Policing the Powerless
How Black Political Power Reduces Racial Disparities in Traffic Stops Outcomes

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Abstract: Across the US, different communities and groups within communities have very different relationships with their police departments. What influences this variation? We propose and show that the political power of the black community influences the degree of disparate policing: as the political power of the black community increases, disparities in policing decrease. In cities with low black population share and low black share of elected seats on the city council or in the mayor's office, disparities are higher. Police in such cities may feel less pressure to accommodate a large and politically powerful black community. At the higher end of political representation and power among black communities, police may be more careful to avoid alienating such an important part of the local community. Either way, political representation of blacks is strongly associated with reduced bias in the behavior of the local police. To test this, we create a new data set of over 400 municipal police departments across several states and explain variation in search rate disparities between black and white drivers. Controlling for socioeconomic factors, segregation, and composition of the police force, we find evidence for our hypothesis: as black political power increases, disparate treatment decreases.

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As national attention has focused on questions of racial justice and the relations between police departments and the communities they serve, there has been a surge of scholarship exploring the validity of claims of a “driving while black” phenomenon. With few exceptions, recent findings have shown that black drivers are indeed treated differently than whites on the nation’s roadways. In many states, black drivers are substantially more likely to be searched or arrested following a traffic stop, and they are frequently pulled over at rates that far exceed their numbers in the population (Peffley and Hurwitz 2010; Burch 2013; Lerman and Weaver 2014; Epp et.al. 2014; Moore 2015; Baumgartner et.al. 2017; Pierson et.al. 2017; Baumgartner, Epp, and Shoub 2018). Altogether, the evidence for profound and widespread racial differences is indisputable, but there remain important questions about what causes disparate treatment and what can be done about it.

This article focuses on the latter question. Regardless of where racial differences originate, they are clearly a significant element of American criminal justice. A solution that we explore in this article starts with the very simple premise that no one enjoys being subject to police scrutiny. If police officers routinely pull you (or your friends and family members) over as you drive to work or the grocery store that is undoubtedly a sad state of affairs. In fact, intensive police scrutiny can be so unpleasant that it might prompt many of us to take action such as complaining to our representatives in the local government or even hiring a lawyer to fight back in court. We believe that the degree to which different communities can voice their displeasure at being subjected to police stops and searches is a powerful factor underlying observed racial differences in traffic stops. After all, the police are ultimately answerable to elected officials, and therefore only one step removed from the voters. From this perspective, racial differences in traffic stops are symptomatic of larger disparities in representation and political power. Middle-class white communities do not experience the same type of intensive policing as lower-income minority communities because they have the political resources to push back against that kind of treatment. We believe this is an important part of the story.

To test these claims, we assemble traffic stops data spanning 64 police departments across six states for a total of 401 observations. We then measure the relative likelihood of black and white drivers being subjected to a search following a traffic stop for each jurisdiction. The resulting search-rate ratio is our dependent variable and we find that it varies systematically with measures of black political power such as factor summarizing black political power or whether a municipality has a black mayor. Because we are able to control for a variety of potentially confounding factors and because our observations come from police departments from around the country, we can be confident that our findings are highly robust. Voice matters. Voting matters. Where blacks do not vote or gain electoral success, police are significantly more likely to target them for disproportionate enforcement actions.

Racial differences in the treatment of white and black citizens are well-documented at every level of the criminal justice system. The next step in this research agenda is to ask how we can go about resolving these differences. Of course, there are no easy answers, but we believe that descriptive representation will be a key part of the solution. In some ways, the results of this article are encouraging because they imply that local police forces are responsive to constituents, exactly what we should want and expect from democratic accountability systems. The discouraging element is that this calculus often appears to work against minority communities. But that can change and we hope that this article (and others like it) helps provide those working to improve police-community relations with some guidance on a fruitful area to focus their efforts.

Traffic stops and representation: what do we already know?

Since the 1960s, aggressive police targeting of minority communities has been justified by the "war on crime." Even routine traffic stops were seen as a means by which the police could target drug couriers and put an end to the epidemic of drug abuse that has long generated so much concern. In declaring a "war on crime" and a "war on drugs" political leaders asked our police forces to target those responsible for crime and to use all means to inhibit their actions. In particular, the war on crime saw the introduction of the "investigatory stop," which are stops where an officer pulls a driver over because they look suspicious or out-of-place, rather than in response to a serious traffic violation.

Investigatory stops are legal because there are so many traffic laws that virtually every driver is routinely guilty of breaking one or another of them. The Court ruled in its unanimous 1996 *Whren v. United States* decision that any traffic violation provided the opportunity for an officer to pull over a car. Crucially, there was no requirement that the officers act in an equitable manner when deciding which car to pull over. If 10 cars are speeding, the officer may decide to pull over that one driver who seems to be of interest, perhaps because of how they look. By the Court's logic, it is unreasonable to arrest all the speeders, so the police must have discretion to pull over this driver rather than that one. And, by breaking the speed limit, all drivers open themselves up to the possibility of a traffic ticket and a conversation with an officer. Of course, once that conversation starts, the officer may decide that they would like to search the driver or the vehicle, and they may seek probable cause or ask for consent. In *Whren*, the Court essentially declared that all drivers were subject to police stop, and that the stops need not be distributed in an equitable manner. Police could use their best judgment in deciding whom to stop.

Unfortunately, this approach is an extremely blunt way to try and prevent violent crime. Consistently, police agencies have made clear that "you have to kiss a lot of frogs before you find your prince”—very large numbers of traffic stops would have to occur before an officer might find a large cache of drugs, contraband, or a felon on the run. Unstated in that calculation was that many Americans would be subjected to police investigations so that a small number could be searched or arrested. Those who were momentarily detained were said by the Court to have suffered only a trivial inconvenience. The key element in this targeting, which kept it hidden for so long from those who might have objected, was that middle-class white Americans were largely exempt from its consequences. On the other hand, members of minority groups, especially young men, were subjected to a lot more than just an occasional trivial inconvenience. Police routinely targeted poor neighborhoods, individuals with certain forms of dress, males rather than females, younger people rather than older ones, and minorities rather than whites. Thus, millions of Americans have been targeted for more intensive police attention outside of the gaze or knowledge of most middle-class whites.

