



MASTER PROJECT

MEDIA AND BEHAVIORAL RESPONSE:
THE CASE OF #BLACKLIVESMATTER

Economics Program 2019

Julie Balitrand Joseph Buss Ana Monteiro
Jens Oehlen Paul Richter

Supervisors: Larbi Alaoui, Gianmarco León

Media and Behavioral Response: The Case of #BlackLivesMatter*

Julie Balitrand
BGSE

Joseph Buss
BGSE

Ana Monteiro
BGSE

Jens Oehlen
BGSE

Paul Richter
BGSE

May 2019

Abstract

We study the effects of the #BlackLivesMatter movement on the law abiding behavior of African-Americans. First, we derive a conceptual framework to illustrate changes in risk perceptions across different races. Second, we use data from the Illinois Traffic Study Dataset to investigate race ratios in police stops. For identification, we apply a linear probability OLS regression on media coverage as well as an event study framework with specific cases. We find that the number of black people committing traffic law violations is significantly reduced after spikes in media coverage and notable police shootings. In the latter case, we further find that the effect holds for an approximate ten day period. We argue that these observed changes in driving behavior are a result of the updated risk beliefs.

Keywords: Risk Perceptions, Media Economics, Racial Bias, Crime

JEL Codes: L82, J15, K42

*We would like to thank then-State Senator Barack Obama for introducing the legislation that led to the creation of the Illinois Traffic Stop Data. We are further grateful for insightful comments by Gianmarco Leon, Nikolas Schöll and Larbi Alaoui.

Contents

I	Introduction	3
II	Conceptual Framework	6
II.A	Decision Environment	6
II.B	Model Predictions	8
II.C	Hypothesis Testing Setup	11
III	Empirical Analysis	13
III.A	Data	13
III.B	Identification Strategy	14
III.C	Results	16
IV	Conclusion	20

*"It's almost like we're living our lives at gunpoint. And I'm scared to even move. Honestly.
#BlackLivesMatter"*¹

I Introduction

In the United States racial discrimination is, despite large efforts, still prevalent in many domains of public life. From labor markets (Bertrand and Mullainathan, 2004) to education (Brooks, 2012) and health (Williams, 1999), minorities in general and African Americans in particular, have been subjects of structural discrimination. In recent years, public attention has increased specifically on police behavior towards minorities. Historically, the latter have disproportionately been stopped, arrested, and faced physical force against them by police officers (Smith and Petrocelli, 2001). Evidence of racial bias reach from simple patrol stops (Pierson et al., 2017), to fatal police shootings (Ross, 2015). In the latter study, the author demonstrates that the bias is not just a result of different race-specific crime rates.

Between the years 2014-2016 there were heavily publicized events of police officers using excessive force on African-Americans. Given this documented structural bias, we aim to study how African-Americans change their behavior following these events that are covered extensively in the media. Specifically, we are looking at how the risk perceptions of African-Americans change. Using data from Illinois that documents every police traffic stop, we are able to analyze the different aspects of the interactions between these groups. This data will provide insights into how African-Americans change their perceptions of risk and consequently alter their behavior after these events. The traffic data provides a good foundation for this analysis because approximately 20 million Americans are stopped every year by the police (Bureau of Justice Statistics, 2018) corresponding to one of the most common ways police interact with citizens (Pierson et al 2017). This study further explains the extent

¹Retrieved from <https://twitter.com/nelldmakaveli/status/750942807196655616> on 16.05.2019

to which the police do have a bias towards African-Americans in both highway stops and municipal police stops.

The number of these discriminatory events which were publicly covered have seen a very rapid and recent increase, probably due to the gravity of some cases. On the 26th of February 2012, Trayvon Martin was shot and killed by a neighborhood watchman although the 17 year old was unarmed (New York Times, 2012). This event was covered on national television all over the United States and the rest of the world. It led to the creation of the hashtag #BlackLivesMatter, and further to the Black Lives Matter movement. From their website, Black Lives Matter describes themselves as "a chapter-based, member-led organization whose mission is to build local power and to intervene in violence inflicted on Black communities by the state and vigilantes". Following Trayvon Martin's death, 13 other African Americans lost their lives due to police brutality between 2014 and 2016. These events received further and alternative coverage on twitter following Eric Garner's death, which spawned the hashtag #ICantBreathe after he was choked by a policeman. The hashtags which were first seen on Twitter, were then used in traditional media platforms such as newspapers and TV. In our study, we will focus on the cable coverage of these events. The three channels used are Fox News, MSNBC and CNN.

The role of media in these events is not to be underestimated. Certainly, media plays a large role in behavioural changes, which is specifically what we are analyzing. In the study by Wakefield, Loken and Hornik (2010), the authors find that media coverage has had a strong impact in changing health behaviours. The authors look at different campaigns such as use of tobacco, alcohol, and other drugs, heart disease risk factors, sex-related behaviours, etc... They assert that "Mass media campaigns can directly and indirectly produce positive changes or prevent negative changes in health-related behaviours across large populations". This provides evidence that mediatization, in general, enables behavioural changes. Furthermore, Yadav et al (2015) and Thomson et al (2014) find that mass media has a role to play in

the reduction of these acts. By documenting the role of media campaigns preventing drunk driving they find that media led to an estimated 6 to 14% decrease in alcohol-related crashes. Thus, media coverage may have a large impact in behavioural changes.

Our paper's main contributions to the state-of-the-art literature are twofold. First, we derive a conceptual framework illustrating how media influences individuals law-abiding behavior. In detail, we demonstrate how updating beliefs about risks has varying degrees of effects across different racial groups. Secondly, we provide evidence on how individuals law-abiding behavior is changed as a result of #BlackLivesMatter media coverage. We estimate that at peak media coverage intensity, black individuals were more than 10% less likely to commit traffic violations. We further find that the effect across all investigated shootings levels off after a period of ten days.

Finally, targeting the literature on racial profiling and the impact of media, Graziano et al (2010) prove that attitudes about the prevalence of racial profiling depend on the manner in which the media depicts incidents of police brutality. Overall, these studies provide strong links between media coverage and changes in behaviour. This enables us to link events of police brutality to behavioural changes through the channel of mass media coverage.

