Measuring the Effect of News Coverage of Black Crime on Racial Bias in Traffic Stops

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Abstract

In this paper, I investigate how news coverage of crime involving black perpetrators affects the level of racial bias in traffic stops. I identify 25 black crime news events from 2000-2019 that received coverage on ABC, CBS, NBC, CNN, or Fox News and measure how racial bias in traffic stops changes after the news coverage airs using two metrics of racial bias: *relative stop rate*, which is the rate at which black drivers are stopped minus the rate at which white drivers are stopped, and *relative hit rate*, which is the probability that police officers conduct a search of an innocent black driver minus the probability that they conduct a search of an innocent white driver. I calculate these metrics on a daily basis using traffic stop data from 24 state and local police departments from across the U.S. I find no evidence that racial bias against black drivers increases following television coverage of black perpetrators. My estimates show that it is unlikely that high coverage black crime events (those receiving at least 6 minutes and 40 seconds of television coverage) increase relative stop rates by more than 0.000869 stops per 10,000 people or decrease relative hit rates by more than 7.232% in the week following the news coverage (95% confidence level). This suggest that news coverage of black crime does not have a large influence on police officers' behavior in traffic stops.

1 Introduction

Racial bias is a pervasive issue, and one domain in which racial bias can be particularly problematic is law enforcement. In a perfect world, police officers would be impartial stewards of the law, but this may not always be the case. Police officers, just like all humans, have the potential to be subconsciously influenced by external factors, such as the people around them, their own experiences, and the media. For my project, I focus in on the potential influence of the media on the racial bias of police officers. Specifically, I answer the question *Does media coverage of crime involving black perpetrators increase racial bias in traffic stops?*

Traffic stops are an important realm for analysis because they are the most common interaction that Americans have with the police (Eith and Durose (2005)). Thus, if there exists a systemic bias in the way traffic stops are conducted, this could affect a large number of people. There is high potential for bias within traffic stops because they require subjective decision making. A police officer decides to conduct a traffic stop based on whether they have reasonable suspicion that a crime has occurred or is about to occur. After stopping the vehicle, the police officer can then decide to search the vehicle if they believe there is probable cause. The crime or suspected crime can range from a traffic violation, such as speeding or failing to stop at a stop sign, to having windows that are too darkly tinted, which was upheld as a valid reason for initiating a traffic stop in *United States v. Palmer (2016)*. However, the suspected crime is often used as a pretext to conduct a search for evidence of an unrelated crime, and this is especially true for minority drivers. Based on Police-Public Contact Survey data, Engel and Calnon (2004) found that young black and Hispanic male drivers who are stopped by the police are at increased risk for citations, searches, arrests, and uses of force, even though they are no more likely than white drivers to be carrying contraband. Lundman and Kaufman (2003) similarly found that African-American and Hispanic drivers are more likely to report being stopped by police officers for no legitimate reason. Among African Americans, this phenomenon is so well-known that they have given it a name: "driving while black." Legal scholar David A. Harris even argues that "searching cars for narcotics is perhaps the major motivation for making [stops of African American and Hispanic drivers]" (Harris (1996)). Starting with North Carolina in 1999, state and local police departments have begun collecting data on the race and ethnicity of drivers who are stopped, which has allowed for statistical tests for racial bias.

There is ample evidence that racial bias exists in traffic stops (Rojek, Rosenfeld, and Decker (2004), Hernández-Murillo and Knowles (2004), Pierson et al. (2017)), but less attention has been devoted to how this racial bias changes in response to external factors, particularly news coverage. One example of previous work done in this area is Warren and Farrell (2009), who conduct a time series analysis of 38,437 traffic stops in Rhode Island and find that racial bias in traffic stops decreases following increased media coverage of racial profiling. Their explanation for this effect is that this type of media coverage exerts positive pressure on the RI police department to be less racially biased in their interactions with the pubic. For my project, I investigate the effect of a different type of news coverage: black crime news coverage. By "black crime news coverage," I am referring to news coverage of crimes involving African American perpetrators.

I hypothesize that black crime news coverage causes a temporary increase in the level of racial bias in traffic stops. This hypothesis is grounded in the findings of several previous studies. According to priming research, when people are exposed to negative stereotypical portrayals of black males, they tend to adopt more negative perceptions of black males and become more likely to attribute responsibility of wrongdoing to them (Power, Murphy, and Coover (1996)). This suggests that viewing black crime news coverage might activate police officers' negative stereotypes about African Americans, which may in turn affect their behavior. Eren and Mocan (2018) found that an upset loss by the home state college football team causes judges to become harsher in sentencing in the week following the game, which illustrates how an emotional event can have effects on criminal justice outcomes. This indicates that it is possible that any racial bias that is activated by viewing black crime news coverage will affect police officers' decision making as they conduct traffic stops in the days that follow. An example of how news coverage of crimes involving minority suspects can shape people's judgements is Valentino (1999), who shows that study participants that are primed with a news story featuring a minority suspect rather than a white suspect are subsequently less likely to say they support Clinton, the sitting president at the time of the study.

In this project, I test the idea that black crime news coverage has priming effects that impact real world behavior by activating police officers' negative stereotypes about African Americans and causing them to become more biased against black drivers in the days following the news coverage. My measure of black crime news coverage is the amount of television coverage about black perpetrators of high profile crimes that aired on ABC, CBS, NBC, CNN, or Fox News between 2000 and 2019. I choose to focus on television coverage over other forms of media because I believe that television is likely to have a bigger impact on bias, which is supported by Ogloff and Vidmar (1994), who find that television exposure has a stronger impact on the bias of jurors than print media. I measure racial bias in traffic stops using two different metrics. The first metric is $relative\ stop\ rate$, which measures the difference in the frequency that black drivers are stopped in comparison to the black population and the frequency that white drivers are stopped in comparison to the white population. A higher relative stop rate suggests more bias against black drivers. The second metric is $relative\ hit\ rate$, which measures the difference in the probability that a police officer searches an "innocent" black driver and the probability that they search an "innocent" white driver.[1] A more negative hit rate suggests more bias against black drivers.

I test my hypothesis visually by plotting $relative\ stop\ rate$ and $relative\ hit\ rate$ in a window of seven days around the airing of black crime news coverage. These plots show that these bias metrics do not change in a significant way following black crime news coverage. I quantify these results by estimating an OLS regression using $\Delta Average\ relative\ stop\ rate$, which is calculated by averaging the relative stop rate over the seven days following the day that black crime news coverage first airs and also for the seven days prior, then taking the difference between these averages. I do the same for $\Delta Average\ relative\ hit\ rate$. I find that news coverage of black crime does not have a statistically significant effect on racial bias in traffic stops. With 95% confidence, I conclude that black crime events that receive less than 6 minutes and 40 seconds of coverage increase relative stop rates by less than 0.0906 stops per 10,000 people and decrease relative hit rates by less than 6.097%. For black crime events that receive more than 6 minutes and 40 seconds of coverage, I conclude with 95% confidence that they increase relative stop rates by less than 0.00086 stops per 10,000 people and decrease relative hit rates by less than 7.232%. These effect sizes are small when compared to the standard deviations of relative stop rate and relative hit rate for the average police department (1.57 per 10,000 people and 28.8%, respectively).

My primary analysis relies on several assumptions, including the assumptions that news coverage that airs on different channels have similar effects on racial bias, the influence of televised news coverage has stayed constant over the years, and that the impact of news coverage on racial bias can be observed within a week-long time window around the news coverage. I show that my results hold even when I relax these assumptions.

[1] By "innocent," I mean a driver who does not possess contraband.

My project builds upon work by Philippe and Ouss (2018), who investigate how news coverage of crime affects criminal sentencing and find that, on average, an additional story about felonies leads to a 26 day increase in sentences handed down the subsequent day. Like them, I look at how news coverage of crime affects criminal justice decisions, but the decisions I focus on are the decisions that police officers make when conducting traffic stops. My project also contributes to the study of the external validity of laboratory findings (Kessler and Vesterlund (2015)) by demonstrating that priming effects of black crime news coverage do not have a detectable effect on police behavior in traffic stops. This is in line with the findings of Philippe and Ouss (2018), who find that the effect sizes they identify are smaller than the effects identified in laboratory experiments.

The rest of the paper proceeds as follows: Section 2 describes the data. Section 3 explains the methodology I employ to answer my research question. Section 4 presents my main results and several robustness checks. Section 5 discusses some limitations of my approach and directions for future work. Section 6 concludes.

