward because higher arrest rates are likely associated with protests. In fact, several of the regressions feature small spikes in force usage in the several days following the killing. Finally, I have not performed any extensive work on changes in use of force policy throughout this time window in Dallas. Dallas does not publicly post changes in use of force, but rather supplies use of force policies upon a FOIA request.

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Tracking changes in use of force policy would therefore be extremely difficult for the scope of this paper. However, major changes could significantly change force rates, and may be associated with high-profile killings.

Overall, additional research will be necessary to parse out if high-profile killings do indeed affect force rates. This study suggests that they do not but is limited by not using officer-IDs, addressing certain internal threats, and separating potential opposite effects from each other.

### **Additional Research Questions**

Through exploration of additional models, I found interesting complementary findings to our central hypothesis. Summarily, force rates did not change when the treatment group was restricted to only certain races of citizens. This is surprising. If part of the “Accountability Effect” is associated with the Black Lives Matter Movement and increased scrutiny of police officers with respect to the treatment of black citizens, we should expect that the greatest treatment effect would occur with force used on black citizens. However, no significant treatment effect is present. This may lower the credibility of police being held more “accountable” by high-profile killings.

Furthermore, I explored an effect on a secondary but related outcome variable, citizen injury rates, and I found likewise that no change had occurred after the George Floyd killing. The additional dimension of force usage here is severity. We should expect that if there was an underlying effect, it probably would not only affect use of force frequency as a proportion of total incidents, but also its severity. If an officer is worried about using discretionary force or conversely is feeling antagonized and stressed, frequency and severity of force may follow suit. While citizen injuries may not be a perfect representation of level of force usage, a measure of potential “brutality” may be just as useful.

### **Conclusion**

Has the BLM Movement made a difference? Are the nature of police encounters changing? With respect to force rates, our study shows that high-profile killings have had little bearing. This may befuddle current narratives, like the “Ferguson Effect.” It may also diminish the activist’s notion of progress, which might expect that police are changing their discretionary levels of force in lieu of national news stories. Whether for good or bad, this initial study provides an answer of uncertainty. With all available evidence on force usage, I still suspect that some kind of change is occurring. While the nature of the effect and its causal chain remain unknown, I believe there is a real possibility both an “Antagonism” and “Accountability” Effect are acting in opposition to each other – officers may

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be more stressed but also more accountable. In future research, I hope to access larger data sets, use varied causal methods, and address lingering internal threats mentioned in this paper.

## Work Cited

- Mesic, Aldina et al. "The relationship between structural racism and black-white disparities in fatal police shootings at the state level." *Journal of the National Medical Association*, vol. 110 no. 2, 2018, pp. 106-116. Elsevier.
- Skoy, Evelyn. "Black Lives Matter Protests, Fatal Police Interactions, and Crime." *Contemporary Economic Policy*, vol. 39, no. 2, 2021, pp. 280-291. Wiley Online Library.
- Hand, Laura C. and Ching, Brandon D. "Maintaining neutrality: A sentiment analysis of police agency Facebook pages before and after a fatal officer-involved shooting of a citizen." *Government Information Quarterly*, vol. 37, no. 1, 2020, Elsevier.
- Campbell, Bradley A, et al. "Is the number of citizens fatally shot by police increasing in the post-Ferguson era?" *Crime & Delinquency*, vol. 64, no. 3, 2018, pp. 398-420. SAGE Publications Sage.
- Weisburst, Emily K, "Police use of force as an extension of arrests: Examining disparities across Civilian and Officer Race", *AEA Papers and Proceedings*, vol. 109, 2019, pp. 152 – 156.
- Verhage, et al., "Force, Stress, and Decision-Making Within the Belgian Police: The Impact of Stressful Situations on Police Decision-Making" *Journal of Police and Criminal Psychology*, vol. 33, no. 1, 2018, pp. 345 – 357.
- Fryer, RG. "An empirical analysis of racial differences in police use of force." *Journal of Political Economy* vol. 127, no.3, 2019, pp. 1210-1261.
- Manzoni, Patrik, and Manuel Eisner. "Violence between the police and the public: Influences of work-related stress, job satisfaction, burnout, and situational factors." *Criminal justice and behavior*, vol. 33, no. 5, 2006, pp. 613-645.
- Alpert, G. P., MacDonald, J. M., & Dunham, R. G. (2005). Police suspicion and discretionary decision making during citizen stops. *Criminology*, 43(2), 407-434.
- Hine, K. A., Porter, L. E., Westera, N. J., & Alpert, G. P. (2018). Too much or too little? Individual and situational predictors of police force relative to suspect resistance. *Policing and society*, 28(5), 587-604.
- Crawford, C., & Burns, R. (1998). Predictors of the police use of force: The application of a continuum perspective in Phoenix. *Police Quarterly*, 1(4), 41-63.
- Garner, J. (1996). *Understanding the use of force by and against the police*. US Department of Justice, Office of Justice Programs, National Institute of Justice.
- Johnson, R. A., & Garner, J. (1999). *The Phoenix Project: Predictors of Suspect Use of Force*. National Institute of Justice.
- Mourtgos, S. M., Adams, I. T., & Nix, J. (2021). Elevated police turnover following the summer