Our study contributes to previous literature by identifying determinants of individuals' attitudes towards the police. Further, it adds to the literature on media economics. Some studies in media economics relate to the ideological position of media, for instance, through the work of Gentzkow and Shapiro, 2010 or Groseclose and Milyo, 2005. Others look at the impact of media on voting turnout (Gentzkow, Shapiro and Michael Sinkinson, 2011; Felix Oberholzer-Gee and Joel Waldfogel, 2009) and on electoral outcomes (e.g. Stefano DellaVigna and Ethan Kaplan, 2007; Ruben Durante and Brian Knight, 2012; Ruben Enikolopov, Maria Petrova and Ekaterina Zhuravskaya, 2011). This paper demonstrates that media, related to police brutality, drives changes in the perception of risk and further in behaviour.

In our study, we will therefore use media data as well as creating an event study to determine the changes in behaviour of African Americans. We expect both methods to provide similar results.

Our findings suggest that the proportion of African Americans being stopped by the police decreases after media coverage of these events (for all stops). Furthermore, when using traffic data on moving violations, our coefficient remains negative and significant although to a somewhat lower extent. A qualitatively similar picture emerges in the event study identification strategy. We conclude that the media coverage of these events led to a change in risk perception and thus behaviour of African Americans towards the police, while the attitudes of other racial groups remains unchanged.

In the following section of the paper we will draw a conceptual framework using a theoretical model, and will then explore the predictions taken from the model. In section 3 we will expound on the data we used. Section 4 will cover the empirical strategy of the model. We will finally provide results in section 5 and a discussion of the results in Section 6.

II Conceptual Framework

In this section we lay out the decision making framework, make assumptions about the effect of media on different parts of this framework, and then create a way to verify the model and assumptions.

II.A Decision Environment

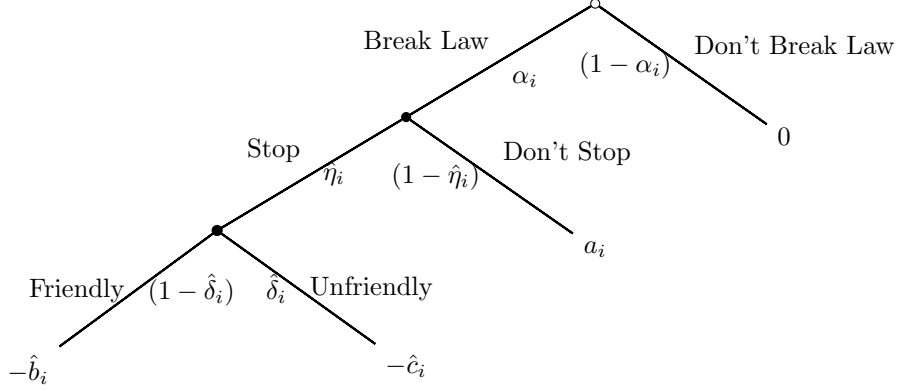
The population is split up into different ethnic groups, denoted by i . Within each ethnic group, each individual faces the decision tree shown below. The first node represents the

individual's decision of whether to commit a moving violation. Moving violations include offenses such as speeding, not stopping at a stop sign, following too closely, etc. We focus our analysis on moving violations, because they are contemporaneous choices made by drivers, and solely rely on behavior of the drivers. Further, a moving violation is immune to arbitrary traffic stops by police because they are concrete and an individual cannot be stopped for not committing a moving violation. We consider the decision of not driving to be a subset of the decision to not break the law. This allows us to capture the people who choose not to drive in order to be more cautious. We normalize the payout from this choice to 0. Next, we will further develop the possible consequences of choosing to break the law.

If an individual decides to commit a moving violation, then there is a probability, η_i , of them being pulled over. When an individual makes a decision, they will perceive η to be at a certain level. We will use hats to discern that a certain variable is a perceived probability, instead of the true probability. We assume that the perceived value of η is constant within each ethnic group. So, for an individual of type i , the perceived chance of being pulled over whilst committing a moving violation is $\hat{\eta}_i$.

If an individual is not stopped, then they receive a payoff a_i . We allow the a_i to be heterogeneous within each ethnic group. We now assume that the driver's payoff comes from a distribution $F_i(a_i)$, which is supported on a closed interval, $[\underline{A}_i, \bar{A}_i]$, and there exists a positive density $F'_i(a_i) = f_i(a_i) > 0$ for all a_i . These distributional assumptions are intentionally very lax, to remain as general as possible. These payoffs are heterogeneous because we believe drivers can vary significantly in their preferences. For example, some people enjoy speeding, while others may actively dislike driving fast.

If the individual is stopped for a moving violation, then there is a chance, δ_i , that the police officer will act in an unfriendly way. This outcome includes anything from being asked to get out of the vehicle, to being shot and killed. The payoff for being stopped in a friendly manner is $-b_i$, where $b_i > 0$, and the payoff for being stopped in an unfriendly manner is $-c_i$,



where $c_i > 0$. Since the consequences from a friendly stop are less severe than an unfriendly stop, $c_i > b_i$. This completes our proposed decision environment.

II.B Model Predictions

In this environment, an individual makes the decision whether to commit a moving violation or not, based off of the possible outcomes. We assume this representative individual follows the vNM utility axioms and is therefore maximizing expected utility. We are aware that individuals do not consciously perform these calculations while driving, however we do believe that individuals choose not to commit crimes based on the possible negative consequences. This framework captures this thought process. Since no agent knows the true probability of possible police actions, these utility calculations are made with perceived probabilities. Under this framework, an individual will choose to commit a moving violation if the perceived expected utility is higher than the utility of following the law (normalized to 0). This is when

$$\underbrace{(1 - \hat{\eta}_i)a_i}_{\text{not stopped}} + \hat{\eta}_i \left(\underbrace{\hat{\delta}_i(-\hat{c}_i)}_{\text{unfriendly}} + \underbrace{(1 - \hat{\delta}_i)(-\hat{b}_i)}_{\text{friendly}} \right) > 0$$

stopped

This means an individual will commit a moving violation if

$$a_i > \underbrace{\frac{\hat{\eta}_i}{1 - \hat{\eta}_i}}_{\text{odds ratio of stop}} \underbrace{\left(\underbrace{\hat{\delta}_i \hat{c}_i}_{\text{unfriendly}} + \underbrace{(1 - \hat{\delta}_i) \hat{b}_i}_{\text{friendly}} \right)}_{\text{dis-utility of stop}} = \bar{a}_i$$

This \bar{a}_i is the threshold value for which an individual will choose to commit a moving violation. If the individual's personal payoff, a_i , is above this value, then the payout from committing a moving violation is greater than the dis-utility of being stopped adjusted by the odds of being stopped.