2 Data

2.1 News coverage data

In order to identify news coverage of crime involving black perpetrators, I first assemble a list of black perpetrators who committed high-profile crimes between 2000 and 2019. The primary type of crime I look at is mass shootings. I utilize an online database of mass shootings since 1982 compiled by *Mother Jones*, which is a U.S. magazine focused on investigate journalism.[2] This database includes information on the date and location of each shooting; the shooter's name, gender, race, and mental health status; and additional details. Using this database, I create a list of 13 mass shooting events involving black perpetrators that occurred between 2000 and 2019. To supplement this list, I manually search through *Wikipedia*'s lists of U.S. crimes by year and identify five accused black serial killers and three additional shootings involving black perpetrators.[3]

I then use the *Vanderbilt Television News Archives* to find television segments that have been aired about each of the black perpetrators. The Vanderbilt Television News Archives contains evening news broadcasts from ABC, CBS, and NBC starting in 1968, one hour of daily CNN programming starting in 1995, and one hour of daily Fox News programming starting in 2004. According to Pew's 2010 State of the News Media Report, 22.3 million Americans in 2010 watched evening news broadcasts on ABC, CBS, NBC, CNN, or Fox each weeknight.[4] Thus, the news segments available through the Vanderbilt Television News Archives are a good representation of the broadcast news coverage consumed by

[2] *Mother Jones*' database available at https://www.motherjones.com/politics/2012/12/mass-shootings-mother-jones-full-data/

[3] For example, here is Wikipedia's list of 2009 crimes in the U.S.: https://en.wikipedia.org/wiki/Category:2009_crimes_in_the_United_States

[4] Report available at https://www.journalism.org/2019/06/25/archived-state-of-the-news-media-reports/

the typical American.

To find relevant news segments in the archives, I perform two searches. First, I search for the perpetrator's name (e.g., "Gary Martin") using Search Type = Phrase Search. Using Phrase Search eliminates false positive news segments that are about people who share a first or last name with the perpetrator. This search is effective in identifying the majority of relevant news segments. To find additional news segments that are relevant but are not coded with the perpetrator's name, I perform an additional search with the state where the crime occurred along with the crime type (e.g., "Illinois shooting"). For this search, I use the default search type, Word Search, and I restrict the time range to be the two week period following the crime. For a small number of perpetrators, this second search uncovers additional relevant news segments.

For each relevant segment, I record the date it aired, the channel it aired on, and the length in seconds. For segments coded as covering multiple topics, I divide the total length of the segment by the number of topics covered to get an estimate of the amount of time spent covering the black crime event. For one of the mass shooters in my original list, there was not any news coverage that aired on the channels included in the Vanderbilt Television News Archives, so I exclude that name from my list. The final list of black perpetrators that I include in my analysis is shown in Table A1 of the Appendix.

The x-axis of Figure 1 shows how the news coverage of the perpetrators I selected is distributed over time. For the most part, news coverage of each perpetrator is temporally separated from coverage of other perpetrators. The smallest gap between coverage of different perpetrators is between the coverage of Micah Johnson on June 11, 2016 and the coverage of Gavin Long on June 17, 2016. In general, the temporal separation between coverage of different perpetrators is much larger, which allows me to isolate the effects of black crime news coverage by looking at a small window before and after the news coverage occurs. The y-axis of Figure 1 illustrates the variability in the amount of news coverage each perpetrator received.

Using the news segment data I collected, I identify *news events*. I define a news event as consecutive coverage about the same perpetrator. I use a generous definition of "consecutive" to include all news coverage about a perpetrator that airs within 14 days of the latest coverage of that perpetrator. Figure 2 helps illustrate why it can be useful to separate news coverage of a perpetrator into separate news events. Although for most perpetrators, news coverage about the perpetrator ends a few days after the first news story airs, there are some perpetrators that receive coverage months after the first news story about them airs. This news coverage is not shown on the plot for readability purposes. It makes sense that this later news coverage should be considered separately from the initial news coverage, which is why I define news events. For the majority of perpetrators, there is one associated news event—the news coverage of the crime immediately following the crime. Three perpetrators have two associated news events according to my definition, and one has three associated news events. An example of a perpetrator having multiple associated news events is a perpetrator who receives news coverage immediately following the crime

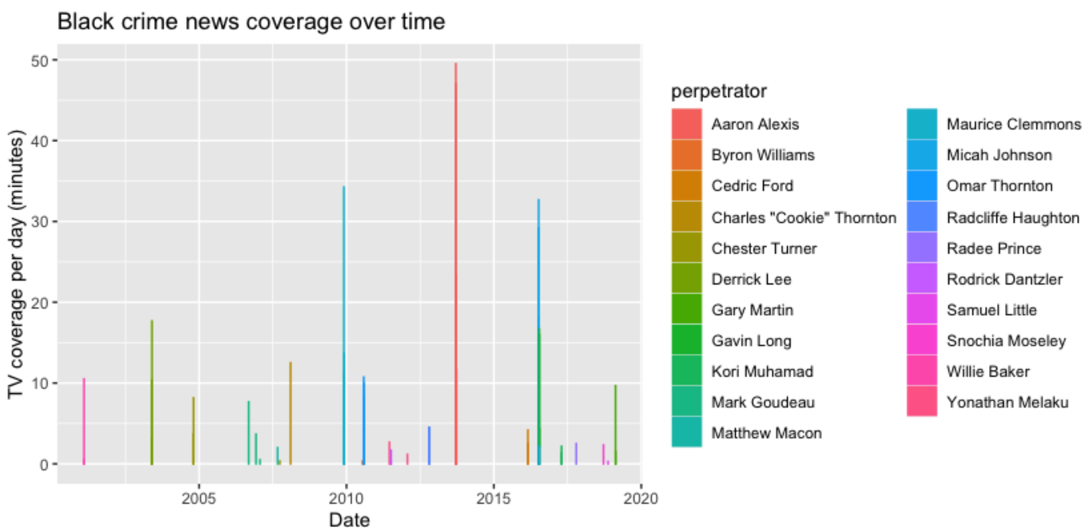

Figure 1: Daily news coverage over time of the black perpetrators that I use in my analysis.

(the first news event) and later receives additional coverage when he goes on trial months later (the seconds news event). The total number of news events in my data set is 25. For each news event, I record the date that the first relevant news segment aired as the start date of that news event.

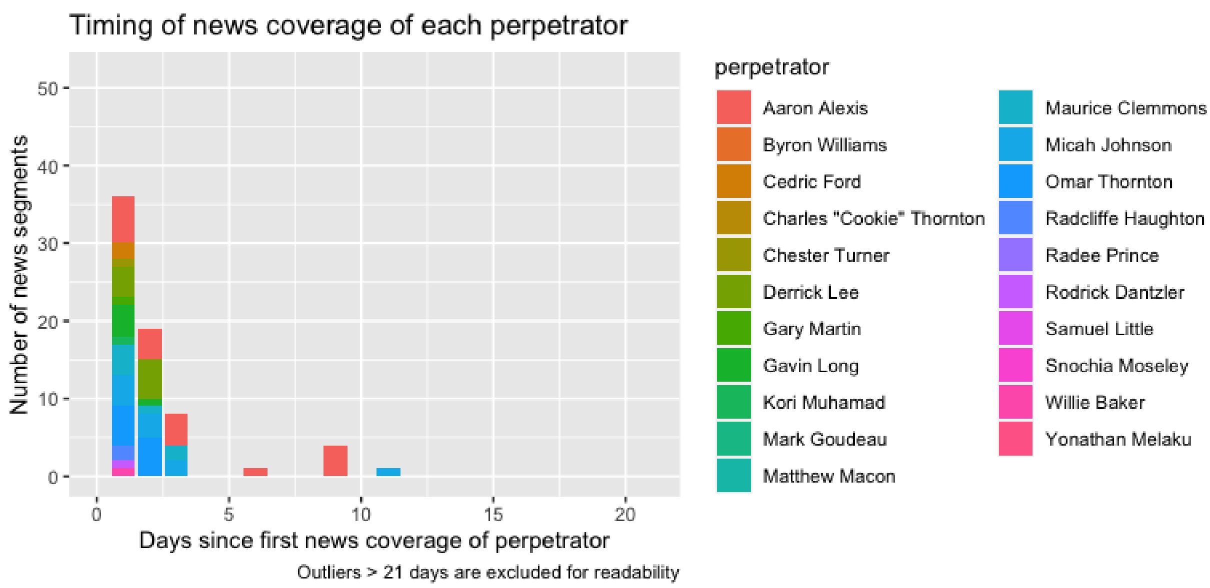

Figure 2: Distribution of the timing of news coverage about each perpetrator.

Figure 3 shows the amount of coverage that each of the 25 news events received. The median amount of coverage is 6.67 minutes, and the mean is 19.37 minutes. The news event that received the least amount of coverage (0.28 minutes) was associated with the serial killer Samuel Little. The news event that received the most amount of coverage (143.70 minutes) was associated with the mass shooter Aaron Alexis.