Another reason such targeting occurs is because members of the black community often lack the political power to voice their displeasure at investigatory police stops. So, we believe that descriptive representation matters. Cities with no black or minority representation on the city council, mayor’s office, or other elected bodies may see less attention to issues of racial equity during routine deliberations. Those with large numbers of minorities on the city council may see attention regularly paid to concerns of minority groups within the population and electorate. Descriptive representation amplifies concern for minority-relevant issues over and above what it might otherwise be. Scholars have previously found that the female share of seats in state legislatures is related to legislative attention to issues of particular concern to women (Branton 2005, Branton and Ray 2002, Cammisa and Reingold 2004), and the same has been found with regards to racial minorities, (Cannon 1999, Grose 2011), LGBT representatives (Hansen and

Treul 2015), and blue-collar workers (Carnes 2013, Carnes 2012). Closely associated with our own interest in policing, but not focused on traffic stops, Salzstein (1989) and Stucky (2011) both investigated the linkage between having black elected officials and the relative rates at which black men are arrested, across a number of cities. On average, these studies suggest that the presence of a black mayor and/or a majority black city council decreases the black arrest rate.

Theory

As discussed above, a driving force in explaining racial disparities is political power. By political power, we mean the extent to which a minority group is incorporated into the political process. Incorporation has three faces: presence, voice, and representation. We expect that all three to be associated with the degree of disparity in policing: less the power, results in greater the disparity.

First, a group has some power in the system merely due to its *presence* in the community. Numbers matter, and small minorities are easier to target for harsh treatment than larger groups or majorities. Elected officials aim to represent the interests of their communities. Bureaucratic agencies are attuned to their constituents. No local political leader would reasonably be expected to support policies that alienate a majority of the population. For smaller minorities, it may be easier to justify or ignore some problems. As a group's presence grows, then their political power grows. Because law enforcement is one aspect of local government, the presence and relative size of different groups in the population should influence its policies and practices. We would expect the same in schools or other local bureaucracies.

While high population share may result in voice, descriptive representation also matters. Cities with no black or minority representation on the city council, mayor's office, or other elected bodies may see less attention to issues of racial equity during routine deliberations. Those with large numbers of minorities on the city council may see attention regularly paid to concerns of minority groups within the population and electorate. Descriptive representation amplifies concern for minority-relevant issues over and above what it might otherwise be. We incorporate several indicators of descriptive representation: the share of city council seats held by blacks, whether the mayor is black, and whether the police chief is black. Of course, these variables may be highly correlated with the black population share, but we incorporate all of them into our measure of black political power.

Taken together, various factors combine to make up the political power of a given group. As each increases, influence over policy grows. One such group that responds to these pressures because they are a part of the local government is the local police department. Public agencies cannot be expected to ignore the needs or preferences of large, loud, and well represented constituencies. They may or may not choose to do so for those with low values on the variables we have enumerated. Based on this, we formulate a series of observable implications to test. Understanding that our theory of political power relates individually but especially in combination to its components, our expectations are very simple.[1]

H: Higher levels of political power are related to lower levels of racial disparity in traffic stops outcomes.

We understand that many other factors may drive differential policing, most particularly economic differences between blacks and whites. Therefore, using census data, we incorporate indicators of the share of blacks with a high school education, the black unemployment rate, and the black poverty rate. If a higher share of blacks are educated, fewer unemployed, and fewer in poverty, then any class-based or poverty-related policing disparities should be reduced. We also

[1] Baumgartner et al. (2018) used three variables in their index of black political power: community share, voters share, and city-council share. The share of voters by race is not available for all states included here, so we cannot replicate their analysis.

use census-based indicators of residential segregation. Where black-white segregation is higher, precinct-based policing differences may exacerbate disparities in traffic-stops outcomes. Finally, we look at the black share of the sworn officers in the local police department. We would expect that cities with lower shares of blacks on the police force would have higher rates of racial disparities in their traffic-stops outcomes. Our main theoretical interest is in the political representation variables, but of course our model must be as complete as possible so we include these variables in the models as well.

Data and Methods

In order to assess the role that political power plays in traffic stops disparities, we turn to a dataset of traffic stops collected over the last several years. Some states collect traffic stop information from all agencies while others may only collect information for its highly populated cities. We exclude any agencies that do not correspond to a city or town, like the state highway patrol or county sheriff's office, for which political city council and mayor information is either nonexistent or incompatible. From these traffic stops reports, we record the number of stops and searches by racial group.

The data is in the agency-time window format. That is, an observation consists of the aggregate totals of traffic stops and searches by racial group, by agency, and by year or time window. To maximize the number of observations in our dataset, we subset our data by agency and time window. We establish thresholds that a given agency-window must meet to be included in the analysis at all in order to ensure robustness of the measures. First, an agency-window must include at least 10,000 traffic stops. Second an agency-window must include at least 100 stops of white drivers and 100 stops of black drivers. The first step in creating these subsets was to divide the data into agency-year subsets. Agency-years that meet this threshold were entered into the dataset. For those agency-years where the threshold was not met, we combine data across adjacent years for that same agency until the thresholds are met. See Appendix B for additional information on this process.

The resulting number of agency-windows that meet these thresholds and are included in the models[2] are presented in Table 1.[3] Year represents the start year, if the observation consists of a time window. For Colorado, Oregon, and Texas, only a single large city reports traffic stop data. For Missouri, North Carolina, and Illinois, all agencies report data. Note, however, that the time range varies by state. Overall, we have 401 agency-windows included in the analysis.