Using this threshold and the distribution of a_i , we can now calculate the proportion of individuals from an ethnicity who choose to speed, α_i . We calculate

$$\alpha_i = 1 - \int_{-\infty}^{\bar{a}_i} f_i(a) da = 1 - F_i(\bar{a}_i).$$

Next, we will highlight the assumptions we make on how media coverage intensity affects the perception of different variables in our decision environment. Note that we are only looking at changes in perceptions, and not the actual changes in reality. We will use these assumptions, along with our expression for α_i , to predict the effect of media on the proportion of people who choose to behave cautiously. We will represent the intensity of media coverage of police brutality on a given day with the variable M .

First consider a_i . We assume that the benefits of committing a moving violation and not getting caught remains unchanged by media coverage of police brutality. This implies the distribution of a_i , f_i , remains unchanged.

Assumption 1.

$$\forall a, i \quad \frac{df_i(a)}{dM} = 0$$

Next, consider the perceived chance of being pulled over, $\hat{\eta}_i$. After media coverage of police

brutality increases, it is unreasonable for any individual to think that they have a lower chance of being pulled over. We assume that a white (W) individual, would not have a reason to believe that they have a higher chance of being pulled over. Therefore,

Assumption 2.

$$\frac{d\hat{\eta}_{AA}}{dM} \geq \frac{d\hat{\eta}_W}{dM} = 0$$

Furthermore, the dis-utility of a friendly stop should remain unchanged, since the view of what a friendly stop is remains unchanged. Therefore, \hat{b}_i is not affected by media coverage of police brutality.

Assumption 3.

$$\frac{d\hat{b}_{AA}}{dM} = \frac{d\hat{b}_W}{dM} = 0$$

However, the perceptions of what might happen when a police officer pulls them over might change in response to media coverage of police brutality. This can either be through a change in the perceived chance of an unfriendly stop, $\hat{\delta}_i$, or through a change in the perceived dis-utility of when police perform an unfriendly stop, \hat{c}_i . After seeing media coverage of police acting brutally towards an African-American (AA), an African-American individual might increase the perceived dis-utility of police performing an unfriendly stop. Since these acts of police brutality depict an African-American victim, this adjustment in \hat{c}_i should be greater for African-Americans, since it is more relevant to their own ethnicity. Someone who is not a minority might not see this media coverage as relevant at all, and thus doesn't change their \hat{c}_i . This leads to the following assumption

Assumption 4.

$$\frac{d\hat{c}_{AA}}{dM} > \frac{d\hat{c}_W}{dM} \approx 0.$$

The last variable left to consider is the perceived chance that a stop will be non-friendly, $\hat{\delta}_i$. We assume that after being reminded of the possibility of having a violent encounter, people

will raise their perceived chance that a stop is violent. Again, since the race of the victim is black, we assume that black people adjust more than others. This leads to

Assumption 5.

$$\frac{d\hat{\delta}_{AA}}{dM} > \frac{d\hat{\delta}_W}{dM} \approx 0.$$

To sum up the assumptions above, we assume African-American’s perceive media coverage of prejudice policing to be more relevant to their decision making procedure. More specifically, they increase their perceived risk of police brutality associated with breaking the law, while whites don’t make any significant changes. This causes them to have a higher percentage decrease in moving violations committed than whites. This is represented by

Theorem 1.

$$\text{Assumptions 1-5} \implies \frac{d\alpha_{AA}}{dM} < \frac{d\alpha_W}{dM} \approx 0 \implies \frac{d \log(\alpha_{AA})}{dM} < \frac{d \log(\alpha_W)}{dM} \approx 0.$$

This theorem is formally proved in the appendix. Since the total number of people in each ethnicity stays approximately constant in the short run, this shows that the model predicts that African-Americans will have a higher percent decrease in the total number of people breaking the law than whites.

II.C Hypothesis Testing Setup

At the end of our model we hypothesized that African-Americans have a higher percent decrease in the proportion of people breaking the law than Whites in response to an increase in media coverage of police misconduct. One intuitive approach to testing this hypothesis is looking at the changes in total number of stops for each race. However, we don’t use this approach because police might change their behaviour in response to media coverage about

police behaviour. Using total stops, one is not able to fully disentangle the change in driver behavior, and the change in police behavior. Another disadvantage of using total stops per day is the decrease in total data points through aggregation.

Instead, we use the probability that a stopped driver is African-American, P_{AA} . When the number of African-American's committing crimes changes at a different rate than that of other ethnicities, the composition of the drivers that are stopped changes. Therefore, the variable P_{AA} captures the model prediction. In order to remove the effect of police behavior, we will only consider situations where police don't have any prejudices. This assumption can be written as

Assumption 6.

$$\forall i, j, \quad \eta_i = \eta_j$$

where η , without the hat, is the actual chance that someone committing a moving violation is pulled over. Unfortunately, this assumption is not always true; however, Grogger and Ridgeway (2005) showed that at nighttime, police officers are not able to discriminate. Therefore, for our analysis we will only consider traffic stop data from the nighttime (8pm-6am).