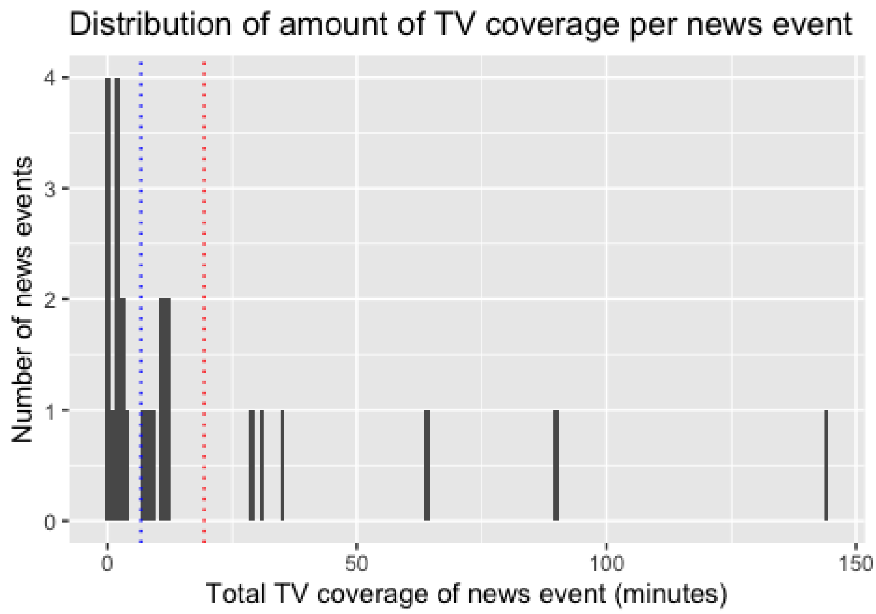

Figure 3: Histogram of the total length of news coverage that each news event received, using a bin width of one minute. Coverage is summed over all days that are part of the news event. The blue line at 6.67 minutes is the median. The red line at 19.37 minutes is the average.

2.2 Traffic stop data

In order to measure racial bias in traffic stops over time, I use traffic stop data from Stanford's Open Policing Project (Pierson et al. (2017)). The Open Policing Project includes traffic stop records beginning as early as 1999 and ending as recently as 2019. The data comes from dozens of state and local police departments from around the U.S., but some police departments have records that are more complete than others. For my analysis, I choose to only use data from police departments whose records include the stop date, the driver's race, whether a search was conducted, and whether contraband was found. My traffic stop data set includes data on a total of 103,464,877 traffic stops from the following 24 police departments: *Arizona State Patrol; Oakland, CA; San Diego, CA; San Francisco, CA; San Jose, CA; Colorado State Patrol; Connecticut State Patrol; Illinois State Patrol; Massachusetts State Patrol; New Orleans, LA; Charlotte, NC; Winston-Salem, NC; North Carolina State Patrol; Philadelphia, PA; Pittsburgh, PA; Rhode Island State Patrol; South Carolina State Patrol; Nashville, TN; San Antonio, TX; Plano, TX; Texas State Patrol; Burlington, VT; Vermont State Patrol; and Washington State Patrol.*

Using this traffic stop data, I compute several metrics. First, I compute the *stop rate* of race r (black or white) on day t for police department p as

$$stop\ rate_{r,t,p} = \frac{\text{\# of stops on day } t \text{ involving driver of race } r}{\text{population of race } r \text{ in jurisdiction of } p} \times 10,000$$

The black and white population in the jurisdiction of each police department is calculated by multiplying the U.S. Census estimate of the percentage of black (or white) people in a geographic area and the population in that geographic area, as reported in the 2010 Census.[5] For local police departments, I use the city as the geographic area. For state patrols, I use the state as the geographic area. I multiply by 10,000 to get the stop rate per 10,000 people, which helps make the numbers more interpretable.

In order to use stop rate as a metric for racial bias, I consider the black stop rate relative to the white stop rate and compute the *relative stop rate* on day t for police department p as

$$relative\ stop\ rate_{t,p} = stop\ rate_{black,t,p} - stop\ rate_{white,t,p}$$

Intuitively, if the relative stop rate is positive (i.e., black drivers have a higher stop rate than white drivers), this suggests that police officers are biased against black drivers. However, one should use caution before jumping to such a conclusion, as there are other possible explanations for such a discrepancy. For example, if there are many black drivers who live outside of a given city but drive into the city for work, this may inflate the black stop rate for that city. Despite this, (relative) stop rate is still a useful metric for my purposes because I am looking at changes over time. Even if stop rate is a biased metric, as long as it is biased in the same way over time, I can use it to detect if the level of racial bias changes following black crime news coverage.

To compensate for the deficiencies of using relative stop rate as a metric for racial bias, I compute two additional metrics: hit rate and relative hit rate. The *hit rate* of race r on day t for police department p is given by

$$hit\ rate_{r,t,p} = \frac{\text{\# of searches of drivers of race } r \text{ on day } t \text{ by dept. } p \text{ that uncover contraband}}{\text{total \# of searches of drivers of race } r \text{ on day } t \text{ by dept. } p}$$

and the *relative hit rate* on day t for police department p is given by

$$relative\ hit\ rate_{t,p} = hit\ rate_{black,t,p} - hit\ rate_{white,t,p}\ .$$

Hit rate is an example of an outcome test. Becker (2010) first proposed the idea of using the outcomes of decisions as a way of measuring bias, and Knowles, Persico, and Todd (2001) helped develop this idea in the context of traffic stops and laid the framework for using hit rates to measure racial bias in traffic stops. We can interpret relative hit rate as a measure of the inherent suspicion police officers have towards black drivers as compared towards white drivers. If relative hit rate is *negative* (i.e., the black hit rate is *lower* than the white hit rate), this implies that police officers apply a lower threshold of evidence when deciding whether or not to search black drivers. In other words, a negative relative hit rate means that police officers are more likely to conduct a search of a black driver who does not possess contraband than they are to conduct a search of a white driver who does not possess contraband.

