Does the police retaliate against in reaction to racial injustice protests?

Aurel Mäder, Theodoros Bitsakis, Ludovica Schaerf

17.12.2020

1 Abstract

Civil rights movements have protested for decades against police brutality and racial bias of law enforcement towards black people. Racial injustice protests have regularly sparked reactions from government officials and have been greatly referred to in the media. However, it is unclear how police officers in their everyday duties react to racial justice protests. In this research project we estimate the effect of racial injustice protest on the racial bias in police traffic stops against black people. A possible relation between racial injustice protest and police traffic stop rates of minorities can be estimated by combining a data set on police traffic stops (Leung and Perkins, 2020) with two different protest data sets, one of racial injustice protest (Trump et al., 2018) and one of black lives matter (BLM) protest (Pierson et al., 2020). Based on this data we visually examine if there is any change in the stop rates before and after big racial justice protest. We also train a difference-in-difference regression model to estimate if there is any statistical relationship between the number of protest attendees and traffic stop rates of black motorists after the protests. Neither in our visual examination nor with our diff-in-diff regression model we find any statistically significant relationship between racial justice protests and traffic stop rates of minorities.

2 Introduction

In this project we investigate the relation between the number of attendees at racial injustice protests and the racial bias in police traffic stop rates as shown in Pierson et al. (2020). To discuss this question we will proceed with following structure: First, we give an in depth review of the existing literature at the intersection of racial policing biases and of the functionalities and possible effects of social justice protests. The literature review also shows the relevance of further investigation in the intersection of the two literature areas. Afterwards we will specify and justify the chosen data sets. We will also illustrate the given data sets with selected summary statistics. Then we will proceed by explaining the chosen statistical methods, in particular the difference-in-difference regression model. We will quickly refer to the plots which show pre- and post-trends of search rates for some selected cities with very big protest. Then we will asses our results and interpreter our regression model and our plots. At last we will conclude our findings.

3 Literature Review

Our project is at the intersection of two very rich literature areas in the social sciences. On one hand our project deals with institutional biases towards minorities, on the other hand our project explores the functionality and effects of protest onto governmental institutions. A primary source for our project is a data set from a paper which deals with racial bias in police traffic stops conducted across the United States. Pierson et al. (2020) show with a large scale analysis of nearly 100 million traffic stops, that the police has a persistent bias against black and Hispanic motorists. The researchers assert causality with a 'veil of darkness' test, which shows that black drivers are less likely to get stopped after sunset when 'veil of darkness' covers their race. Earlier Coviello and Persico (2013) showed by analysing the "stop and frisk program" conducted by the New York Police Department (NYPD), that there is persistent bias against Afro-Americans also in pedestrian controls. Coviello and Persico (2013) identify two different sources of this racial bias, the allocation of police forces in the quarter of minorities and individual racial bias of the police officers making the stop decision. Goncalves and Mello (2020) extend on the analysis of the racial bias in traffic stops by providing a empirical model which estimates that " 40% of officers explain all of the aggregate discrimination" .
On the other hand our project also references to the literature of the effects of protest by minorities against governmental institutions, in particular the police. WASOW (2020) show with a instrumental variable (IV) analysis of black-led protests between 1960 and 1972 that non-violent protest increased voting share for the democratic party, which is considered to be more minority friendly. However violent protest lead to an increase in republican vote share, which was known to implement more repressive 'law and order' politics. Williamson et al. (2018) take the opposite angle and estimate the effect which police brutality has on the size of protests. They show that protests are more likely to occur in places where black people have been shot by police officers.
However the question if racial injustice protest lead to any reaction in the policing of minorities, stays unanswered.

4 Data Collection

In order to answer this question, we use three different types of data collections.

Protests: We use "Count Love" data set (Leung and Perkins, 2020) as the primary source for protest information. This collection includes 37.090 USA protest events