This additional assumption allows us to establish the following relationship between P_{AA} and our model prediction:

Theorem 2.

$$\text{Assumption 6} \implies \left(\frac{dP_{AA}}{dM} < 0 \iff \frac{d \log(\alpha_{AA})}{dM} < \frac{d \log(\alpha_W)}{dM} \right)$$

This result, which is thoroughly proved in the Appendix, shows that a procedure testing whether $\frac{dP_{AA}}{dM} < 0$ is logically equivalent to testing our model prediction. Therefore, to verify our model, our empirical analysis will mainly focus on the response of the probability a stop involves a black driver, P_{AA} , to media coverage, M .

III Empirical Analysis

In this section we will explain what data we used, and how we use this data in order to test our hypothesis. After this, we report the results, the interpretation, and what it implies with regard to our hypothesis test.

III.A Data

Our data comes from two sources, Illinois Traffic Study Data, and media coverage data from the ‘Global Database of Events, Language, and Tone’ Project (GDELT). These sources provide us with data that allows us to link daily media coverage intensity with daily traffic stops.

In order to study the media coverage of Black Lives Matter, we take advantage of the database from the GDELT Project. We use this dataset which breaks up cable news segments into 15 second increments to document if the keywords “Black Lives Matter” were mentioned. This is then compared to the total media coverage of that day and gives a percentage of time throughout the day that this keyword was talked about. The data is taken from three channels, which have the highest viewership ratings among African-Americans in the United States, CNN, Fox News, and MSNBC². A majority of the effect that we are measuring will be coming from MSNBC coverage of these events. Not only do they cover police shootings for longer periods of time but, because MSNBC is left-leaning, we anticipate that the coverage of these events is more sympathetic to the victims. Furthermore, among African-Americans, they have the highest ratings. Indeed, MSNBC averaged 483.096 African American viewers across its weekday primetime, compared to the next best CNN averaging only 306.359 (Nielson Live + SD data).

²<https://variety.com/2014/tv/news/fox-news-dominates-cable-news-ratings-in-2014-msnbc-tumbles-1201386523/>

We use traffic stop data because it allows us to disentangle the behaviors of Police officers and citizens; in most other interactions police behavior cannot be separated from potential biases. There are several studies that document police bias in traffic stops, for example from the Stanford Open Policing Project (2019): “when pulled over for speeding, black drivers are 20% more likely to get a ticket (rather than a warning) than white drivers, and Hispanic drivers are 30% more likely to be ticketed than white drivers. Black and Hispanic motorists are about twice as likely to be searched compared to white drivers”. However, many of these biases only affect the interaction after the driver is stopped. Our data from Illinois includes the time of the stop, which allows us to only consider nighttime stops in order to circumvent the effect of these biases.

III.B Identification Strategy

In the hypothesis testing subsection of the conceptual framework section above, we set up a hypothesis regarding the marginal effects of media intensity on the probability a stopped individual is Black. We show that, under our conceptual framework, testing this hypothesis is equivalent to testing whether Blacks change their law-abiding behaviour more than other racial groups. We employ a linear probability model, since we are testing marginal effects of media coverage intensity on a probability outcome variable. In addition, we use an event study approach to capture the dynamics after an event occurred. This approach allows us to verify that media coverage has only a temporary effect, and no significant long term effect on risk perception. This is an implicit assumption of our conceptual framework.

As a main specification to test whether we see behavioral change in black driving, we run the following OLS regression with robust standard errors to allow for heteroskedasticity.

$$Black_{it} = \alpha + \beta \times Media_t + X'_{it} \times \gamma + u_{it} \quad (1)$$

where $Black_{it}$ is a dummy with value equal to unity if a suspect was black and zero otherwise. The expected value of $Black_{it}$ is the P_{AA} variable discussed in the conceptual framework section of this paper. $Media_t$ denotes media coverage of the keywords "Black Lives Matter" as described in the Data section. X'_{it} is a matrix with controls for vehicle age, age of the driver, gender and includes day of the week, year and car brand fixed effects. Following the theoretical prediction, we expect the β coefficient to carry a negative sign. The precise interpretation would be that black people would drive more cautiously following days of intensified media coverage on black lives matter related issues.

The validity of our identification strategy requires that non-black people, the counterfactual in our estimates, as well as police officers' bias, remain unaffected by media coverage. Naturally, we are limited in testing these assumptions, but we took measures to circumvent confounding influence. Again, we restrict the data analysis to nighttime driving. Changes in police attitudes should therefore not be captured by the night time analysis. Secondly, we argue that non-blacks' behaviour is unaffected by coverage on the Black Lives Matter movement since at its core it is inherently linked to police brutality against the black minority. Note, that the non-black sample includes a share of neither white nor black people, e.g. latinos. However, were latinos similarly affected by black lives matter media coverage as black people, we would underestimate the true effect with our β coefficient. Nevertheless, our identification would not be less valid, but would instead give a lower bound estimate.

As an alternative identification strategy we conduct an event study specified by

$$Black_{it} = \alpha + \beta \times Event_t + X'_{it} \times \gamma + u_{it} \quad (2)$$

Here, the difference to Equation (1) is, that, instead of regressing on media intensity, the main variable of interest are days on which a fatal shooting starts garnering media attention. Hence, we code $Event_t$ equal to one for seven days after and zero for seven days before a

fatal event entered the media sphere ³. The list of events that we use for the event study comes from 2 timelines of police shootings: one published by ABC and another published by the Boston area NPR channel, WBUR, and these will be placed in the appendix. For identification, the same arguments hold as described above.

III.C Results

The results of our main specification are depicted in the first column of Table 1. We find that media coverage related to the Black Lives Matter movement reduces the proportion of stopped people who are black by Illinois police officers at a highly significant level. This validates the hypothesis set up in the conceptual framework section of this paper. An increase in one standard deviation of media intensity decreases the share black people among those being stopped by 0.14%. Putting this into perspective, following the 9th of July 2016, a few days after the deaths of Philando Castile and Alton Sterling, the media coverage index increases to 14.12 units of standard deviation. This corresponds to an estimated decrease of 2% in the probability of a stopped driver being black. Given that in the overall sample close to 20% of suspects are black, we find that the probability of a driver being stopped is black was close to 10% lower. A similar picture emerges for the subsample of moving violation stops (column 2); The estimated effect size, however, is 42% smaller.