[5] Available at `https://www.census.gov/quickfacts`

Police department	Date range	Daily averages										
		Total stops	# B stop	# W stop	# B search	# W search	$stoprate_B$	$stoprate_W$	$hitrate_B$	$hitrate_W$	rel. stop rate	rel. hit rate
	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
AZ State Patrol	Jan '09-Dec '17	1230 (637)	78.1 (46.6)	715 (361)	7.5 (7.08)	30 (20.2)	2.41 (1.43)	1.36 (0.678)	0.408 (0.36)	0.39 (0.324)	1.05 (0.91)	-0.00211 (0.223)
CA Oakland	Mar '13-Dec '17	81.4 (33.5)	48.2 (19.5)	9.54 (6.32)	18.3 (8.67)	1.46 (1.45)	5.22 (2.11)	0.676 (0.448)	0.129 (0.171)	0.159 (0.317)	4.55 (1.89)	-0.0253 (0.276)
CA San Diego	Dec '13-Mar '17	323 (123)	36 (13.7)	137 (62)	3.26 (2.4)	3.8 (2.85)	4.23 (1.61)	1.61 (0.732)	0.0914 (0.182)	0.118 (0.2)	2.62 (1.19)	-0.0257 (0.27)
CA San Francisco	Dec '06-Jun '16	261 (70.1)	43.9 (13.7)	107 (37.4)	6.81 (3.27)	3.38 (2.57)	9.74 (3.02)	2.52 (0.876)	0.0947 (0.136)	0.244 (0.29)	7.21 (2.56)	-0.15 (0.312)
CA San Jose	Aug '13-Mar '18	91.4 (34.4)	8.1 (4.23)	15.8 (6.7)	2.63 (2.1)	3.83 (2.71)	2.85 (1.49)	0.417 (0.177)	0.201 (0.294)	0.212 (0.26)	2.44 (1.41)	-0.0125 (0.375)
CO State Patrol	Jun '09-Jun '17	1070 (287)	30.4 (10.3)	738 (202)	0.219 (0.55)	2.13 (2.28)	1.31 (0.447)	1.68 (0.461)	0.407 (0.477)	0.541 (0.399)	-0.37 (0.328)	-0.144 (0.542)
CT State Patrol	Sep '13-Sep '15	1610 (453)	222 (62.8)	1150 (332)	16.2 (7.58)	32.7 (12.7)	5.17 (1.46)	4.04 (1.16)	0.22 (0.139)	0.293 (0.117)	1.13 (0.647)	-0.073 (0.156)
IL State Patrol	Dec '11-Dec '17	5820 (1060)	1170 (263)	3670 (691)	80.3 (19.8)	133 (32)	6.26 (1.4)	3.72 (0.7)	0.218 (0.0696)	0.218 (0.0569)	2.54 (1.09)	-0.000285 (0.0648)
LA New Orleans	Dec '09-Jul '18	164 (66.3)	112 (47.2)	41.5 (17.6)	18.6 (10.9)	4.9 (3.54)	5.46 (2.3)	3.55 (1.51)	0.193 (0.12)	0.159 (0.203)	1.9 (1.5)	0.0335 (0.225)
MA State Patrol	Dec '06-Dec '15	1040 (347)	107 (36.6)	770 (264)	2.56 (2.41)	10.5 (8.08)	1.84 (0.628)	1.45 (0.498)	0.471 (0.374)	0.531 (0.237)	0.381 (0.31)	-0.0562 (0.418)
NC Charlotte	Dec '99-Dec '15	276 (150)	137 (80.2)	101 (55.6)	10.8 (7.3)	3.31 (2.67)	5.36 (3.12)	2.8 (1.53)	0.267 (0.164)	0.269 (0.282)	2.56 (1.88)	-0.000343 (0.319)
NC State Patrol	Dec '99-Dec '15	3470 (1160)	1060 (409)	2040 (641)	47.6 (20.7)	45.2 (20.5)	4.55 (1.76)	2.75 (0.865)	0.255 (0.102)	0.273 (0.097)	1.8 (0.995)	-0.018 (0.118)
NC Winston-Salem	Jan '00-Dec '15	86.9 (38.4)	38.7 (17.7)	38.3 (18.5)	0.875 (1.06)	0.614 (0.873)	4.84 (2.21)	2.96 (1.42)	0.356 (0.423)	0.305 (0.422)	1.88 (1.48)	0.0469 (0.567)
PA Philadelphia	Dec '13-Apr '18	1190 (305)	795 (201)	240 (76.1)	50.9 (17.5)	13.3 (7.32)	11.9 (3.01)	3.51 (1.11)	0.275 (0.0931)	0.288 (0.179)	8.41 (2.15)	-0.0134 (0.181)
PA Pittsburgh	Dec '07-Apr '18	72.8 (39.3)	22.4 (12.9)	38.5 (25.7)	22.3 (13)	37.6 (25.6)	3.17 (1.82)	1.89 (1.26)	0.0315 (0.0475)	0.0201 (0.0568)	1.28 (1.22)	0.0132 (0.0585)
RI State Patrol	Jan '05-Dec '15	134 (45.5)	18 (7.36)	90.5 (35.2)	1.13 (1.24)	2.62 (2.08)	2.04 (0.828)	1.03 (0.396)	0.375 (0.417)	0.406 (0.364)	1.01 (0.695)	-0.0282 (0.539)
SC State Patrol	Dec '04-Dec '16	2120 (645)	696 (223)	1320 (400)	21.1 (12.7)	30.4 (15.4)	5.55 (1.78)	4.15 (1.26)	0.261 (0.193)	0.241 (0.156)	1.4 (0.809)	0.02 (0.23)
TN Nashville	Dec '09-Mar '19	918 (393)	346 (151)	496 (221)	20.2 (10.1)	14.2 (7.94)	20.6 (9)	13 (5.83)	0.224 (0.128)	0.217 (0.157)	7.58 (3.97)	0.00663 (0.189)
TX Plano	Dec '11-Dec '15	170 (78.1)	24 (10.9)	103 (51)	2.41 (1.96)	4.6 (2.97)	11 (4.99)	6.04 (2.99)	0.00436 (0.0461)	0.00783 (0.0569)	4.96 (2.86)	-0.00306 (0.0627)
TX San Antonio	Dec '11-Apr '18	452 (176)	44.8 (17.7)	168 (63.4)	0.598 (0.884)	1.4 (1.39)	4.89 (1.93)	1.58 (0.594)	0.0801 (0.251)	0.106 (0.255)	3.32 (1.47)	-0.0158 (0.335)
TX State Patrol	Dec '05-Dec '17	6260 (2200)	621 (241)	3520 (1470)	19.5 (12.5)	59.2 (45.7)	1.67 (0.649)	1.54 (0.642)	0.364 (0.15)	0.368 (0.111)	0.134 (0.346)	-0.00385 (0.152)
VT Burlington	Dec '11-Dec '17	14.4 (9)	1.14 (1.23)	11.9 (7.84)	0.0412 (0.201)	0.123 (0.361)	5.07 (5.45)	3.31 (2.17)	0.618 (0.489)	0.705 (0.452)	1.76 (5.06)	0.182 (0.603)
VT State Patrol	Jun '10-Dec '15	141 (54.7)	2.86 (2.15)	132 (51.4)	0.136 (0.414)	1.36 (1.5)	3.26 (2.45)	2.25 (0.873)	0.718 (0.439)	0.853 (0.302)	1.01 (2.19)	-0.149 (0.533)
WA State Patrol	Dec '08-Sep '18	3210 (654)	114 (33.6)	1780 (441)	6.08 (3.97)	47 (22.5)	3.49 (1.03)	2.97 (0.734)	0.115 (0.169)	0.132 (0.0832)	0.525 (0.702)	-0.018 (0.17)
Summary	Dec '99-Mar '19	1260 (377)	241 (80.3)	726 (231)	15 (7.01)	20.3 (10.2)	5.50 (2.33)	2.95 (1.20)	0.266 (0.226)	0.249 (.224)	2.54 (1.57)	-.0182 (0.288)

Table 1: Summary statistics of the traffic stop data for each police department. Column (2) is the date range covered by each department's records. For Columns (3)-(13), all values are given as *daily average (standard deviation)*. Column (3) is the average number of traffic stops per day. Columns (4) and (5) are the average number of black and white drivers, respectively, that are stopped per day. Columns (6) and (7) are the average number of black and white drivers, respectively, that are searched per day. Columns (8) and (9) are the black and white stop rates per 10,000 people. Columns (10) and (11) are the black and white hit rates. Columns (12) is the relative stop rate per 10,000 people. Column (13) is the relative hit rate. The last row summarizes the date range covered by the data and shows the average of the department-level means with the average standard deviation in parentheses.

Table 1 shows summary statistics of the traffic stop data for each police department. Looking down each column, one can see that there is a good amount of variation between police departments, both in terms of the number of stops and also the various bias metrics. State patrols and large cities, such as Philadelphia, tend to conduct more traffic stops, presumably because they employ more police officers and have more residents under their jurisdiction. It is worth noting that for most police departments, the average relative stop rate is positive and the average relative hit rate is negative, which is suggestive of racial bias against black drivers. However, the standard deviation is quite large, meaning that there is a lot of variation in these metrics from day to day.

3 Methodology

My hypothesis is that news coverage of black crime leads to an increase in racial bias in traffic stops, which manifests as an increase in relative stop rate and a decrease in relative hit rate. Furthermore, I expect news coverage to have a "dosage effect", meaning that these metrics will change more following a high coverage black crime news event than a low coverage one.

3.1 Visualization

I first test my hypothesis visually by creating plots of (relative) stop rates and hit rates before and after news coverage of black crime occurs. I split my set of 25 news events into "high coverage" and "low coverage" events. I define events that received at least the median amount of news coverage (6.67 minutes, as seen in Figure 3) to be "high coverage" events, and I define events that received less than the median amount of coverage to be "low coverage" events. For each high coverage event and for each police department, I compute the bias metrics (black stop (hit) rate, white stop (hit) rate, and relative stop (hit) rate) for the seven days preceding the day the news event begins and for the seven days after the news event begins. I then use all event $\times$ department pairs to compute an average for each bias metric for each day relative to the day the news event begins. I do the same for low coverage news events. If my hypothesis is true, we should see an increase in the black stop rate and the relative stop rate after the start of the news event. We should also see a decrease in the black hit rate and relative hit rate because, according to my hypothesis, black crime news coverage will activate negative racial stereotypes, causing police officers to apply a lower threshold of evidence when deciding whether to search black drivers.

3.2 Regressions

I quantify my results by estimating the following OLS regressions:

$$\Delta Average\ relative\ stop\ rate_{i,p} = \alpha + \beta High\ coverage_i + \mu_{i,p} \tag{1}$$

$$\Delta Average\ relative\ hit\ rate_{i,p} = \alpha + \beta High\ coverage_i + \mu_{i,p} \tag{2}$$

The unit of analysis is event $\times$ police department pairs (i, p). Each of the two regressions uses a different bias metric as the outcome of interest: $\Delta Average\ relative\ stop\ rate_{i,p}$ is the average relative stop rate for police department p in the seven days *after* news event i begins (excluding the day the event begins) minus the average relative stop rate the seven days *before* the news event begins. An analogous procedure is used to calculate $\Delta Average\ relative\ hit\ rate_{i,p}$, but one caveat is that, since hit rate cannot be computed if no searches were conducted on a given day, days with undefined hit rates are excluded when computing the average. $High\ coverage_i$ is an indicator for whether news event i received high news coverage and $\mu_{i,p}$ is an error term. For each regression, α tells us the average effect that low coverage news events have on the bias metric, and β tells us the additional effect that high coverage news events have on the bias metric relative to low coverage news events. $\alpha + \beta$ tells us the total effect that high coverage news events have on the bias metric.