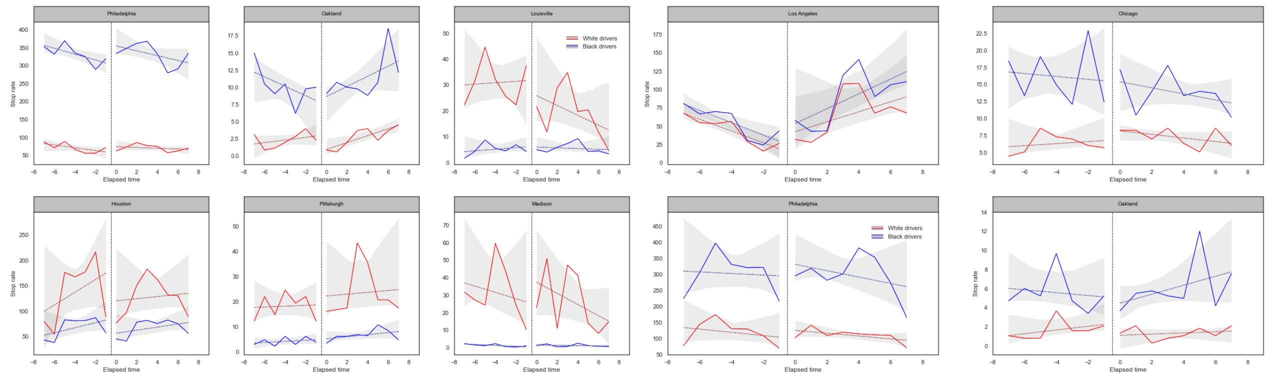

Figure 1: **Stop rate before and after an important racial disparity protest.** The lines show the stop rates for each day in the period of 7 says before and after the protest. The vertical line delineates the protest day. The dashed lines denote the fitted trends, with corresponding confidence levels. For each of the 6 cities in the image on the left, the biggest protest is plotted. The numbers of attendees of the 6 protests, from left to right, top to bottom are: 2000, 450, 200, 1000, 300, 200. For each of the 4 cities of the image on the right, also the biggest protest is plotted. The numbers of attendees of the 4 protests, from left to right, top to bottom are: 5000, 2000, 2000, 3000

that take place between 2017 and 2020. Each event provides information for several features (date, location, attendees, event, tags, curated, total articles), as well as a list of sources that link the event with online articles. We draw our attention to events with a Racial Injustice tag for the time period between 2017 and 2018. In addition, we use as a second source, a collection of 780 protests organized by the "Black Lives Movement" (Trump et al., 2018) between 2014 and 2015. In addition to protest-specific features, this collection also includes census information.

Police traffic stops: In order to investigate possible police bias triggered from protests, we analyze a large collection of police traffic stops provided by Pierson et al., 2020. This data set provides more than 100 million traffic stops carried out by 21 state patrol agencies and 35 municipal police departments in USA, from 2010 to 2018. During our analysis we examine only county traffic stops that match the time period of protests.

Census: To normalize the rate of traffic stops for the racial composition of a given county in the data of Leung and Perkins (2020), we use census data from 2019 from the US census bureau (Bureau, 2020).

5 Methods

To estimate a potential relationship between protests for racial justice and the racial bias in policing as observed during traffic stops, we chose to estimate a difference in difference regression model. The difference-in-difference regression model is a widely used statistical tool in the social sciences and in economics to estimate a quasi causal effect (see Stock and Watson (2015)) with non experimental, often historical data. To fit our situation to this model we have to assume that each protest in our data set functions as some kind of treatment, which inherently affects black people, treatment group, differently then white people, control group. This model then estimates the effect of a protest, treatment, on black motorist by comparing the mean difference of the pre-post-period period and furthermore subtracting the pre-post-trend of the control group to account for a possible trend in the data. Formulating this in a regression yields the following model:

$$
\begin{aligned}
Y_{i,t} &= \beta_0 + \beta_1 Race + \beta_2 Period \\
&+ \beta_T RacePeriodAttendees + \beta_x X + e_i
\end{aligned}
$$

Where $Y_{i,t}$ is the mean of the stop rate pre or post the protest in a city i. β_0 is an intercept, $\beta_1 Race$ is a dummy for the race, $\beta_2 Period$is a dummy for the period, $\beta_T RacePeriodAttendees$ is the interaction term between race and period and attendees which models the treatment effect of the protest onto the traffic stop race of black people given the number of attendees. Furthermore $\beta_x X$ models covariates which can enrich our model, e_i models the error of our model.

One assumption which has to be fulfilled so that the diff-in-diff model can claim validity is the 'parallel-trends-assumption'. This assumption states that the trends before the treatment must be parallel so that we can assume that the change in control group accounts for a potential time trend in the treatment group. We assess this assumption by plotting several time trend of traffic stop rates in cities with big protests.

In particular, we choose 6 protests from the Count Love dataset and 4 protests from the Black Lives Matter (BLM) dataset and plot the stop rate by day for the period between a week before and a week after the protest. We also plot the regression line on the two periods separately, with corresponding 95% confidence interval, to assess the trend. The two plots can be seen in Figure 1.

6 Results

In the plots of Figure 1 no clear pattern appears. In some cases, the traffic stops in the period before and after the protests remain generally unchanged. In the city of Philadelphia, for both protests (one is in 2017 and