- of George Floyd protests: A synthetic control study. *Criminology & Public Policy*.
- Bor, J., Venkataramani, A. S., Williams, D. R., & Tsai, A. C. (2018). Police killings and their spillover effects on the mental health of black Americans: a population-based, quasi-experimental study. *The Lancet*, 392(10144), 302-310.
- Turchan, B. (2021). A high-profile police-involved shooting, civil unrest, and officers' perceptions of legitimacy: insights from a natural experiment. *Journal of experimental criminology*, 17(3), 507-518.
- Gibson, C. L., Swatt, M. L., & Jolicoeur, J. R. (2001). Assessing the generality of general strain theory: The relationship among occupational stress experienced by male police officers and domestic forms of violence. *Journal of Crime and Justice*, 24(2), 29-57.
- Sanders, Linley. "Most Americans Know George Floyd's Name and Say Race Was a Major Factor in His Death." YouGov, 31 May 2020, <https://today.yougov.com/topics/politics/articles-reports/2020/05/31/george-floyd-protest-poll>.
- "A Look at High-Profile Cases over Killings by US Police." *AP NEWS*, Associated Press, 24 June 2021, <https://apnews.com/article/us-police-killings-history-39a3bde7d53f9ea523f45e70a271a8d5>.
- "Yahoo! News Race and Justice - May 31, 2020." YouGov, 31 May 2020, [https://docs.cdn.yougov.com/s23agrrx47/20200531\\_yahoo\\_race\\_and\\_justice\\_crosstabs.pdf](https://docs.cdn.yougov.com/s23agrrx47/20200531_yahoo_race_and_justice_crosstabs.pdf).
- "Police Shootings Database" Washington Post, 6 May 2022, <https://www.washingtonpost.com/graphics/investigations/police-shootings-database/>.
- C D Spielberger; L G Westberry; K S Grier; G Greenfield, and Corporate Author University of South Florida Address Tampa. "Police Stress Survey - Sources of Stress in Law Enforcement." *Police Stress Survey - Sources of Stress in Law Enforcement | Office of Justice Programs*, <https://www.ojp.gov/ncjrs/virtual-library/abstracts/police-stress-survey-sources-stress-law-enforcement>.
- "Have the George Floyd Protests Changed Public Opinion on Race and Policing? It's Complicated. ." *PoliticalScienceNow.com* -, 22 July 2021, <https://politicalsciencenow.com/have-the-george-floyd-protests-changed-public-opinion-on-race-and-policing-its-complicated/>.
- Morin, Rich, et al. "Comparing Police Views and Public Views." *Pew Research Center's Social & Demographic Trends Project*, Pew Research Center, 17 Aug. 2020, <https://www.pewresearch.org/social-trends/2017/01/11/police-views-public-views/>.
- Nix, Justin, et al. "Compliance, Noncompliance, and the in-between: Causal Effects of Civilian Demeanor on Police Officers' Cognitions and Emotions." *Journal of Experimental Criminology*, Springer Netherlands, 2 July 2019, <https://link.springer.com/article/10.1007/s11292-019-09363-4>.