3.3 Assumptions

My approach relies on the following assumptions:

Police officers depend on ABC, CBS, CNN, NBC, and Fox News as their primary source of news about high-profile black crime events. This assumption is likely reasonable because (1) According to a 2019 survey conducted by Pew Research Center, despite the rise in online news, a plurality of Americans prefer to get their news via television and (2) According to 2019 Nielsen data compiled by Variety magazine, ABC, CBS, CNN, NBC, and Fox News are the most-watched news channels in the U.S. If this assumption does not hold, this may inflate my estimate of the causal effect of TV coverage of black crime events, because some of the observed effect may be attributable to news coverage by other media outlets. However, even if this were the case, as long as we make the more mild assumption that coverage levels on other media platforms is proportional to the coverage levels on ABC, CBS, CNN, NBC, and Fox News, my approach yields estimates that are valid, up to a scaling factor.

When covering black crime, news broadcasts make clear what the race of the perpetrator is. TV is inherently a visual medium, so crime coverage that appears on TV usually includes video or still images of the perpetrator, from which their race can be inferred. I confirmed that this was true by manually reviewing several of the black crime news segments on the Vanderbilt Television News Archives.

Other popular media outlets do not cover the news event before ABC, CBS, CNN, NBC, or Fox News. If police officers learn about the black crime event from another source more than a day before the news event airs on the channels included in my analysis, this may manifest as a change in the bias metrics before the start of the news event (by my definition), which would bias my estimates. However, since the news events included in my data set are all high profile crimes and the television channels I focus on all have substantial reporting resources, it is likely that these channels cover these news events on the same day (or an earlier day) as compared to other news outlets.

The level of racial bias in traffic stops before high coverage black crime news events and low coverage ones is similar. This assumption makes it reasonable for me to view low coverage news events as a counterfactual for what would have happened if high coverage news events had received less coverage, which allows me to isolate the effect of receiving high news coverage. I test this assumption by plotting the average stop/hit rate before high coverage and low coverage news events.

The $High\ coverage_i$ indicator is sufficient for detecting any potential dosage effects of black crime news coverage. Recall that the secondary part of my hypothesis is that black crime news events that receive more news coverage will have a bigger effect on bias metrics than those that receive less news coverage. However, since it is unclear how the marginal effect of news coverage changes as the amount of news coverage increases, I choose to use an indicator variable rather than trying to estimate a regression of an arbitrary form (e.g., linear or polynomial). Using an indicator variable for high coverage allows for the detection of any positive or negative dosage effects even when we do not know what the shape of the underlying relationship should be. To make my results more robust, I also estimate OLS regressions with different definitions of "high coverage" and include results from a linear regression of my bias metrics on the total length of coverage.

The effect of black crime news coverage on racial bias in traffic stops can be observed within a week after each news event starts. As we saw in Figure 1, most news coverage occurs within a three day window following the start of the black crime news event. If this news coverage activates negative racial stereotypes about African Americans, we would expect the effects to kick in immediately after someone watches the news coverage (e.g., we would not expect there to be a gap of more than one day between the day the news coverage is aired and the day that the bias metrics are affected). Thus, this assumption is for the most part reasonable. For robustness, I relax this assumption by computing $\Delta Average\ relative\ stop\ rate_{i,p}$ and $\Delta Average\ relative\ hit\ rate_{i,p}$ over different window lengths and repeating my regression analysis.

Black crime news coverage has an equal effect on racial bias over the years. My methodology implicitly assumes that news coverage that airs in 2005 has the same effect on racial bias in traffic stops as news coverage that airs in, say, 2015. However, the rise of the Internet has undoubtedly changed the way that Americans consume the news, so it is possible that television coverage of black crime had a stronger effect in the 2000s than in the 2010s. To test this idea, I split my list of news events into an early group (2000-2009) and a late group (2010-2019) and estimate regressions for each group separately in my robustness checks.

Black crime news coverage on different news channels has an equal effect on racial bias. ABC, CBS, CNN, NBC, and Fox News are all popular television channels, but some of these channels have higher viewership than others. Furthermore, there may be qualitative differences in the way each channel covers black crime. It may not be the case that a minute of black crime news coverage on one channel is equivalent to one minute of black crime news coverage on another channel. Fortunately, my approach does not rely too heavily on this assumption since I use an indicator variable for high coverage. If I instead used total coverage length as my explanatory variable, I would have to rely more heavily on this assumption. However, I test this assumption by separating out the amount of coverage each event received on each channel and rerunning my regressions.

In the absence of black crime news coverage, racial bias would, on average, stay constant. This assumption allows me to say that changes in relative stop rate and relative hit rate that occur after black crime news coverage airs are causal effects of the news coverage. This assumption is reasonable because, given the large temporal variation in the occurrence of black crime news events, it is unlikely that confounding factors would be systemically present every time a black crime news event occurs. To check this assumption, I treat white crime news events as a control group and investigate how the bias metrics change relative to these events. If this assumption holds, we would not expect to see a statistically significant change in the bias metrics following white crime news events.

There are no qualitative differences in the news events besides coverage length. This assumes that if a news event featuring a less violent perpetrator and one featuring a more violent perpetrators receive an equal amount of coverage, the two news events will have an equal effect on racial bias. However, it is possible that viewers react more strongly to news stories about black perpetrators who committed more violent crimes. I test this assumption by repeating my regressions with controls for the type of crime and the number of victims.

4 Results

4.1 Main Results

Figure 4 shows how stop rates of black and white drivers change following news coverage of black crime. First, consider the top plot. If black crime news coverage increased racial bias in traffic stops, we would expect to see a bump in the black stop rate following the news event, with high coverage events causing a bigger bump. We do not see evidence of this in the plot. In this plot and all following plots, error bars represent a 95% confidence interval. We see that the 95% confidence interval of the stop rates before and after the news event begins do not differ significantly, suggesting that news coverage does not have a significant effect on the stop rate. Additionally, the confidence intervals of the average stop rate before high coverage black crime news events and low coverage black crime news events overlap, suggesting that news coverage does not have the hypothesized dosage effect. This plot also validates my assumption that the stop rates before high coverage news events and low coverage news events are not statistically different prior to the start of the news event.

The bottom plot of Figure 4 acts as a falsification test. According to my hypothesis, white stop rates should not be affected by news coverage of black crime. This is supported by the plot. However, when we consider the top and bottom plots together, we see that the black and white stop rates follow a similar trend, which suggests that there is an exogenous

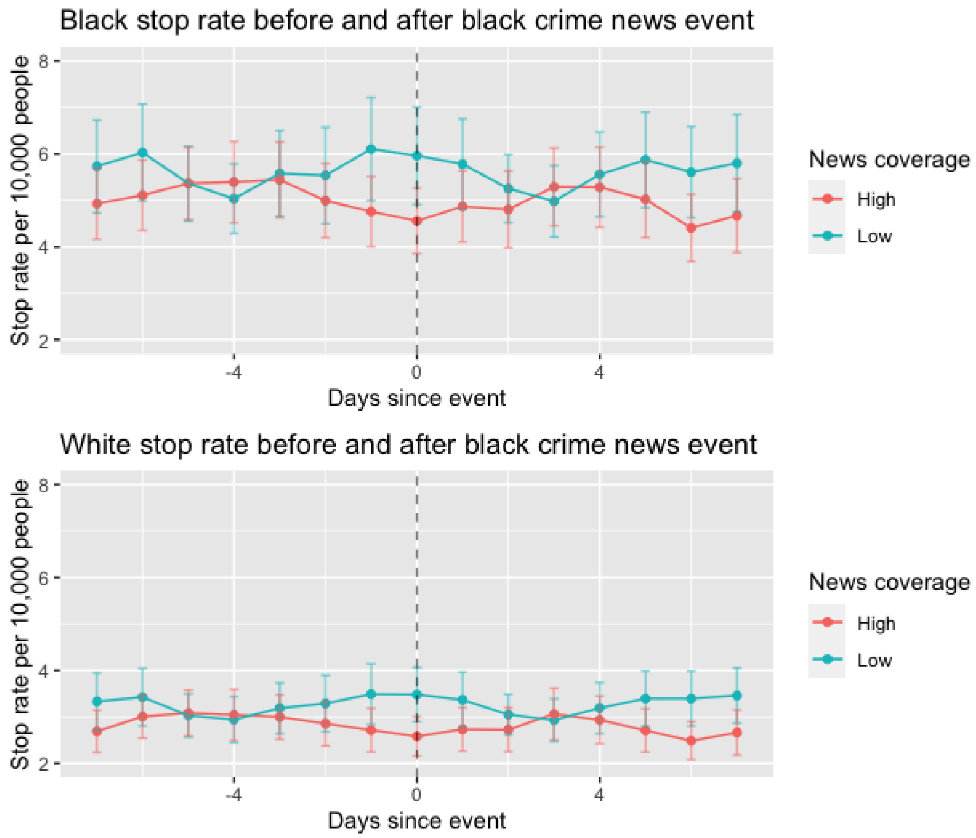

Figure 4: Stop rates for black and white drivers over a 14-day window around news events involving black perpetrators are shown in the top and bottom plots, respectively. Red (blue) line is the stop rate averaged over events that received more (less) than 6.67 minutes of news coverage.

determinant of stop rates (e.g., the number of police officers active on a given day) that should be controlled for. This supports the idea that we should look at relative stop rates rather than black stop rates alone.