Moreover, in Figure 1 we depict coefficient estimates for up to four day lead (left hand side) and four day lagged values (right hand side) of media coverage. Note that one might expect non-significant coefficient estimates for the lead variables. However, this need not be the case due to high cross-day correlation of media coverage. Our identification would only be harmed if lead variables show stronger effects than the present day or lagged day variables. However, this is not evident in the data. In fact, in both directions we find decreasing effect

³For example: LaQuan McDonald died on October 20,2014. However, media coverage did not begin until 13 months later, when a video of the incident appeared. In this case our analysis starts on the November 2015, not the October 2014 date

sizes and increasing confidence intervals while the effect is largest for the night of the day on which media coverage intensifies. Thus the lead-lag analysis corroborates our main finding that media influences risk perceptions and, in turn, driving behavior of black people.

The results to our alternative specification, the event study setup, are depicted in columns (3) and (4) of Table 1. Following the days of first media coverage, we estimate a decrease in the probability of a stopped driver being black of approx. 0.4% which is significant at 1%. Therefore, like the other model, this validates the hypothesis set up in the conceptual framework section of this paper. The decrease corresponds to an overall estimated decrease of 2% of the black suspect pool. This result is robust to different studied time horizons. Figure 2 depicts coefficient estimates from three to ten day event horizons including 95% confidence intervals. All of the estimates are negative and highly distinguishable from zero. Subsetting the sample to moving violations only (column 4), the estimate decreases again, but remains significant at 10%.

Finally, we conduct several further robustness checks to strengthen our identification and characterize how long individuals appear to be affected by #BLM coverage. First, we investigate whether it is black people that show a change in behavior, as opposed to non-black people. We therefore regress the total number non-black people stopped per day on our media coverage index and proceed similarly for black people. The results can be found in Table 3 of Appendix B. The estimates show that media coverage does not significantly influence the number of stops of non-black people. However, we find evidence of a reduction in the total number of black stops, which is significant at 95%. This indicates that our assumption, that only black people are affected, leaving non-black people unaffected, is likely satisfied.

We conduct the same exercise within the event study frame work. The results are displayed in Table 4 of Appendix B, where we find qualitatively similar evidence. Only the number of African-American stops is reduced at a significant level while the coefficient estimate on the number non-black stops is not significantly different from zero.

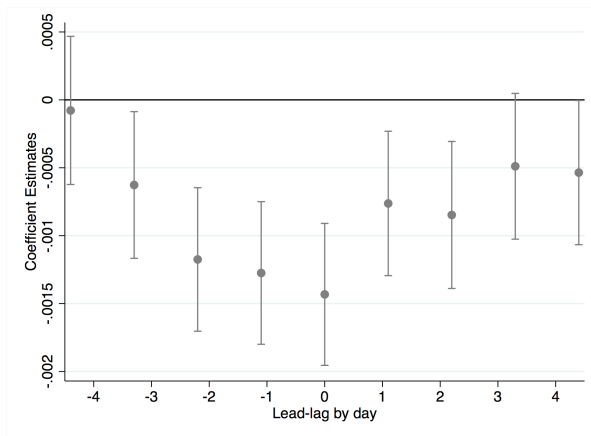
Table 1: Basic Regressions

VARIABLES	Media		Event	
	(1) All Stops	(2) Mov. Violations	(3) All Stops	(4) Mov. Violations
Media	-0.00144*** (0.000267)	-0.000849** (0.000339)		
Event			-0.00355*** (0.000935)	-0.00219* (0.00117)
Vehicle Year	-0.000282*** (4.34e-05)	-0.000348*** (5.87e-05)	-0.000282*** (4.34e-05)	-0.000348*** (5.87e-05)
Age	0.00127*** (1.80e-05)	0.00128*** (2.24e-05)	0.00127*** (1.80e-05)	0.00128*** (2.24e-05)
Gender	-0.0213*** (0.000565)	-0.0148*** (0.000719)	-0.0213*** (0.000565)	-0.0148*** (0.000719)
Observations	2,503,633	1,493,221	2,503,633	1,493,221
R-squared	0.034	0.033	0.034	0.033
Day of the Week FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Car Brand FE	Yes	Yes	Yes	Yes

Notes: OLS regressions. The dependent variable is an indicator variable that takes the value one if the person being stopped is black and 0 otherwise. Media intensity variable is standardized. Robust standard errors in parentheses.

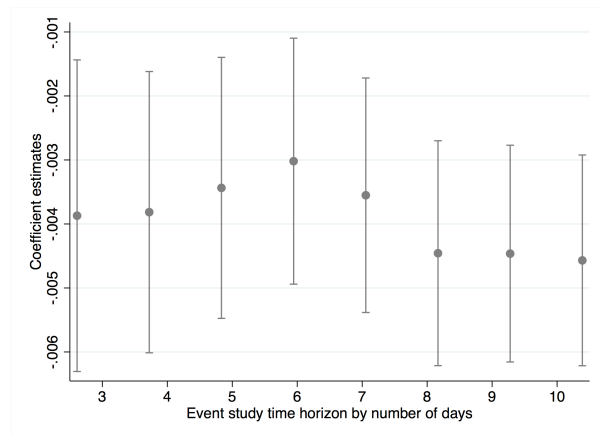
*** p<0.01, ** p<0.05, * p<0.1

Figure 1: Lead Lag Estimates



Notes: Coefficient estimates and respective 95% confidence intervals of the media regressions. Variable of interest: media coverage intensity (leads and lags). Controls included: vehicle year, age, gender and year, day of the week and car brand fixed effects.

Figure 2: Event Study Estimates



Notes: Coefficient estimates and respective 95% confidence intervals of the event study for different time horizons, ranging from 3 to 10 days. Controls included: vehicle year, age, gender and year, day of the week and car brand fixed effects.