Table 1: Distribution of States, Agencies, and Years included in Analysis

State	Agency	Years	Frequency	Percent	Cum.
Colorado	Denver	2001-2002	2	0.5	0.5
Illinois	Multiple	2004-2014	228	56.86	57.36
Missouri	Multiple	2015	12	2.99	60.35
North Carolina	Multiple	2002-2016	146	36.41	96.76
Oregon	Portland	2009-2014	6	1.5	98.25
Texas	Austin	2009-2015	7	1.75	100
Total			401	100	

The compiled list of agencies and time windows generated by the traffic stop data dictated the observations for our dataset. We then collected political variable and demographic data for the city or town to which the police agency corresponded. We limited our dataset to police agencies corresponding to cities and towns, rather than county police, as there can be overlap between county and city police jurisdictions.

Table 2 reports descriptive statistics for some of our key independent variables and control variables. For population, education, unemployment, and poverty data, we used the

[2] Observations may have been excluded from the analysis if they were missing on any of the independent variables as well.
[3] We also have traffic stop data for Connecticut and Maryland. However, we have not completed our coding yet of the political variables for Connecticut. Maryland data from agencies large enough to meet our threshold requirements are mostly from counties, rather from cities, and for those cities where we do have data, segregation data are generally not available, so Maryland is not included here.

Census and the American Community Survey (ACS). For years between 2000 (when the Census reports) and 2006 (when the first ACS report is available), we interpolated values. See Appendix A for a more detailed explanation of this process. After obtaining the raw numbers from the Census or ACS, we constructed the variables presented below by transforming them into proportions.

The black-white segregation score reported in Table 2 comes from a segregation database that uses information from the Census. This score is the dissimilarity index between black and white residences. We used data for the years 2000, 2009, and 2010 to generate an average segregation score for the town/city. See Appendix A for more detail on this process. Higher numbers indicate higher levels of segregation. The variable ranges from approximately 3 to 83, with a mean of 36.

The proportion of black officers on the police force is a variable collected from the Law Enforcement Management and Administrative Statistics (LEMAS) survey. The LEMAS survey was administered for the years 2000, 2003, 2007, and 2013, with 87 agencies reporting at some point in time. Only 27 agencies completed more than one LEMAS survey, and of those 27, only seven completed all three years of surveys. Because it is so common that there is only one data point for LEMAS, we took the average of the proportion of black officers on the police force that is available and used that number for all years corresponding to the agency. See Appendix A for more detail. Table 2 reports that the mean proportion of black officers on the police force is 0.09, with a minimum of 0 and maximum of 0.46.

Finally, the political variable data was hand collected by a team of graduate and undergraduate students, hired by the authors. This is still a working dataset.[4][5] From Table 2, we can see that the mean proportion of black individuals on the city council is 0.10, with a minimum of 0 and maximum of 1.00. The data for whether the mayor and police chief are black are based on findings of 30 black mayors and 37 black police chiefs out of the 401 observations.

Table 2: Descriptive Statistics

	Min	Mean	Maximum	N
Proportion Black on City Council	0.00	0.15	0.67	401
Proportion Black in the Population	0.00	0.16	0.54	401
Proportion Black with HS Diploma	0.02	0.33	0.80	401
Proportion Black Unemployed	0.00	0.13	0.37	401
Proportion Black in Poverty	0.00	0.23	0.67	401
Black-White Segregation	8.49	40.57	83.15	401
Proportion Black on Police Force	0.00	0.09	0.33	401
Black Mayor	0.00	0.07	1.00	401
Black Police Chief	0.00	0.09	1.00	401

Using the information collected about local descriptive representation and proportion of the community that is black, we construct a factor to estimate the political power of the black community. The political power factor variable is estimated using confirmatory factor analysis (CFA). The indicators for the factor were proportion of the population that is black, proportion of the city council that is black, whether the mayor is black, and whether the police chief is black. All of the indicators load fairly well onto the factor and explains approximately 53% of the variance in the latent variable.[6] From this factor, we extracted factor scores for each of our

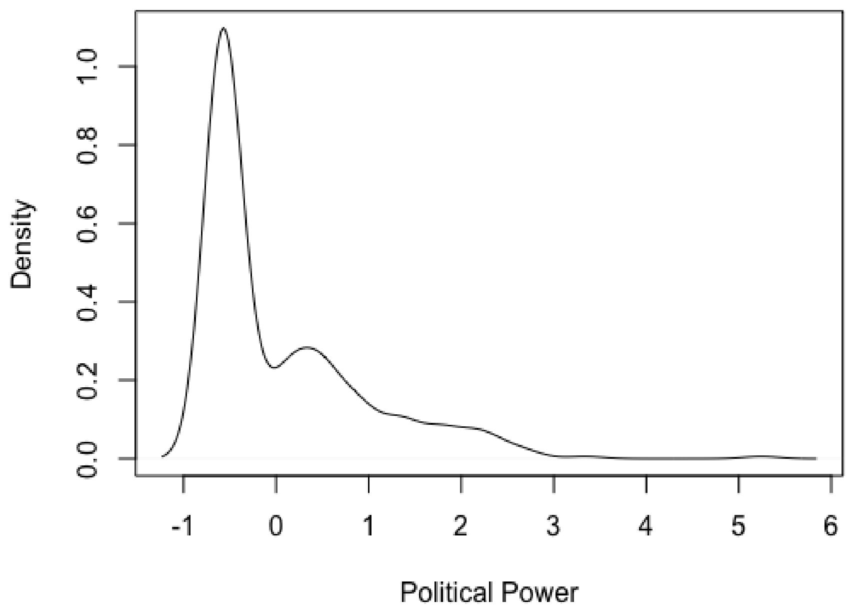
[4] All of the data corresponding to agency-year observations (those that do not need to incorporate a time window because they are large enough to reach the threshold with a single year), have been completed. These are the observations that make it into the models presented in the body of the paper anyway, because these larger cities and towns are the ones for which segregation and LEMAS data is available. So, the unfinished political variable data likely only effects models presented in Appendix A that exclude the LEMAS and segregation variables. Further, additional states are being added to the data set, such as Missouri.