Figure 5 shows the relative stop rate before and after black crime news coverage. This plot allows us to see how black stop rates change *relative to white stop rates*. Any exogenous factors that influence black and white stop rates equally are cancelled out when we take the difference between the stop rates. If black crime news coverage increases racial bias in traffic stops, we would expect the black stop rate to increase relative to the white stop rate, which would translate into an increase in the relative stop rate. However, we do not see a significant change in the relative stop rate for high coverage or low coverage news events.

Figure 6 is similar to Figure 5, except it plots relative hit rate rather than relative stop rate. If racial bias increases after black crime news coverage, we would except the relative hit rate to decrease, but we do not observe statistically significant evidence of this.

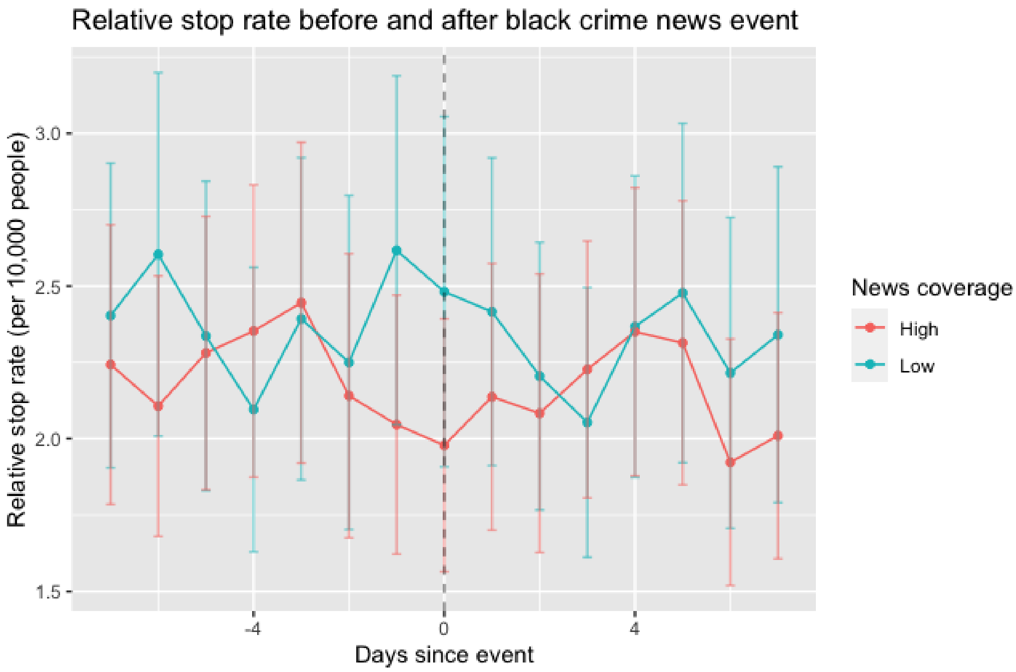

Figure 5: Difference in stop rates for black and white drivers over a 14-day window around news events involving black perpetrators. Red (blue) line is the relative stop rate averaged over events that received more (less) than 6.67 minutes of news coverage.

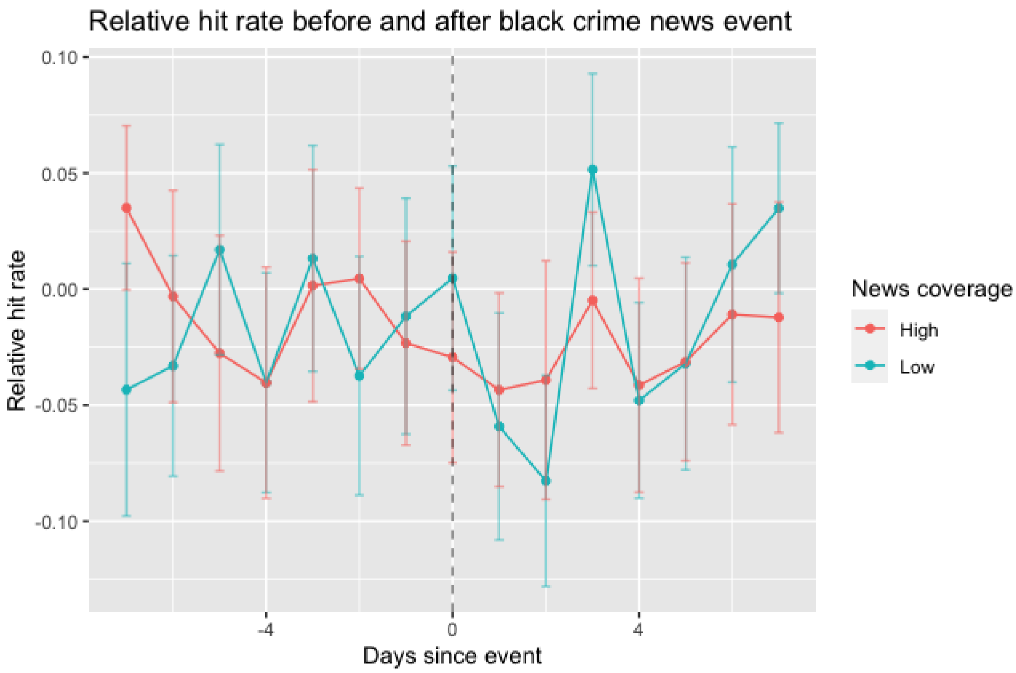

Figure 6: Difference in hit rates for black and white drivers over a 14-day window around news events involving black perpetrators. Red (blue) line is the relative hit rate averaged over events that received more (less) than 6.67 minutes of news coverage.

The first column of Table 2 quantifies the results explored visually in Figure 5, and the second column quantifies the results explored visually in Figure 6. The intercepts represent the change in average relative stop/hit rate following a low coverage black crime news event, and the coefficient of $High\ coverage$ represents the additional effect of receiving high news coverage. The signs of the coefficients in Column (2) align with my hypothesis, but the coefficients in Column (1) do not. The negative intercept in Column (1) suggests that police officers stop black drivers less frequently relative to white drivers following a low coverage black crime news event, and the negative coefficient of $High\ coverage$ suggests that black crime events that receive high news coverage cause a bigger decrease in racial bias than black crime events that receive low coverage. However, the standard errors are large relative to the estimated coefficients, so none of the coefficients are statistically different from 0, even at the 10% confidence level, so we should not read too much into the signs of these coefficients.

	$\Delta Avg\ relative\ stop\ rate$	$\Delta Avg\ relative\ hit\ rate$
	(1)	(2)
(Intercept)	-0.0470 (0.0622)	-0.01746 (0.02220)
$High\ coverage$	-0.0883 (0.0913)	-0.00578 (0.03286)
Observations	257	217[a]
R^2	0.00363	0.000143

Table 2: Regression results from Regressions (1) and (2) described in Section 3.2. Observations are event $\times$ police department pairs. Standard errors are given in parentheses.

[a] The number of observations of average relative hit rate is lower than for average relative stop rate because hit rate cannot be computed if no searches are conducted on a given day.

The 95% confidence interval for the intercept in Column (1) of Table 2 tells us that it is unlikely that black crime news events that receive less than a total of 6 minutes and 40 seconds of coverage will increase the average relative stop rate by more than $-0.0470 + 1.96(.0662) = 0.08275$ stops per 10,000 people per day during the week following the start of the news event. The standard error of the coefficient of $High\ coverage$ in Column (1) tells us that we can be 95% confident that, relative to low coverage black crime news events, black crime news events that receive more than 6 minutes and 40 seconds of coverage have an additional effect of no more than $-0.0883 + 1.96(0.0913) = 0.0906$ stops per 10,000 people per day. To determine the confidence interval for the effect of high coverage events on relative stop rates as compared to no news coverage, I perform a t-test using only high coverage events with the null hypothesis that $\Delta Average\ relative\ stop\ rate = 0$. The 95% confidence interval is (-0.271597, 0.000869), which tells us that a high coverage black crime news event is unlikely to increase $Average\ relative\ stop\ rate$ by more than 0.000869 stops per 10,000 people. These maximum likely effect sizes are all quite small, especially when we consider them at the level of an individual person. This tells us that the difference in the probability that a black driver will be stopped by the police and the probability that a white driver will be stopped by the police increases by less than 0.00000869% following a high coverage black crime news event. As another point of comparison, for the average police department, the standard deviation of the relative stop rate is 1.57 stops per 10,000 people.