Figure 3: Three Day Interval Event Study
Black Stops

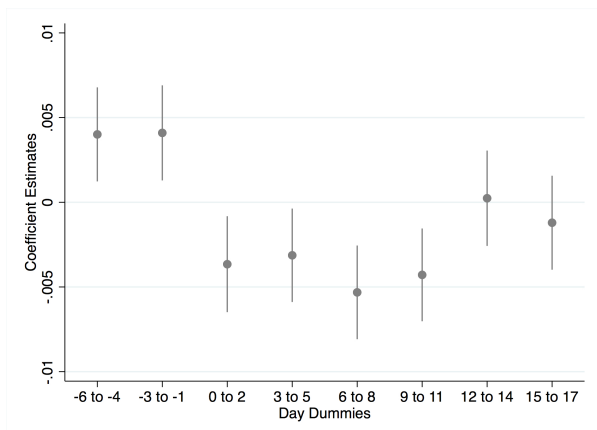
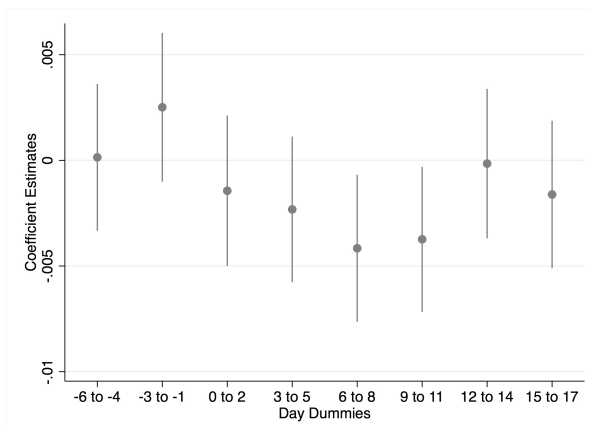


Figure 4: Three Day Interval Event Study
Black Moving Violation



Notes: Coefficient estimates and respective 95% confidence intervals of the event study. Interval dummies surrounding investigated events. Controls included: vehicle year, age, gender and year, day of the week and car brand fixed effects.

Second, we run placebo tests on both specifications using news coverage and specific dates of international airplane crashes, where we hypothesize no significant changes. For the media intensity regression we create an index following the same procedure as for the keywords 'Black Lives Matter'. For the event study we compiled a list of specific dates for major airplane crashes with at least 50 fatalities. The results are displayed in Table 5. Both estimates in the media regression suggest that there are no significant changes in the black-non-black ratio of stopped drivers. However, the event study estimates are positive⁴ and significant at 5%. We argue that this result is rather arbitrarily data driven. Nevertheless, we acknowledge that the event study is very sensitive to the precise choices of dates.

In a last exercise, we study the temporal development of behavioral changes. That is, we run an event study regression, with a set of dummies that denote three day intervals surrounding the relevant dates. The coefficient estimates and 95% confidence bands are displayed in Figures (3) and (4) for the whole and the moving violations sample respectively. First note that the dummy coefficients for the days before an event, i.e. -6 to -1, are either positive or

⁴Note that this is the opposite sign of the Black Lives Matter event study.

insignificantly different from zero. However, a downward trend in the black-non-black ratio materializes with the start of an event ($=0$) and appears to sustain for up to eleven days. Dummies denoting intervals above this threshold are again non-significantly distinguishable from zero. We therefore conclude that black people’s driving behaviour after a fatal police shooting is subject to change for an approximate ten day period.

IV Conclusion

Beginning with our model, we show that media related changes in risk perceptions cause a change in the proportion of people committing crimes. Using this model, we further predict that this change would be different across different racial groups. More specifically, it predicts that Blacks became more cautious in order to decrease the chance of a negative interaction with the police. On the other hand, whites were predicted to not change their behavior, since the violence in media coverage is not relevant to their driving decisions.

In order to test our model, we develop a hypothesis testing strategy that allows us disentangle police actions from civilian decisions. By considering the proportion of stopped people who are black at nighttime, we completely remove any effect caused by changes in policing intensity and bias. Instead, we create a testable hypothesis that only focuses on the differences in behavior between racial groups.

To test this hypothesis, we use a linear probability model along with traffic data from Illinois. We test the hypothesis using both an event study approach, as well as using media intensity data from the GDELT Project. Both approaches verify our model’s predictions with high significance levels. Therefore, we have shown that Blacks became more cautious in response to these events compared to other racial groups. In addition, our robustness check on the total number of stops supports the claim that non-blacks do not have a significant response

to media coverage of police brutality toward Blacks. This leads to the conclusion that the expected proportion of Blacks breaking traffic laws goes down in response to coverage of these events.

An implicit assumption in our model was that as media coverage goes to zero, Blacks would revert back to their original level of caution. To test this we looked at three days intervals following each media event. We showed that after approximately 10 days, the coefficients were not significant anymore, showing that the media only caused a short term change in behaviour. Since this was a robustness check, and not a main focus of our model, we did not investigate this further. This is an interesting conclusion, and warrants future analysis.

On a final note, we want to address the type of media we use for our analysis. Our model section considers media in a general sense. This can include, but is not limited to, social media platforms such as Twitter and Facebook, as well as more traditional media platforms such as television and print newspapers. All of these sources cover police brutality cases at similar intensities. We use TV data for media intensity, since it affects the broadest demographic and therefore best represents the average driver's exposure to the topic. Different media age medians might affect different demographics more or less. For example, social media may have a greater effect on younger drivers than older drivers. We believe this topic warrants further analysis, in addition to the topic of the previous paragraph.