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**Appendix**
**Table 1: Individual Citizen Force Usage RD Models (All Races, 60-day windows)**

|                                 | George Floyd                 | Alton Sterling /<br>Philando Castile | Stephon Clark               | Michael Brown                |
|---------------------------------|------------------------------|--------------------------------------|-----------------------------|------------------------------|
|                                 | (1)                          | (2)                                  | (3)                         | (4)                          |
| Treatment                       | -5.593e-03<br>(6.556e-03)    | 9.873e-04<br>(4.465e-03)             | -4.867e-04<br>(5.593e-03)   | 6.425e-03<br>(5.851e-03)     |
| I (day – day death)             | -8.654e-05<br>(1.343e-04)    | -1.344e-04<br>(9.150e-05)            | 3.760e-05<br>(1.146e-04)    | -2.546e-04***<br>(1.199e-04) |
| Treatment * I (day – day death) | 8.608e-05<br>(1.877e-04)     | 2.044e-04<br>(1.278e-04)             | -9.787e-05<br>(1.601e-04)   | 3.114e-04*<br>(1.675e-04)    |
| Constant                        | 2.958e-02 ***<br>(4.712e-03) | 1.794e-02***<br>(3.209e-03)          | 2.779e-02***<br>(4.019e-03) | 2.455e-02***<br>(4.205e-03)  |
| Observations                    | 120                          | 120                                  | 120                         | 120                          |
| R-squared                       | 0.054                        | 0.024                                | 0.004                       | 0.039                        |
| Adjusted R-squared              | 0.030                        | -1.922e-04                           | -0.021                      | 0.014                        |
| Residual Standard Error         | 0.018                        | 0.012                                | 0.015                       | 0.016                        |
| F-Statistic                     | 2.249                        | 0.992                                | 0.189                       | 1.587                        |

Notes: Data taken from 2014 – 2020 Dallas Police Department “Response to Resistance” and “Incident” data. “Response to Resistance” data contains 19,451 use of force instances, “Incident” data contains 875,973 police interactions. Variable notes and descriptions listed in data section. \*Significant at 10% level, \*\* Significant at 5% level, and \*\*\* Significant at 1% level

**Table 1 (Continued): Individual Citizen Force Usage RD Models  
(All Races Citizens, 60-day windows)**

|                                    | Rayshard<br>Brooks<br>(5)    | Botham Jean<br>(6)           | Terence<br>Crutcher<br>(7)   |
|------------------------------------|------------------------------|------------------------------|------------------------------|
| Treatment                          | -5.593e-03<br>(6.556e-03)    | 9.873e-04<br>(4.465e-03)     | -4.867e-04<br>(5.593e-03)    |
| I (day – day death)                | -8.654e-05<br>(1.343e-04)    | -1.344e-04<br>(9.150e-05)    | 3.760e-05<br>(1.146e-04)     |
| Treatment * I (day – day<br>death) | 8.608e-05<br>(1.877e-04)     | 2.044e-04<br>(1.278e-04)     | -9.787e-05<br>(1.601e-04)    |
| Constant                           | 2.958e-02 ***<br>(4.712e-03) | 1.794e-02 ***<br>(3.209e-03) | 2.779e-02 ***<br>(4.019e-03) |
| Observations                       | 120                          | 120                          | 120                          |
| R-squared                          | 0.054                        | 0.024                        | 0.004                        |
| Adjusted R-squared                 | 0.030                        | -1.922e-04                   | -0.021                       |
| Residual Standard Error            | 0.018                        | 0.012                        | 0.015                        |
| F-Statistic                        | 2.249                        | 0.992                        | 0.189                        |

Notes: Data taken from 2014 – 2020 Dallas Police Department “Response to Resistance” and “Incident” data. “Response to Resistance” data contains 19,451 use of force instances, “Incident” data contains 875,973 police interactions. Variable notes and descriptions listed in data section. \*Significant at 10% level, \*\* Significant at 5% level, and \*\*\* Significant at 1% level