Turning our attention to Column (2) of Table 2, we can conclude with 95% confidence that low coverage black crime news events are unlikely to decrease the relative hit rate by more than $-0.01746 - 1.96(0.02220) = -0.06097 = -6.097\%$. Relative to low coverage black crime news events, black crime news events that receive more than 6 minutes and 40 seconds of coverage are unlikely to have an additional effect of more than $-0.00578 - 1.96(0.03286) = -0.07018 = -7.018\%$. A t-test using only high coverage events with the null hypothesis that $\Delta Average\ hit\ stop\ rate = 0$ tells us that the confidence interval for $\Delta Average\ hit\ stop\ rate$ for high coverage events is (-0.07232, 0.02584), meaning that a high coverage black crime news event is unlikely to decrease $Average\ relative\ hit\ rate$ by more than 7.232%. To put this in perspective, we saw in Table 1 that, for all police departments, the standard deviation of the relative hit rate was at least 10%, and the average standard deviation across departments was 28.8%.

4.2 Robustness Checks

4.2.1 Police department fixed effects

My panel of event $\times$ police department pairs is unbalanced because some departments only have traffic stop data available on a restricted time range. To address any bias that this unbalance causes, I repeat my main regressions with department fixed effects. These results are shown in Table 3. The estimated coefficients and standard errors are similar to those estimated in my main regression in Table 2.

	$\Delta Avg\ relative\ stop\ rate$ (1)	$\Delta Avg\ relative\ hit\ rate$ (2)
$High\ coverage$	-0.10873 (0.08871)	-0.017625 (0.032689)
Dept. fixed effects	Yes	Yes
Observations	235	196

Table 3: Regression results from Regressions (1) and (2) described in Section 3.2 with added police department fixed effects. Observations are event $\times$ police department pairs. Standard errors are given in parentheses.

4.2.2 Varying the measure of news coverage

For my primary analysis, I use a threshold of 6.67 minutes for splitting news events into ”high coverage” and ”low coverage” events. 6.67 minutes is the median amount of news coverage, so this threshold conveniently separates the news events into two sets of approximately equal size. However, one may argue that this threshold is somewhat arbitrary, so I test the effect of using a different threshold. I define an independent variable

$(Coverage \geq mean)_i$, which is an indicator variable for whether event i received at least the mean amount of coverage (19.37 minutes). Regression A of Table 4 shows the result of using $Coverage \geq mean$ as the independent variable.

It is also possible that the length of news coverage matters less than the number of news segments covering it. The reasoning behind this is that, if there are more news segments (airing on different channels or at different times throughout the evening), more viewers will be exposed to the news event. To test this idea, I define a third measure of "high coverage" that depends on the number of segments that cover a given news event. The median number of segments covering each news event is two, so I define $(Coverage > 2\,segments)_i$ as an indicator for whether event i was covered in more than two news segments. Regression B of Table 4 shows the result of using $Coverage > 2\,segments$ as the independent variable.

In Regression C of Table 4, I test the idea that there is a linear relationship between the bias metrics and the total length of coverage. I define the variable $Total\ coverage_i$ to be the total news coverage in minutes that event i received on ABC, CBS, CNN, NBC, and Fox News.

The coefficients of Regressions A–C are all statistically insignificant, with the exception of the coefficient of $Total\ coverage$, which is significant at the 10% level. However, this is almost surely just statistical noise, because the sign of this coefficient is inconsistent with the sign of the coefficients of $Coverage \geq mean$ and $Coverage > 2\,segments$. The negative sign suggests, implausibly, that more black crime news coverage leads to a decrease in racial bias against black drivers.

	$\Delta Avg\ relative\ stop\ rate$	$\Delta Avg\ relative\ hit\ rate$
	(1)	(2)
Regression A		
(Intercept)	-0.0522 (0.0546)	-0.0121 (0.0194)
$Coverage \geq mean$	-0.1171 (0.0988)	-0.0274 (0.0359)
Regression B		
(Intercept)	-0.0963 (0.0646)	-0.01659 (0.02309)
$Coverage > 2\,segments$	0.0167 (0.0912)	-0.00706 (0.03273)
Regression C		
(Intercept)	-0.03036 (0.05338)	-0.009919 (0.019202)
$Total\ coverage$	-0.00219 (0.00108)*	-0.000384 (0.000381)
Observations	257	217

Table 4: Regression results using different measures of news coverage. $Coverage \geq mean$ is an indicator for whether a news event received at least the mean amount of news coverage (19.37 minutes). $Coverage > 2\,segments$ is an indicator for whether a news event received news coverage in more than two news segments. $Total\ coverage$ is the number of minutes of news coverage a news event received. Observations are event $\times$ police department pairs. Standard errors are given in parentheses.

* $p < 0.1$

4.2.3 Varying the window length

My initial regression relies on the assumption that the effect of racial bias on traffic stops can be detected at the time scale of one week. However, according to work done by Lewis and Rao (2015) on measuring the effects of advertising, "Unless there is limited decay in the ad effect over time, short windows are optimal from a power perspective." Although advertising and racial bias in traffic stops may seem unrelated at first glance, since I hypothesize that news coverage has a short term effect on racial bias in traffic stops, much like how advertising has a short term effect on sales, Lewis and Rao's argument also applies to my analysis. Thus, I check how my regression coefficients change when I compute $\Delta Average\ relative\ stop\ rate$ over shorter window lengths. Specifically, I compute the difference in the average $relative\ stop\ rate$ for the n days after the start of a news event and the n days before the start of the event for $n = 1, 3, 5$. Additionally, since some news events continued to receive news coverage more than a week after they first received coverage, I test the possibility that the racial bias effects accumulate over a longer timescale by also computing these metrics using $n = 14$. Using these different versions of $\Delta Average\ relative\ stop\ rate$ and $\Delta Average\ relative\ hit\ rate$, I reestimate my original regressions. The results are shown in Table 5.

Most coefficients are not statistically different from 0. For $n = 1$, the coefficient of $High\ coverage$ in the regression involving $\Delta Average\ relative\ stop\ rate$ is positive and statistically significant at the 10% level. This is perhaps just statistical noise, but it is suggestive that news coverage may have a very short term effect on racial bias in traffic stops. As the window length n increases, the coefficient of $High\ coverage$ in the $\Delta Average\ relative\ stop\ rate$ regressions becomes smaller and less statistically significant.

	$\Delta Avg\ relative\ stop\ rate$ (1)	$\Delta Avg\ relative\ hit\ rate$ (2)
$n = 1$		
(Intercept)	-0.208 (0.134)	-0.0145 (0.0356)
$High\ coverage$	0.348 (0.197)*	0.0121 (0.0530)
Observations	256	180
$n = 3$		
(Intercept)	-0.1929 (0.0953)**	-0.0133 (0.0236)
$High\ coverage$	0.1351 (0.1404)	-0.0163 (0.0355)
Observations	256	199
$n = 5$		
(Intercept)	0.00382 (0.06493)	-0.0452 (0.0255)*
$High\ coverage$	-0.09167 (0.09560)	0.0361 (0.0377)
Observations	256	208
$n = 14$		
(Intercept)	-0.0470 (0.0622)	-0.01746 (0.02220)
$High\ coverage$	-0.0883 (0.0913)	-0.00578 (0.03286)
Observations	257	217

Table 5: Regression results using different window lengths (n) to compute $\Delta Average\ relative\ stop\ rate$ and $\Delta Average\ relative\ hit\ rate$. Observations are event × police department pairs. Standard errors are given in parentheses.

* $p < 0.1$, ** $p < 0.05$

4.2.4 Considering pre-2010 and post-2010 news event separately

Another assumption that underlies my initial analysis is that the effect that black crime news coverage has on racial bias in traffic stops has not changed over the years. I relax this assumption by splitting my list of news events into an early group (2000-2009) and a late group (2010-2019) and checking if statistically significant effects can be observed in either group. Table 6 shows the result of these regressions. The coefficients are statistically insignificant in both time periods.

	$\Delta Avg\ relative\ stop\ rate$ (1)	$\Delta Avg\ relative\ hit\ rate$ (2)
$2000 - 2009$		
(Intercept)	-0.0297 (0.1338)	-0.0270 (0.0454)
$High\ coverage$	-0.0873 (0.1836)	-0.0275 (0.0637)
Observations	62	55
$2010 - 2019$		
(Intercept)	-0.0518 (0.0705)	-0.01452 (0.02555)
$High\ coverage$	-0.0908 (0.1062)	0.00406 (0.03860)
Observations	193	160

Table 6: The top regression only includes news events from 2000-2009. The bottom regression only includes news events from 2010-2019. Observations are event $\times$ police department pairs. Standard errors are given in parentheses.