[5] There was a change in how the time windows were calculated. See Appendix A for a detailed explanation of this change and its effect on political variable calculation. Again, this change likely only effects models in the Appendix rather than those presented in the body of the paper because it only affects smaller towns and cities, without LEMAS or segregation information.

[6] For additional information, see Appendix C.

observations and the distribution of these scores is plotted in Figure 1. Higher values indicate greater black political power.

Figure 1: Descriptive Statistics for the Political Power Factor Variable



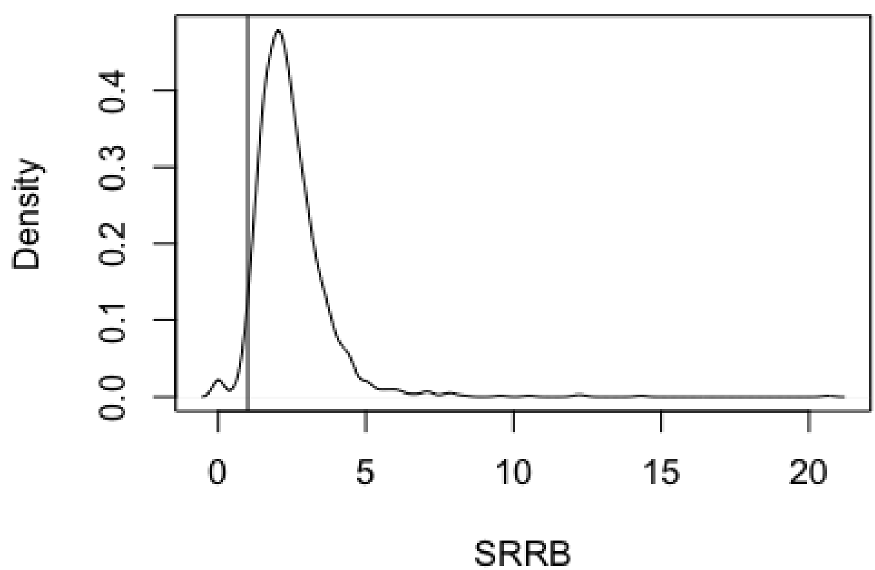
Note: Mean = 0.058, Min = -0.65, Max= 5.25

Finally, the black-white search-rate ratio obtained from the traffic stops data serves as our dependent variable. The search-rate ratio is calculated with the raw search rates, by racial group. The white search rate and black search rate are first separately calculated by dividing the total number of searches by the total number of stops, for a given time period. Then, the black search rate is divided by the white search rate to obtain the search rate ratio. Where SRRB stands for the black-white search rate ratio, mathematically this statistic can be represented as:

$$SRRB = \frac{Searches\ of\ Black\ Drivers / Stops\ of\ Black\ Drivers}{Searches\ of\ White\ Drivers / Stops\ of\ White\ Drivers}$$

Values below 1 indicate that white drivers are searched at higher rates than black drivers, while values above 1 indicate that black drivers are searched at higher rates. This is a robust indicator of racially disparate treatment by the police (Baumgartner, Christiani, et al. 2018). Figure 2 plots the distribution of the SRRB in our data. There is a vertical line at 1. Values below that line are observations for which the white search rate exceeds the black search rate, while observations above the vertical line are those in which black drivers are disproportionately searched. The mean of this variable is 2.45, indicating that on average, black drivers are more than twice as likely to be searched as their white counterparts. It is almost always the case that black drivers are searched more than white drivers, across all agency-windows.

Figure 2: Distribution of black-white search rate ratio (SRRB)



Note: Mean = 2.45, Min = 0.00, Max = 20.66

In order to explain why the black-white search rate ratio is higher, indicating greater racial disparities, in some places but lower in others, we estimate the SRRB using the explanatory variables previously outlined. The first model incorporates a political power variable, which is the constructed factor variable from four indicators: proportion of the city council that is black, proportion of the population that is black, whether the city has a black mayor, and whether the city has a black police chief. The second model includes all of these as separate independent variables. The models are represented here:

- Political Power Model:
$$SRRB \sim \propto + \beta_1(edu) + \beta_2(unemploy) + \beta_3(poverty) + \beta_4(segregation) + \beta_5(officers) + \beta_6(political\ power) + \varepsilon$$

- Deconstructed Model:
$$SRRB \sim \propto + \beta_1(edu) + \beta_2(unemploy) + \beta_3(poverty) + \beta_4(segregation) + \beta_5(officers) + \beta_6(city\ council) + \beta_7(population) + \beta_8(police\ chief) + \beta_9(mayor) + \varepsilon$$

Analysis and Findings

Table 4 reports the results from two linear regressions. Model 1 includes the black political power factor variable, while model 2 includes the component parts of this factor but not the factor itself. Both of these models explain a little less than 30% of the variance in the dependent variable, the black-white search rate ratio.