**Table 2: Pooled Force Usage RD Models by Race (60-day windows)**

|                                 | All Citizens<br>(1)         | Black Citizens<br>(2)        | White Citizens<br>(3)       | Other Citizens<br>(4)       |
|---------------------------------|-----------------------------|------------------------------|-----------------------------|-----------------------------|
| Treatment                       | -1.109e-04<br>(2.093e-03)   | -2.387e-04<br>(1.503e-03)    | -1.153e-04<br>(8.153e-04)   | 2.431e-04<br>(8.680e-04)    |
| I (day – day death)             | -6.730e-05<br>(4.288e-05)   | -4.873e-05<br>(3.079e-05)    | -1.341e-05<br>(1.671e-05)   | -5.164e-06<br>(1.779e-05)   |
| Treatment * I (day – day death) | 7.564e-05<br>(5.991e-05)    | 6.808e-05<br>(4.302e-05)     | 1.472e-05<br>(2.334e-05)    | -7.167e-06<br>(2.485e-05)   |
| Constant                        | 2.280e-02***<br>(1.504e-03) | 1.261e-02 ***<br>(1.080e-03) | 4.812e-03***<br>(5.860e-04) | 5.383e-03***<br>(6.239e-04) |
| Observations                    | 120                         | 120                          | 120                         | 120                         |
| R-squared                       | 0.006                       | 0.006                        | 0.002                       | 0.001                       |
| Adjusted R-squared              | 0.003                       | 0.003                        | 0.001                       | 0.002                       |
| Residual Standard Error         | 0.015                       | 0.011                        | 0.006                       | 0.006                       |
| F-Statistic                     | 1.950                       | 1.747                        | 0.689                       | 0.340                       |

Notes: Data taken from 2014 – 2020 Dallas Police Department “Response to Resistance” and “Incident” data. “Response to Resistance” data contains 19,451 use of force instances, “Incident” data contains 875,973 police interactions. Variable notes and descriptions listed in data section.

\*Significant at 10% level, \*\* Significant at 5% level, and \*\*\* Significant at 1% level

**Table 3: George Floyd RD Model with Varying Time Windows  
(All Races of Citizens)**

|                                 | 60-days<br>before/after<br>(1) | 120-days<br>before/after<br>(2) | 180-days<br>before/after<br>(3) |
|---------------------------------|--------------------------------|---------------------------------|---------------------------------|
| Treatment                       | -5.593e-03<br>(6.556e-03)      | -9.143e-03*<br>(4.057e-03)      | -1.170e-02***<br>(3.264e-03)    |
| I (day – day death)             | -8.654e-05<br>(1.343e-04)      | 6.758e-05<br>(4.149e-05)        | 1.098e-04***<br>(2.224e-05)     |
| Treatment * I (day – day death) | 8.608e-05<br>(1.877e-04)       | -8.620e-05<br>(5.831e-05)       | -1.211e-04***<br>(3.132e-05)    |
| Constant                        | 2.958e-02 ***<br>(4.712e-03)   | 3.303e-02***<br>(2.892e-03)     | 3.535e-02***<br>(2.321e-03)     |
| Observations                    | 120                            | 240                             | 360                             |
| R-squared                       | 0.054                          | 0.049                           | 0.072                           |
| Adjusted R-squared              | 0.030                          | 0.037                           | 0.064                           |
| Residual Standard Error         | 0.018                          | 0.016                           | 0.016                           |
| F-Statistic                     | 2.249                          | 4.040                           | 9.178                           |

Notes: Data taken from 2014 – 2020 Dallas Police Department “Response to Resistance” and “Incident” data. “Response to Resistance” data contains 19,451 use of force instances, “Incident” data contains 875,973 police interactions. Variable notes and descriptions listed in data section. \*Significant at 10% level, \*\* Significant at 5% level, and \*\*\* Significant at 1% level

**Table 4: George Floyd Citizen Injury Rate RD Model (All Races of Citizens, 60-day windows)**

|                                 | George Floyd<br>(1)       |
|---------------------------------|---------------------------|
| Treatment                       | -0.090<br>(0.080)         |
| I (day – day death)             | 4.747e-04<br>(1.646e-03)  |
| Treatment * I (day – day death) | -8.352e-04<br>(2.299e-03) |
| Constant                        | 0.319 ***<br>(0.058)      |
| Observations                    | 120                       |
| R-squared                       | 0.039                     |
| Adjusted R-squared              | 0.015                     |
| Residual Standard Error         | 0.221                     |
| F-Statistic                     | 1.597                     |