4.2.5 Breaking down news coverage by channel

I test how my findings change if I allow for the possibility that news coverage of black crime on different channels have different impacts on racial bias. I regress $\Delta Average\ relative\ stop\ rate$ and $\Delta Average\ relative\ hit\ rate$ on indicator variables for whether an event received coverage on each news channel. For example, ABC is an indicator for whether an event received coverage on ABC. The coefficients are mostly insignificant, save for statistical noise.

	$\Delta Avg\ relative\ stop\ rate$ (1)	$\Delta Avg\ relative\ hit\ rate$ (2)
(Intercept)	-0.1194 (0.1273)	-0.0584 (0.0462)
ABC	0.1357 (0.1434)	0.0916 (0.0523)*
CBS	-0.0151 (0.1206)	-0.0818 (0.0417)*
CNN	-0.0981 (0.1049)	-0.0556 (0.0362)
FOX	0.0898 (0.1454)	0.0126 (0.0528)
NBC	-0.0779 (0.1193)	0.0670 (0.0426)
Observations	253	213

Table 7: Regression results when news coverage on each news channel is considered separately. Observations are event $\times$ police department pairs. Standard errors are given in parentheses.

* $p < 0.1$

4.2.6 White crime news events

I also investigate how my bias metrics change in response to white crime news events. I expect that bias against black drivers does not increase following white crime news events. I collect data on 14 news events involving eight different white perpetrators (see Table A2 of the Appendix for names of the perpetrators), and repeat my regressions from Table 2 using these white crime news events. The results are shown in Table 8. Most coefficients are not statistically significant, as expected. The coefficient of $High\ coverage$ in Column (1) is statistically significant at the 10% level. The coefficient is negative, suggesting that the bias gap decreases following white crime news coverage, perhaps because police officers become more likely to stop white drivers after viewing the news coverage. However, this can also be attributed to statistical noise. Overall, the results of these regressions lend credence to my assumption that the bias metrics do not exhibit statistically significant trends in the absence of black crime news coverage.

	$\Delta Avg\ relative\ stop\ rate$ (1)	$\Delta Avg\ relative\ hit\ rate$ (2)
(Intercept)	0.0114 (0.0805)	-0.00565 (0.02208)
$High\ coverage$	-0.2252 (0.1216)*	-0.02912 (0.03307)
Observations (event $\times$ police dept.)	222	191

Table 8: Regression results showing how racial bias metrics change after white crime news coverage is aired. Observations are event $\times$ police department pairs. Standard errors are given in parentheses.

*$p < 0.1$

4.2.7 Controlling for violence of crime

It is possible that the effect of news coverage of black perpetrators depends on the type of crime committed by the perpetrator or how violent the perpetrator is perceived to be. To control for the type of crime, I add crime type fixed effects, where ”crime type” is mass shooting, serial killing, or other shooting. To control for the ”violence” of the perpetrator, I use the number of victims as a proxy. For shooters, this is the number killed plus the number injured. For serial killers, this includes the number killed, kidnapped, or sexually assaulted. The results of this regression are shown in Table 9. The coefficients are not statistically significant.

	$\Delta Avg\ relative\ stop\ rate$ (1)	$\Delta Avg\ relative\ hit\ rate$ (2)
$High\ coverage$	-0.101472 (0.116125)	-0.044971 (0.041884)
$Number\ of\ victims$	-0.010950 (0.007044)	-0.003742 (0.002477)
Crime type fixed effects	Yes	Yes
Observations	254	214

Table 9: Regression results controlling for the type of crime and the number of victims. Observations are event $\times$ police department pairs. Standard errors are given in parentheses.

5 Discussion

My approach has several limitations. The first limitation is that there are a limited number of high-profile crimes committed by black perpetrators between the years of 1999 and 2019, which are the years covered by the traffic stop data. This restricts my sample size and limits statistical power. However, my sample size of 25 news events is still large enough that, had news coverage had a substantial effect on racial bias in traffic stops, I likely would have been able to detect this.

There is also a potential concern that the lengths of news segments that are reported on the Vanderbilt Television News Archives are not a precise measure of the length of time actually spent covering the perpetrator. Unfortunately, many of the news segments included in the archives were not available for viewing, so I could not manually verify which portions of each news segments was spent discussing the crime. However, since I use an indicator variable for high coverage as my explanatory variable in my main regression rather than the total coverage length, this makes it so the lack of precision in measuring segment length has a small effect on my results.

Another limitation is that the Vanderbilt Television News Archives is not a comprehensive measure of television news coverage. It does not include all television channels, and it does not include all broadcasts of the channels it does include. Additionally, it only includes Fox News coverage starting in 2004, which may introduce some bias in my measurement of news coverage, since events that happen prior to 2004 may have received news coverage on Fox News, but I am not able to determine this using the Vanderbilt Television News Archives. However, I only include two news events that happened prior to 2004, and both received more than a total of five minutes of news coverage even without accounting for possible Fox News coverage, so both were considered ”high coverage” events. Thus, the lack of Fox News broadcast archives for these events does not effect my main regression results.

Given more time and resources, I would like to construct a more holistic measure of black crime news coverage. Rather than searching for news coverage of perpetrators on a predetermined list, it would be better if I could go through all broadcasts of the most watched news shows during a given time period and identify all segments that are related to black crime that air each day. This reduces the risk that I miss relevant news coverage and would also enable me to do a more typical time series analysis rather than having to focus in on specific news events.

Another direction worthy of exploration is considering qualitative differences in black crime news coverage. Some black crime events may be covered in a more racialized manner than others. News coverage that highlights the perpetrator's race likely has a stronger effect on racial bias than news coverage that does not emphasize the perpetrator's race. The tone of the news coverage likely also has an effect. It would be interesting to construct metrics that would allow me to test these hypotheses. One useful metric would be the number of seconds that the perpetrator's face is shown in news coverage of the crime. Another useful metric would be a measure of how positive or negative the words used to describe the perpetrator are.

6 Conclusion

In this project, I use traffic stop data to investigate how racial bias changes after black crime news coverage is aired on television. I calculate two metrics of racial bias in traffic stops. The first, $relative\ stop\ rate$ measures the racial bias involved in police officers' decisions to initiate a traffic stop. The second, $relative\ hit\ rate$ measures the racial bias involved in police officers' decisions to search a driver after initiating a traffic stop.

Using plots of $relative\ stop\ rate$ and $relative\ hit\ rate$ around the dates of black crime news events, I find that black crime news coverage, regardless of the amount, has no statistically significant effect on these metrics. I quantify these results by regressing $\Delta Average\ relative\ \ stop\ rate$ and $\Delta Average\ relative\ hit\ rate$ on an indicator for whether a black crime event received high news coverage. My analysis tells us that, with 95% probability, high coverage news events increase relative stop rates by no more than 0.000869 stops per 10,000 people and decrease relative hit rates by no more than 7.232% in the week following the news event. This suggests that black crime news coverage has a negligible effect on racial bias in traffic stops. I show that these results are robust to changes in the metric of news coverage and the window length around the event. Separating the news events into pre- and post-2010 also yielded regression coefficients that are not statistically different from 0. The same is true when I separate news coverage by channel and when I control for the violence of the crime committed.

My findings contribute to the study of racial bias in traffic stops and to the understanding of the extent to which the priming effects of media can influence real world behavior. Although laboratory experiments have shown that exposure to negative stereotypical portrayals of black males causes study participants to adopt more negative perceptions towards black males (Power et al. (1996)), I show that these effects do not have a significant effect on the behavior of police officers in traffic stops, at least, not when observed on the order of a few days. It is possible that black crime news coverage does have an effect, but that the effect wears off very quickly. Overall, my findings point to the reassuring conclusion that police officers are not easily swayed by television coverage of black crime.

7 Appendix

Table A1: Names of black perpetrators used to identify news coverage of black crime

List of black perpetrators		
Mass shooters	Serial Killers	Other shooters
Aaron Alexis	Chester Turner	Byron Williams
Cedric Ford	Derrick Lee	Rodrick Dantzler
Charles ”Cookie” Thornton	Mark Goudeua	Yonathan Melaku
Gary Martin	Matthew Macon	
Gavin Long	Samuel Little	
Kori Muhamad		
Maurice Clemmons		
Micah Johnson		
Omar Thornton		
Radcliffe Haughton		
Snochia Moseley		
Willie Baker		

Table A2: Names of white perpetrators used to identify news coverage of white crime

List of white perpetrators		
Mass shooters	Serial Killers	Other shooters
Andrew Engeldinger	–	–
Elliot Rodger		
Jason Dalton		
John Zawahri		
Kurt Myers		
Noah Harpham		
Robert Dear		
Scott Evans		

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