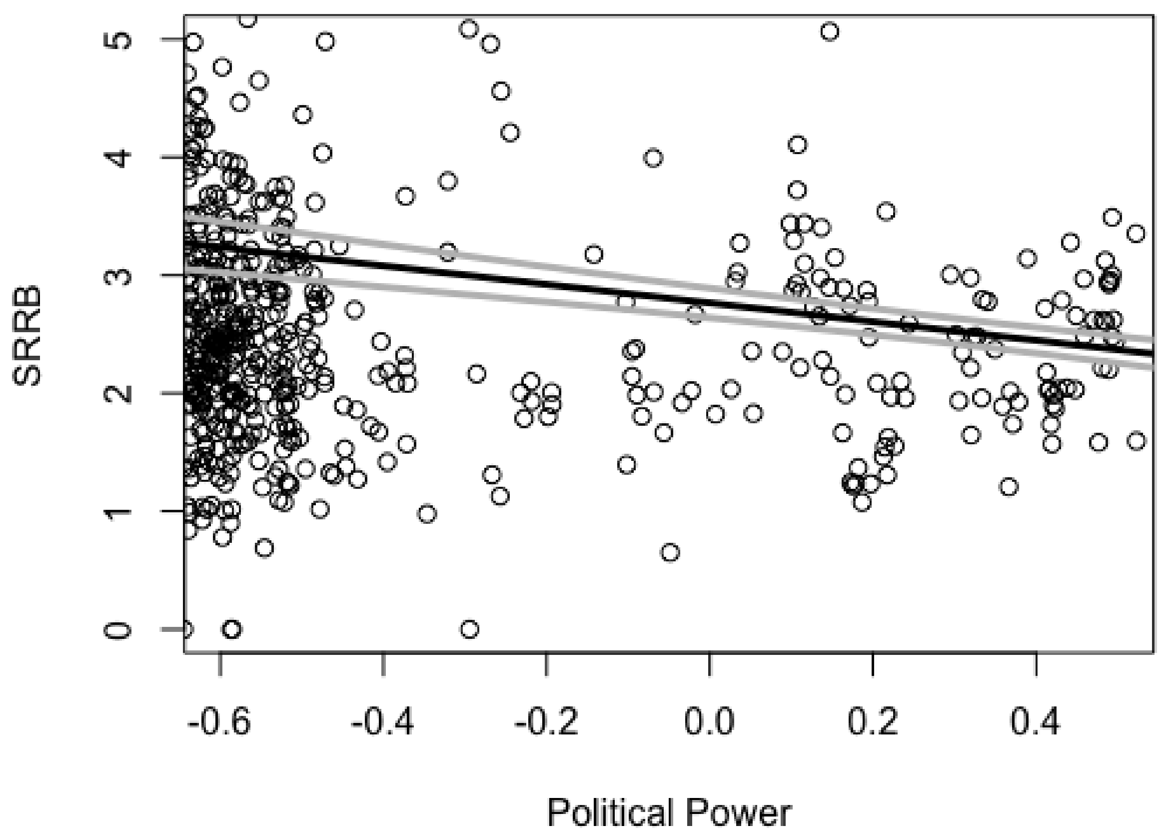
Table 4: OLS Models predicting SRRB

	Model 1	Model 2
Intercept	1.37*	2.04*
	(-0.23)	(-0.20)
Proportion Black w/ HS	-0.85*	-0.95*
	(-0.38)	(-0.37)
Proportion Black Unemployed	4.29*	4.33*
	(-1.13)	(-1.11)
Proportion Black in Poverty	-0.39	-0.38
	(-0.52)	(-0.51)
B-W Segregation	0.01*	0.01*
	(0.00)	(0.00)
Proportion Black Officers	9.78*	11.32*
	(-1.24)	(-1.25)
Black Political Power	-0.79*	
	(-0.10)	
Proportion Black on City Council		-0.55
		(-0.59)
Proportion Black Pop		-5.72*
		(-0.84)
Black Chief		-0.06
		(-0.17)
Black Mayor		-0.39
		(-0.21)
R^2	0.25	0.30
Adj. R^2	0.24	0.28
Num. obs.	401	401
RMSE	0.97	0.94

*p<0.05

In the first model, the black political power variable is negative and significant, indicating that as black political power increases, the racial disparity in searches decreases. This lends evidence to our expectation – as the black population obtains more political power, racial disparities in policing decline. Figure 3 plots the black-white search rate ratio, our measure for disparities, against political power for a visual representation of the effect. The line is the effect that black political power has on disparities, along with 95% confidence intervals. The line slopes downward, again demonstrating this negative effect: as political power increases, disparities decrease. However, estimated effect of political power on SSRB never results in the expectation of equality; the estimated effect never reaches or goes below 1 (equality). The second model produces a significant result for the proportion of the population that is black – indicating that as a black population grows, the traffic stop disparities decline, on average. However, the other indicators used for the political power variable do not have significant effects on the black-white search rate ratio.

Figure 3: Effect of Political Power on SRRB



Note: Covariates held at their means, predicted values for SRRB as a result of political power are plotted

In both models, the black-white segregation (dissimilarity) score is positive and significant, indicating that as segregation rises in a community, racial disparities in traffic stop outcomes similarly increase. This suggests that highly segregated areas are more likely to experience high disparities – potentially as a result of disparate policing practices. Finally, a number of the control variables also appear to contribute to the level of disparity observed in a given community. As black unemployment rises, racial disparities in traffic stops rise. Conversely, as the proportion of the black population with a high school diploma rises, racial disparities in traffic stop outcomes decline. Again, these results suggest that the relative socio-economic success of the black population matters to the level of traffic stop disparity. It appears that the size and power of the black community may help combat disparities in traffic stop outcomes.