	Data: Countlove Dependent Variable: Stop Rates given race				Data: BLM Dependent Variable: Stop Rates given race			
	Simple Diff-in-Diff	Covariates	Only protest > 100 Attendees	Mean of 2 days pre and post	Simple Diff-in-Diff	Covariates	Only protest > 100 Attendees	Mean of 2 days pre and post
Period	-0.8651	-1.4299	-40.3653	-7.5642	-3.2503	0.1983	-8.3356	-2.2485
	(0.858)	(0.935)	(0.135)	(0.657)	(0.776)	(0.976)	(0.626)	(0.838)
White	-51.3236***	-49.9315***	-6.2309	-54.3756**	-23.1146**	-23.1146***	-21.8505	-22.3885**
	(0.002)	(0.002)	(0.808)	(0.002)	(0.042)	(0.000)	(0.194)	(0.041)
$Period * Black * Attendees$	0.0234	0.0120	0.1237***	0.0298	0.0115	0.0030	0.0152	0.0105
	(0.619)	(0.777)	(0.004)	(0.533)	(0.358)	(0.678)	(0.268)	(0.381)
$Period * White * Attendees$	0.0001	-0.0107	0.0511	0.0059	0.0046	-0.0039	0.0079	0.0006**
	(0.998)	(0.800)	(0.217)	(0.902)	(0.714)	(0.580)	(0.566)	(0.049)
Deaths Black						18.6654***		
						(0.000)		
Deaths Unarmed Black						-66.6126***		
						(0.000)		
State/City Fixed Effects	✗	✓	✗	✗	✗	✓	✗	✗
Other Covariates	✗	✓	✗	✗	✗	✓	✗	✗
N-Observations	178	178	50	178	292	292	152	292
Df Model	4	14	4	4	4	7	4	4
R-squared	0.062	0.541	0.194	0.068	0.021	0.685	0.026	0.021
Adj. R-squared	0.040	0.501	0.123	0.046	0.007	0.677	0.000	0.008
F-statistic	2.853	13.72	2.713	3.132	1.530	88.25	0.9956	1.573

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 1: Diff-in-Diff regression model results

the other in 2014), the stops are decreasing before the protest, witness a spike on the day of the protest and continue decreasing. For other cases, the pattern is reversed. The cities of Oakland (both in 2017 and 2014) and Los Angeles exhibit the lowest point on the day of the protest, with a decreasing slope preceding the protest and an increasing one following. The scarcity of visible trends in the visualization is supported by the results of the linear regression. In the base model, 178 observations are fitted according to the formula above (4 degrees of freedom) with target the 7 days mean of stops in the periods pre- and post- protest. The model obtains an R^2 of merely 0.06 (for Count Love) and 0.02 (for BLM). Additionally, the only significant coefficient (with a P-value of < 0.01) is the race of the stopped individual. This indicates that the event of the protest and its size do not influence significantly the bias in traffic stops.

The addition of co-variates to the model, such as the City and State of the protest for the Count Love (CL) dataset and 'Deaths Black' (whether the protest was caused by a death of a black person by the police) and 'Death Unarmed Black' to the BLM dataset cause a great increase in the R^2, which reached 0.54 (CL) and 0.69 (BLM). Despite the model fits considerably more variance of the data, the effects of the protest are still un-influential. We have to pay attention to the nature of a given protest. Protests which were the result of police brutality or which lead to brutality in form of looting or vandalism could have completely different effects than peaceful protests. This can be seen looking from explanatory variables like deaths of black prior or deaths of unarmed blacks prior to the protest.

When limiting the protest size to protests with more than 100 attendees, we obtained a significant increase in stop rates of black people following the protest. However, given the very small number of observations (only 50), this significant effect cannot claim any validity.

Finally, the period taken into consideration influences both the R^2 of the model and the significance of the interaction between period, race and attendees. Surprisingly, the significance increases slightly with the number of days (the effects seem to be more long-term than short-term), while the R^2 is higher for less days (explaining the variation of one or two days before and after the protest appears to be an easier task than a week).

7 Conclusion

In our investigation we did not find any statistically significant relationship between the number of attendees of a given protest and an increase or decrease in racially biased police traffic stops of black people. Neither in our visual exploration nor in our diff-in-diff regression model do we see any clear trends in the effects of protest on police traffic stops. Our analysis was limited by a scarcity of very big protest and we lacked information about the nature or functionality of a given protest, for example, if a given protest resulted in looting. Given the lack of such information which deeply changes the functionality of the data, we can not draw any concluding answer to our question. Further research with more complete data sets is needed to explore the effects of, in particular. big or violent protests on racially biased police traffic stop rates.

References

Bureau, U. C. (2020). Population estimates, july 1, 2019.

Coviello, D. and Persico, N. (2013). An economic analysis of black-white disparities in nypd's stop and frisk program. Technical report, National Bureau of Economic Research.

Goncalves, F. and Mello, S. (2020). A few bad apples? racial bias in policing. *Racial Bias in Policing (June 15, 2020)*.

Leung and Perkins (2020). Count love protest dataset.

Pierson, E., Simoiu, C., Overgoor, J., Corbett-Davies, S., Jenson, D., Shoemaker, A., Ramachandran, V., Barghouty, P., Phillips, C., Shroff, R., et al. (2020). A large-scale analysis of racial disparities in police stops across the united states. *Nature human behaviour*, pages 1–10.

Stock, J. H. and Watson, M. W. (2015). *Introduction to econometrics*.

Trump, K.-S., Williamson, V., and Einstein, K. L. (2018). Vol 16(2): Replication Data for: Black Lives Matter: Evidence that Police- Caused Deaths Predict Protest Activity.

WASOW, O. (2020). Agenda seeding: How 1960s black protests moved elites, public opinion and voting. *American Political Science Review*, 114(3):638–659.

Williamson, V., Trump, K.-S., and Einstein, K. L. (2018). Black lives matter: evidence that police-caused deaths predict protest activity. *Perspectives on Politics*, 16(2):400–415.