Notes: Data taken from 2014 – 2020 Dallas Police Department “Response to Resistance” data. “Response to Resistance” data contains 19,451 use of force instances. Variable notes and descriptions listed in data section. \*Significant at 10% level, \*\* Significant at 5% level, and \*\*\* Significant at 1% level

**Table 5: News Articles Published Containing Citizen Name Within One Month**

| Name               | Date       | Articles Within One Month | Articles Within Two Months |
|--------------------|------------|---------------------------|----------------------------|
| George Floyd       | 5/25/2020  | 72,807                    | 91520                      |
| Alton Sterling     | 7/5/2016   | 4191                      | 4395                       |
| Philando Castile   | 7/6/2016   | 3670                      | 4030                       |
| Rayshard Brooks    | 6/12/2020  | 3366                      | 3655                       |
| Michael Brown      | 8/9/2014   | 3345                      | 4316                       |
| Stephon Clark      | 3/18/2018  | 3250                      | 3608                       |
| Botham Jean        | 9/6/2018   | 1571                      | 1703                       |
| Terence Crutcher   | 9/16/2016  | 1157                      | 1176                       |
| Walter Scott       | 4/4/2015   | 958                       | 1178                       |
| Atatiana Jefferson | 10/12/2019 | 939                       | 964                        |
| Jordan Edwards     | 4/29/2017  | 670                       | 1018                       |
| Tamir Rice         | 11/22/2014 | 504                       | 596                        |
| Jamar Clark        | 11/15/2015 | 441                       | 560                        |
| Eric Harris        | 4/2/2015   | 364                       | 578                        |
| Akai Gurley        | 11/20/2014 | 217                       | 254                        |
| Eric Garner        | 7/17/2014  | 174                       | 313                        |
| Freddie Gray       | 4/12/2017  | 92                        | 175                        |
| Sam DuBose         | 7/19/2015  | 57                        | 61                         |
| William Chapman    | 4/22/2015  | 53                        | 106                        |
| Jeremy McDole      | 9/23/2015  | 26                        | 27                         |
| Laquan McDonald    | 10/20/2014 | 0                         | 0                          |
| Breonna Taylor     | 3/13/2020  | 0                         | 13                         |

Notes: Data collected using University of Illinois Cline Center Archer System. Name and date range entered into search query – resulting articles are published local or national news articles containing the name of the citizen killed within respective time ranges.

**Table 6: Officer and Suspect Demographics**

| Officers        |       |        |
|-----------------|-------|--------|
|                 | Male  | Female |
| American Indian | 78    | 13     |
| Asian           | 535   | 47     |
| Black           | 2296  | 480    |
| Hispanic        | 3890  | 515    |
| White           | 10337 | 52     |
| Other           | 124   | 1084   |
| Citizens        |       |        |
|                 | Male  | Female |
| American Indian | 29    | 15     |
| Asian           | 57    | 24     |
| Black           | 8830  | 1940   |
| Hispanic        | 3712  | 562    |
| White           | 3201  | 931    |
| Other           | 86    | 12     |

Notes: Data taken from 2014 – 2020 Dallas Police Department “Response to Resistance” data. “Response to Resistance” data contains 19,451 use of force instances. Variable notes and descriptions listed in data section. \*Significant at 10% level, \*\* Significant at 5% level, and \*\*\* Significant at 1% level

**Table 7: Other Summary Information**

|                     | Citizen Injured | Citizen Not Injured |
|---------------------|-----------------|---------------------|
| Officer Injured     | 965             | 972                 |
| Officer Not Injured | 4254            | 13260               |

Notes: Data taken from 2014 – 2020 Dallas Police Department “Response to Resistance” data. “Response to Resistance” data contains 19,451 use of force instances. Variable notes and descriptions listed in data section. \*Significant at 10% level, \*\* Significant at 5% level, and \*\*\* Significant at 1% level