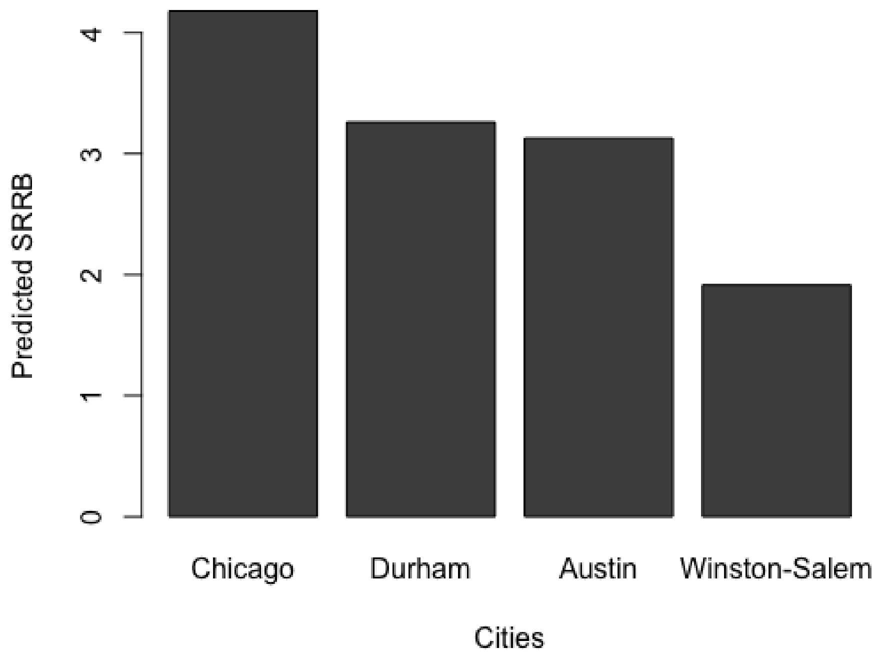
Whereas the economic, segregation, and political power variables show the expected results and confirm our expectations, the black share of the police force shows a very powerful effect, but in the unexpected direction. Search rate disparities increase dramatically for every increase in percentage of blacks on the local police force. This finding clearly calls for further scrutiny. Some preliminary analyses of other states and datasets not including the political power variable suggests that minority officers may have lower search rates overall, but not necessarily lower search rate disparities. The police force composition data also come from the LEMIS survey, which had relatively low response rates among all the cities in our larger study. Clearly, this variable merits further investigation.

To contextualize our findings, Figure 4 plots the predicted SRRB for four cities in the data: Chicago, IL; Durham, NC; Austin, TX; and Winston-Salem, NC. The values used to estimate the predicted SRRB are reported in Table 5. Chicago has a black political power factor score of 1.34, which is above the mean for the factor but lower than Winston-Salem and Durham in this subset of the data. Its predicted SRRB is the highest of all four cities, at 4.18. This means that blacks are searched at over four times the rate of whites, in the city of Chicago. Contrast the finding for Chicago against that of Durham and Winston-Salem. Both of these cities have higher black political power indices (2.44 and 2.02, respectively), and lower SRRBs (3.26 and 1.91, respectively). Austin has a political power factor score that is closest to the overall mean for the dataset, at 0.07, and an SRRB of 3.13, similar to Durham in this particular illustration.

Table 5: Values used to plot predicted SRRB for four cities

City	Educ.	Unemploy.	Poverty	B-W Seg.	Officers	Pol. Power	Pred. SRRB
Chicago	0.36	0.20	0.32	83.15	0.25	1.34	4.18
Durham	0.34	0.11	0.23	48.55	0.32	2.44	3.26
Austin	0.28	0.12	0.27	56.93	0.10	0.07	3.13
Winston-Salem	0.42	0.14	0.27	49.66	0.15	2.02	1.91

Figure 4: Predicted SRRB of Four Cities



Chicago is predicted here to have a much higher search rate disparity than even some southern cities such as Winston-Salem, NC. Indeed, in a previous analysis, Baumgartner and others (2017) found that Chicago and some of its suburbs had observed disparities as high as 8 to 1. The current analysis gives some context for that previous finding and helps explain it based on systematic factors. It may be no anomaly.

Conclusion

We have explored the predictors of racial disparities in policing, focusing on what percentage of black and white drivers are searched after a routine traffic stop. Political power matters. Controlling for relevant factors, the greater the share of political power enjoyed by the black community, the lower the disparities.

This is a work in progress and we have further variables to explore. Of particular note is the possibility that other policing variables may be incorporated, including the share of traffic stops conducted for “safety” v. “investigatory” purposes. We also continue to expand the empirical scope of the study and further explore the preliminary findings reported here concerning the black share of the police force.

References

Baumgartner, Frank R., Leah Christiani, Derek A. Epp, Kevin Roach, and Kelsey Shoub. 2017. Racial Disparities in Traffic Stop Outcomes. *Duke Forum for Law and Social Change* 9: 21-53.

Baumgartner, Frank R., Leah Christiani, Derek A. Epp, Kevin Roach, and Kelsey Shoub. 2018. A Simple but Robust Indicator of Racial Disparities in Traffic Stops. Working Paper.

Baumgartner, Frank R., Derek A. Epp, and Kelsey Shoub. 2018. *Suspect Citizens: What 20 Million Traffic Stops Tell Us About Policing and Race*. New York: Cambridge University Press.

Bratton, Kathleen A. 2005. Critical Mass Theory Revisited: The Behavior and Success of Token Women in State Legislatures. *Politics and Gender* 1(1): 97-105.

Bratton, Kathleen A., and Leonard P. Ray. 2002. Descriptive Representation, Policy Outcomes, and Municipal Day-Care Coverage in Norway. *American Journal of Political Science* 46(2): 28-39.

Burch, Traci. 2013. *Trading Democracy for Justice*. Chicago: University of Chicago Press.

Cammisa, Anne Marie, and Beth Reingold. 2004. Women in State Legislatures and State Legislative Research: Beyond Sameness and Difference. *State Politics and Policy Quarterly* 4(2): 181-210.

Canon, David T. 1999. *Race, Redistricting, and Representation: The Unintended Consequences of Black Majority Districts*. Chicago: University of Chicago Press.

Carnes, Nicholas. 2012. Does the Numerical Underrepresentation of the Working Class in Congress Matter? *Legislative Studies Quarterly* 37(1): 5-34.