References

- Bertrand, Marianne, and Sendhil Mullainathan.** 2004. “Are Emily and Greg more employable than Lakisha and Jamal? A field experiment on labor market discrimination.” *American economic review*, 94(4): 991–1013.
- Brooks, Jeffrey S.** 2012. *Black school, White school: Racism and educational (mis) leadership*. Teachers College Press.
- DellaVigna, Stefano, and Ethan Kaplan.** 2007. “The Fox News effect: Media bias and voting.” *The Quarterly Journal of Economics*, 122(3): 1187–1234.
- Durante, Ruben, and Brian Knight.** 2012. “Partisan control, media bias, and viewer responses: Evidence from Berlusconi’s Italy.” *Journal of the European Economic Association*, 10(3): 451–481.
- Elder, Randy W, Ruth A Shults, David A Sleet, James L Nichols, Robert S Thompson, Warda Rajab, Task Force on Community Preventive Services, et al.** 2004. “Effectiveness of mass media campaigns for reducing drinking and driving and alcohol-involved crashes: a systematic review.” *American journal of preventive medicine*, 27(1): 57–65.
- Enikolopov, Ruben, Maria Petrova, and Ekaterina Zhuravskaya.** 2011. “Media and political persuasion: Evidence from Russia.” *American Economic Review*, 101(7): 3253–85.
- Gentzkow, Matthew, and Jesse M Shapiro.** 2010. “What drives media slant? Evidence from US daily newspapers.” *Econometrica*, 78(1): 35–71.
- Gentzkow, Matthew, Jesse M Shapiro, and Michael Sinkinson.** 2011. “The effect of newspaper entry and exit on electoral politics.” *American Economic Review*, 101(7): 2980–3018.
- Graziano, Lisa, Amie Schuck, and Christine Martin.** 2010. “Police misconduct, media coverage, and public perceptions of racial profiling: An experiment.” *Justice Quarterly*, 27(1): 52–76.
- Grogger, Jeffrey, and Greg Ridgeway.** 2006. “Testing for racial profiling in traffic stops from behind a veil of darkness.” *Journal of the American Statistical Association*, 101(475): 878–887.
- Groseclose, Tim, and Jeffrey Milyo.** 2005. “A measure of media bias.” *The Quarterly Journal of Economics*, 120(4): 1191–1237.
- Pierson, Emma, Camelia Simoiu, Jan Overgoor, Sam Corbett-Davies, Vignesh Ramachandran, Cheryl Phillips, and Sharad Goel.** 2017. “A large-scale analysis of racial disparities in police stops across the United States.” *arXiv preprint arXiv:1706.05678*.

- Ross, Cody T.** 2015. “A multi-level Bayesian analysis of racial bias in police shootings at the county-level in the United States, 2011–2014.” *PloS one*, 10(11): e0141854.
- Smith, Michael R, and Matthew Petrocelli.** 2001. “Racial profiling? A multivariate analysis of police traffic stop data.” *Police quarterly*, 4(1): 4–27.
- Wakefield, Melanie A, Barbara Loken, and Robert C Hornik.** 2010. “Use of mass media campaigns to change health behaviour.” *The Lancet*, 376(9748): 1261–1271.
- Webb, Vincent J, and Chris E Marshall.** 1995. “The relative importance of race and ethnicity on citizen attitudes toward the police.” *American Journal of Police*, 14(2): 45–66.
- Williams, David R.** 1999. “Race, socioeconomic status, and health the added effects of racism and discrimination.” *Annals of the New York Academy of Sciences*, 896(1): 173–188.
- Yadav, Rajendra-Prasad, and Miwako Kobayashi.** 2015. “A systematic review: effectiveness of mass media campaigns for reducing alcohol-impaired driving and alcohol-related crashes.” *BMC public health*, 15(1): 857.

Appendix A

Theorem 1.

$$\text{Assumptions 1-5} \implies \frac{d\alpha_{AA}}{dM} < \frac{d\alpha_W}{dM} \approx 0 \implies \frac{d \log(\alpha_{AA})}{dM} < \frac{d \log(\alpha_W)}{dM}.$$

Proof. We start by calculating the change in the cutoff in response to media coverage. This is done by taking the derivative of the derived expression for \bar{a}_i , and using assumptions 2-5 to determine the sign of the resulting expression. For Note that every variable except for a_i was defined to be strictly positive.

$$\begin{aligned} \frac{d\bar{a}_{AA}}{dM} &= \underbrace{\frac{1}{(1 - \hat{\eta}_{AA})^2}}_{+} \underbrace{\left(\underbrace{\hat{\delta}_{AA}\hat{c}_{AA} + (1 - \hat{\delta}_{AA})\hat{b}_{AA}}_{+} \right)}_{\geq 0} \underbrace{\frac{\hat{\eta}_{AA}}{dM}}_{\geq 0 \text{ Ass.}} + \underbrace{\frac{\hat{\eta}_{AA}}{1 - \hat{\eta}_{AA}}}_{+} \underbrace{\frac{\hat{\delta}_{AA}}{+}}_{+} \underbrace{\frac{d\hat{c}_{AA}}{dM}}_{+ \text{ Ass.}} \\ &+ \underbrace{\frac{\hat{\eta}_{AA}}{1 - \hat{\eta}_{AA}}}_{+} \underbrace{\frac{(1 - \hat{\delta}_{AA})}{+}}_{+} \underbrace{\frac{d\hat{b}_{AA}}{dM}}_{0 \text{ Ass.}} + \underbrace{\frac{\hat{\eta}_{AA}}{1 - \hat{\eta}_{AA}}}_{+} \underbrace{\frac{(\hat{c}_{AA} - \hat{b}_{AA})}{+}}_{+} \underbrace{\frac{d\hat{\delta}_{AA}}{dM}}_{+ \text{ Ass.}} > 0. \end{aligned}$$

For Whites the assumptions show that nothing in \bar{a}_W depends on M . Therefore, we now have

$$\frac{d\bar{a}_{AA}}{dM} > \frac{d\bar{a}_W}{dM} \approx 0.$$

Now using this result and Assumption 1, we use Leibniz's rule for differentiating integrals to differentiate α_i with respect to media coverage intensity, M .

$$\frac{d\alpha_i}{dM} = - \underbrace{f(\bar{a}_i)}_+ \frac{d\bar{a}_i}{dM}$$

This implies that

$$\frac{d\alpha_{AA}}{dM} < \frac{d\alpha_W}{dM} \approx 0$$

Furthermore, this implies that

$$\frac{1}{\alpha_{AA}} \frac{d\alpha_{AA}}{dM} < \frac{1}{\alpha_W} \frac{d\alpha_W}{dM}$$