Carnes, Nicholas. 2013. *White-Collar Government: The Hidden Role of Class in Economic Policy Making*. Chicago, IL: The University of Chicago Press.

Epp, Charles R., Steven Maynard-Moody, and Donald P. Haider-Markel. 2014. *Pulled Over: How Police Stops Define Race and Citizenship*. Chicago, IL: The University of Chicago Press.

Grose, Christian R. 2011. *Congress in Black and White: Race and Representation in Washington and at Home*. New York: Cambridge University Press.

Hansen, Eric R., and Sarah A. Treul. 2015. The Symbolic and Substantive Representation of LGB Americans in the US House. *Journal of Politics* 77, 4: 955-967.

Lerman, Amy E. and Vesla M. Weaver. 2014. *Arresting Citizenship*. Chicago, IL: University of Chicago Press.

Moore, Nina M. 2015. *The Political Roots of Racial Tracking in American Criminal Justice*. New York, NY: Cambridge University Press.

Peffley, Mark and Jon Hurwitz. 2010. *Justice in America: The Separate Realities of Blacks and White*. New York, NY: Cambridge University Press.

Pierson, Emma, Camelia Simoiu, Jam Overgoor, Sam Corbett-Davies, Vignesh Ramachandran, Cheryl Phillips, Sharad Goel. 2017. A large-scale analysis of racial disparities in the police stops across the United States. Working paper. Available online: https://5harad.com/papers/traffic-stops.pdf.

Saltzstein, Grace Hall. 1989. Black Mayors and Police Policies. *Journal of Politics*. 51:525-44.

Stucky, Thomas D. 2011. The conditional effects of race and politics on social control: black violent crime arrests in large cities, 1970 to 1990. *Journal of Research in Crime and Delinquency*: 49 (1): 3-30.

Appendix

Appendix A: Data Collection

Census data
We collected data from the Census and American Community Survey (ACS) using the Social Explorer tool. For 2000, we collected data from the 2000 Census. For 2009-2016, we collected data from the ACS. To interpolate data from 2001-2008, we assumed linearity of growth between 2000 and 2009. So, we generated a variable equal to the difference between 2009 and 2000, divided by 9, and then added this amount to every year between 2000 and 2009. For example, we calculated the difference in total population for a certain place between 2009 and 2000, and divided that number by 9. We then added this amount to the 2000 total population number in order to obtain an estimate for 2001. For 2002, we used the 2001 estimate and added the same increment to obtain an estimate for 2002.

LEMAS data
LEMAS is a survey of select police agencies about their composition and practices. We have LEMAS data for the years 2000, 2003, 2007, and 2013. There are 87 agencies that completed the LEMAS survey at some point in time. Only 27 agencies completed more than one LEMAS survey, and of those 27, only seven completed all three years of surveys. Because it is so common that there is only one data point for LEMAS, we took the average of the data that is available and used that number for all years.

Table A1: Summary of LEMA Number of Black Officers Data

	Percentiles	Most Extreme		
	Percentiles	*Smallest*		
1%	0	0		
5%	0	0		
10%	0	0	Obs	914
25%	0	0	Sum of Wgt.	914
50%	1		Mean	30.59
		Largest	Std. Dev.	239.67
75%	6	2970		
90%	22	3488	Variance	57439.45
95%	62	3489	Skewness	12.54

Table A2: Summary of LEMAS Percent of Black Officers Data

	Percentiles	Most Extreme		
	Percentiles	Smallest		
1%	0	0		
5%	0	0		
10%	0	0	Obs	908
25%	0	0	Sum of Wgt.	908
50%	0.03		Mean	0.07
		Largest	Std. Dev.	0.12
75%	0.09	0.91		
90%	0.19	0.92	Variance	0.01
95%	0.27	1.00	Skewness	3.61

Segregation data

Data on the level of racial segregation of towns and cities comes from the Census. We merged in dissimilarity indices between groups. Variables are included for the years 2000, 2005-2009, and 2010. The estimates are valid for 2000, 2009, and 2010. For the dataset, there are only 147 places that report at some point in time. There are then only 36 places that have segregation data for two time periods. These 36 are the only places for which interpolation would be possible. When analyzing these 36, the mean standard deviation of the Black-White segregation number is 2.5, with a minimum close to 0 and a maximum of 22. While the maximum is high, the 75th percentile still only has a standard deviation under 6. This variable, then, does not appear to vary greatly. As a result, the mean segregation number was calculated for the place and used for all years in our dataset.

Table A3: Summary of segregation data

	Percentiles	Most Extreme		
		Smallest		
1%	0.0424274	0.0424274		
5%	0.0707123	0.0707123		
10%	0.4879054	0.2192041	Obs	36
25%	1.011163	0.4879054	Sum of Wgt.	36
50%	2.570333		Mean	4.771007
		Largest	Std. Dev.	5.54226
75%	5.720495	12.89056		
90%	12.89056	13.32189	Variance	30.71664
95%	21.22734	21.22734	Skewness	1.811811
99%	22.56378	22.56378	Kurtosis	5.909876

Political Variable Data

The political variable data was hand collected by a number of graduate and undergraduate students working for the authors. The traffic stops data was collapsed to construct agency-windows, as discussed in the body of the paper. When the observation consisted of a time windows, rather than a single year, data was collected that corresponds to the first year in that window.

This collapse first used the specifications that the agency has 10,000 stops, 100 black stops, 100 white stops, and 100 Hispanic stops. This specification was then changed to only include 10,000 stops, 100 black stops, and 100 white stops. However, the students were already collecting information from the "old" collapse. They were using a dataset corresponding to the collapse that used to first, more restrictive designations. As a result, not all agencies that were captured in the "new" windows, corresponding to the second collapse, have been given to the students. Specifically, 116 agency-windows have not been extracted and handed out. 206 agency-windows have not been collected.

When an observation for a specific agency was present in both the old and new collapse, but the time window differed between the two, collected political information from the old collapse was used to fill in data for the new collapse. This was the case for 384 agency-windows. However, it is important to note that many of these observations represent small agencies, and thus were ultimately excluded from the model presented in the body of the paper because these small agencies do not have LEMAS or segregation data. So, this process is only meaningful for some of the appendix models (specifically Model 1c and 2c) that exclude LEMAS and segregation information.

Appendix B: Constructing Agency-Windows

Each observation in the data must meet the thresholds laid out in the body of the paper: 10,000 stops, including 100 white drivers and 100 black (Hispanic) drivers must also be stopped. (For calculating white-black comparisons, 100 each of the relevant racial group was needed, no matter the number of Hispanics; for the white-Hispanic comparison, 100 of each, no matter the number of black drivers). If the thresholds were not met, we added the following year for the same agency until the threshold was met. For example, if a given agency did not have more than 10,000 total stops and over 100 stops for each race category in its first year of data (say, 2005), we would add data from the next year, in this case 2006. If this combination met the thresholds, it constituted its own observation in the macro level dataset, and the process would begin again with 2007. If the 2005 and 2006 combination did not break the threshold then we would combine 2005 and 2006 observation with the 2007 observations, repeating this process until the threshold was met (if the threshold was not met for the combination in the last year data was available for that agency, then the data was dropped). Table A1 reports the number of agency-year observations that initially met the thresholds, as well as the number of observations derived from the method described above. As the table makes clear, we increased the number of usable observations from 593 to 1,622.

Table B1: Summary of observations for different aggregation methods

	Agency-Year Observations		Agency-Window
State	All Obs.	Obs. Above Thresholds	Obs. Above Thresholds
IL	9,588	338	1,046
MD	574	41	68
CT	314	5	5
NC	3,535	209	503
Total	14,011	593	1,622

This process did create observations with different time boundaries. Table A2 reports the summary statistics for the time frame (calculated as the end year for the observation minus the start year for the observation plus 1) for the macro level observations. The time range for the observations ranging from one year up to 15 years, with an average of 2.86 years.

Table B2: Summary Statistics for the Number of Years Each Observation Spans

	Observations	Mean	Std. Dev.	Minimum	Maximum
Time Frame	1,628	2.86	2.26	1	15

Appendix C: Descriptive Information About the Political Power Variable

Table C1: Descriptive statistics for constructed factor variable

Factor Loadings	MR1
Proportion of population that is black	0.89
Proportion of city council seats held by black members	0.93
Black mayor	0.51
Black police chief	0.44
Fit of Factor	
SS loadings	2.11
Proportion Variance	0.53
Tucker Lewis Index of factoring reliability	0.905
RMSEA index	0.166 (90% CI: 0.142, 0.192)
BIC	102.84
Fit of Factor Scores	
Correlation of scores with factors	0.95
Multiple R square of scores with factors	0.91
Minimum correlation of possible factor scores	0.82

Appendix D: Alternate Models

Table D1: OLS Models predicting SRRB with state-level random effects

	Model 1a	Model 2a
Intercept	1.52*	1.82*
	-0.35	-0.32
Proportion Black w/ HS	-0.53	-0.58
	-0.34	-0.34
Proportion Black Unemployed	2.69*	2.62*
	-1.00	-1.02
Proportion Black in Poverty	0.06	0.05
	-0.47	-0.46
B-W Segregation	0.01	0.01
	0.00	0.00
Proportion Black Officers	10.33*	10.86*
	-1.08	-1.12
Black Political Power	-0.41*	
	-0.10	
Proportion Black on City Council		-0.40
		-0.53
Proportion Black Pop		-2.70*
		-0.82
Black Chief		-0.23
		-0.15
Black Mayor		-0.19
		-0.19
AIC	1034.94	1033.04
BIC	1070.89	1080.96
Log Likelihood	-508.47	-504.52
Num. obs.	401	401
Num. of States	6	6
Var: States (Intercept)	0.38	0.3
Var: Residual	0.71	0.7

*p<0.05

Table D2: OLS Models predicting SRRB with agency-level random effects

	Model 1b	Model 2b
Intercept	1.94*	2.17*
	-0.37	-0.35
Perc Black w/ HS	-0.64*	-0.70*
	-0.31	-0.32
Perc Black Unemploy	2.17	2.19
	-1.37	-1.36
Perc Black in Poverty	-1.22	-1.13
	-0.71	-0.71
B-W Segregation	0.02	0.02
	-0.01	-0.01
Perc Black Officers	3.86	5.43*
	-2.01	-2.15
Black Political Power	-0.21	
	-0.13	
Perc Black on City Council		0.08
		-0.65
Perc Black Pop		-2.73*
		-1.35
Black Chief		-0.02
		-0.14
Black Mayor		-0.22
		-0.22
AIC	938.78	938.17
BIC	974.72	986.1
Log Likelihood	-460.39	-457.09
Num. obs.	401	401
Num. of agencies	64	64
Var: Agencies (Intercept)	0.63	0.58
Var: Residual	0.41	0.42

*p<0.05

Table D3: Models without segregation and LEMAS predictors

	Model 1c	Model 2c
Intercept	2.29*	2.44*
	-0.15	-0.15
Perc Black w/ HS	-0.56	-0.59
	-0.32	-0.32
Perc Black Unemploy	7.04*	7.05*
	-0.85	-0.85
Perc Black in Poverty	-1.69*	-1.64*
	-0.49	-0.49
Black Political Power	-0.08	
	-0.06	
Perc Black on City Council		0.98
		-0.65
Perc Black Pop		-2.04*
		-0.83
Black Chief		-0.07
		-0.22
Black Mayor		0.16
		-0.26
R2	0.10	0.11
Adj. R2	0.09	0.10
Num. obs.	678	678
RMSE	1.35	1.34

*p<0.05