This then implies our final result,

$$\frac{d \log(\alpha_{AA})}{dM} < \frac{d \log(\alpha_W)}{dM}.$$

□

Theorem 2.

$$\text{Assumption 6} \implies \left(\frac{dP_{AA}}{dM} < 0 \iff \frac{d \log(\alpha_{AA})}{dM} < \frac{d \log(\alpha_W)}{dM} \right)$$

Proof. First, to make our notation simpler we create a new variable:

$$\gamma = \frac{\alpha_{AA}}{\alpha_W}$$

Next, let θ_i be the proportion of the population that is type i . Then the probability that a person is black, given that they are stopped is calculated with Bayes law in the following way:

$$P_{AA} = P(i = AA | \text{stopped}) = \frac{\theta_{AA} \alpha_{AA} \eta_{AA}}{\theta_{AA} \alpha_{AA} \eta_{AA} + \theta_W \alpha_W \eta_W}$$

By assumption 6, all η_i 's are equal and cancel out. This results in the following expression:

$$P_{AA} = P(i = AA|\text{stopped}) = \frac{\theta_{AA}\alpha_{AA}}{\theta_{AA}\alpha_{AA} + \theta_W\alpha_W}$$

By the definition of gamma we know that $\alpha_{AA} = \gamma\alpha_W$. Plugging this in and cancelling out the α_W terms we get

$$P_{AA} = P(i = AA|\text{stopped}) = \frac{\theta_{AA}\gamma}{\theta_{AA}\gamma + \theta_W}$$

Next we differentiate P_{AA} with respect to the media coverage intensity variable. We treat the θ_i 's as constant, because media coverage cannot affect short run population composition.

$$\frac{dP_{AA}}{dM} = \frac{\overbrace{\theta_W\theta_{AA}}^{+}}{\underbrace{(\theta_{AA}\gamma + \theta_W)^2}_{+}} \frac{d\gamma}{dM}$$

Since $\frac{d\gamma}{dM}$ is always a positive multiple of $\frac{dP_{AA}}{dM}$, they will always have the same sign. Therefore,

$$\frac{dP_{AA}}{dM} < 0 \iff \frac{d\gamma}{dM} < 0$$

In addition we show:

$$\begin{aligned} & \frac{d\gamma}{dM} < 0 \\ \iff & \frac{\alpha_W \frac{d\alpha_{AA}}{dM} - \alpha_{AA} \frac{d\alpha_W}{dM}}{\alpha_W^2} < 0 \\ \iff & \alpha_W \frac{d\alpha_{AA}}{dM} - \alpha_{AA} \frac{d\alpha_W}{dM} < 0 \\ \iff & \alpha_W \frac{d\alpha_{AA}}{dM} < \alpha_{AA} \frac{d\alpha_W}{dM} \\ \iff & \frac{1}{\alpha_{AA}} \frac{d\alpha_{AA}}{dM} < \frac{1}{\alpha_W} \frac{d\alpha_W}{dM} \\ \iff & \frac{d \log(\alpha_{AA})}{dM} < \frac{d \log(\alpha_W)}{dM} \end{aligned}$$

Therefore:

$$\frac{dP_{AA}}{dM} < 0 \iff \frac{d \log(\alpha_{AA})}{dM} < \frac{d \log(\alpha_W)}{dM}$$

□

Appendix B

Table 2: Event Study Dates

Date	Victim
July 18, 2014	Eric Garner
August 9, 2014	Michael Brown
August 14, 2014	Ezell Ford
November 22, 2014	Tamir Rice
March 9, 2015	Anthony Hill
April 2, 2015	Eric Harris
April 7, 2015	Walter Scott
April 19, 2015	Freddie Gray
July 13, 2015	Sandra Bland
November 15, 2015	Jamar Clark
November 24, 2014	LaQuan McDonald
July 5, 2016	Alton Sterling
July 6, 2016	Philando Castille

Table 3: Media regression - Absolute number of stops

VARIABLES	(1)	(2)
	Non-Black Stops	Black Stops
Media	7.475 (17.18)	-8.821** (4.420)
All Controls	Yes	Yes
All FE	Yes	Yes
Observations	1,096	1,096
R-squared	0.265	0.391

Notes: OLS regressions. The dependent variable is the absolute number of black/non-black people stopped. Media intensity variable is standardized. Controls included: vehicle year, age, gender and year, day of the week and car brand fixed effects. Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Event study - Absolute number of stops

VARIABLES	(1)	(2)
	Non-Black Stops	Black Stops
Event	-44.72 (71.68)	-29.78* (17.75)
All Controls	Yes	Yes
All FE	Yes	Yes
Observations	1,096	1,096
R-squared	0.255	0.368

Notes: OLS regressions - event study. The dependent variable is the absolute number of black/non-black people stopped. Controls included: vehicle year, age, gender and year, day of the week and car brand fixed effects. Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Placebo regressions - Airplane crashes

VARIABLES	Media		Event	
	(1) All Stops	(2) Mov. Violations	(3) All Stops	(4) Mov. Violations
Media	-0.000251 (0.000260)	-0.000144 (0.000329)		
Event			0.00210** (0.000988)	0.00266** (0.00125)
Vehicle Year	-0.000283*** (4.34e-05)	-0.000348*** (5.87e-05)	-0.000283*** (4.35e-05)	-0.000348*** (5.88e-05)
Age	0.00127*** (1.80e-05)	0.00128*** (2.24e-05)	0.00126*** (1.80e-05)	0.00128*** (2.24e-05)
Gender	-0.0213*** (0.000565)	-0.0148*** (0.000719)	-0.0213*** (0.000565)	-0.0148*** (0.000719)
Observations	2,503,633	1,493,221	2,503,633	1,493,221
R-squared	0.034	0.033	0.034	0.033
Day of the Week FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Car Brand FE	Yes	Yes	Yes	Yes

Notes: OLS regressions. The dependent variable is the absolute number of black/non-black people stopped. Media intensity for airplane crashes is standardized. Robust standard errors in parentheses.

*** p<0.01, ** p<0.05, * p<0.1