Can Violent Protest Change Local Policy Support?: A Replication Attempt by Prachi Naik *

First Author
Ryan D. Enos

Second Author
Aaron R. Kaufman

Third Author
Melissa L. Sands

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Abstract

Enos, Kaufman, and Sands (2019) show that the 1992 Los Angeles Riot— one of the most well-known and documented instances of political violence in recent American history— caused a significant liberal shift in policy support at the polls due to the increased mobilization of Black and White voters, a mobilization that has endured over a decade later. The replication attempted in this project successfully found that White voters demonstrated a 0.028 increase in support for public school funding relative to university funding (CI: [0.018, 0.039]) and Black voters demonstrated a 0.073 increase (CI: [0.066, 0.081]). To extend the work of this paper, this project sought to examine the effects the Riot had on Asian American voters. The findings were inconsistent with what the authors found for White and Black voters– the riot appears to have caused a decrease in liberal policy support for Asians. This matters because heterogeneous treatment effects are worth further scrutiny and complication, especially given climates of racial polarization.

1 Introduction

This paper seeks to answer the following fundamental question: what, if any, impact can a violent protest have on changing political behavior? In order to explore this question, Enos, Kaufman, and Sands used a difference-in-differences approach to analyze measures of policy support before and after the 1992 Los Angeles Riot. The Riot was sparked by a series of events that began with the release of a video in which four White police officers were captured violently beating an unarmed black man named Rodney King on March 3, 1991. A little more than a year later, the four officers were subsequently acquitted by an all-White jury. Within hours of the verdict being announced, "a series of violent and destructive incidents occurred around the intersections of Florence Avenue and Normandie Avenue in South Central LA, a predominantly African American neighborhood," which would serve as the Riot's epicenter Enos, Kaufman, and Sands (2019a). Though the Riot was a nonrandom event, the authors see the release of the video as exogenously timed in relation to the 1992 election. They were able to manipulate a certain symmetry in the

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1990 vs 1992 ballot measures to stand for treatment and control measures. For the treatment, they chose to measure support for policy measures concerning k-12 education; for the control, they chose to focus on policy measures concerning University education. The assumptions undergirding this decision will be discussed later on, but most salient here, is that the authors adopt the basic idea that the riot brought the racialized unequal allocation of public goods (k-12 education) to the forefront of voters' minds and thus impacted the way citizens voted on increasing k-12 educational spending.

Analysis was conducted on the individual voter level instead of on the aggregate level in order to differentiate between racial and geographical effects. Using geocoded individual and precinct-level data, the authors were able to measure the effects of the riot on voters at any proximity to its epicenter. The effect of the Riot itself was estimated by "differencing out" the change in support for University funding (which was assumed to remain constant) from the difference in support for k-12 education funding. Support was measured via a population-weighted mean of "yes" votes for each of the 4 ballot initiatives under consideration. The authors refer to the treatment effect as "EdDiff" Enos et al. (2019a).

$$EdDiff_i = (PubSchool_{i1992} - PubSchool_{i1990}) - (HigherEd_{i1992} - HigherEd_{i1990}).$$

To further isolate the effect of the riot, the authors also cross-verified the correlation between EdDiff and proximity from the epicenter in order to check for omitted variable bias. The findings that the effect is more pronounced closer to the epicenter supports the authors' finding that the riot itself (as opposed to merely the beating and trial) was the mechanism behind the main difference-in-differences effect. Using Ecological Inference (EI) methods developed by Gary King, the authors used a combination of precinct-level digitized vote returns from the LA County registrar and UC Census Bureau demographic data to estimate individual voting behavior by racial group King (1997). They input the demographic proportions of each precinct (what proportion of the precinct is White, African-American, Asian, etc) and the proportion of "yes" votes in each precinct for each of the four ballot initiatives. The difference-in-difference estimator helps answer the following counterfactual: "Among voters in the LA basin, how would support for public schools have changed in the absence of the video, trial, and subsequent riot?" Enos et al. (2019a). While it is difficult, if not impossible to disentangle the three events, the authors attempt to isolate the impact of the riot by posing the secondary counterfactual: "How would support for public schools have changed in the LA basin in the absence of the riot, conditional on the beating and trial happening?" Enos et al. (2019a). This question is answered by the heterogeneous treatment effects by distance from the riot's epicenter– EdDiff is larger closer to the epicenter.

My replication is focused on the main finding of the paper, Figure 1, which displays three histograms indicating the distribution of EdDiff for all voters, White voters, and Black voters for 1,676 precincts in the Los Angeles Basin. Each histogram shows a positive mean value for EdDiff, indicating an increase in support for public schools net of changes in support for universities. The authors conduct a t-test to construct confidence intervals around this weighted mean. In order to replicate these results, I combed through the replication code and data files the authors made available on the Harvard Dataverse (Enos, Kaufman, & Sands, 2019b). Ryan Enos had these files linked on his personal web page, ryandenos.com.

The files needed to replicate Figure 1 were:

(1) The 1992 Voter File;

(2) The file containing the results of the race imputation of voters, which was done outside of R using Census data and ArcGIS-based geolocation-coding into precincts. It is worth noting that I had to work with whatever assumptions went into the imputation itself, as no other race-based data was available;

(3) The votes for Propositions 121 and 123 in 1990;

(4) The votes for Propositions 152 and 153 in 1992.

I used R to conduct this analysis R Core Team (2019).

Conspicuously missing from Figure 1 is a treatment of other minority voter populations, though the existing data contains information on Asians and Hispanics. Upon emailing with the authors, they recommended that I pursue an investigation of Asian voting populations. I did so in my extension.

2 Paper Review

At the heart of this paper is a longstanding question in political science: though violent protests are undoubtedly eye-catching and dramatic, do they actually have an effect on political behavior? Focusing on the 1992 LA "Race Riots" (also commonly called the "Rodney King Riots"), one of the most high profile events of political violence in recent years, Enos and his colleagues found that the riot caused a significant liberal shift in policy support at the polls for issues said to have motivated the riots themselves. For the purposes of their inquiry, the authors defined these issues generally as the racialized (mis)allocation of public goods, within which support for education emerged as the ballot referendum of interest. To estimate the effect of the riot, the authors measured the difference in support for ballot initiatives focused on k-12 education (thought to be closely associated with African Americans) against the difference in support for ballot initiatives focused on university funding (less associated with African Americans) in the June 1990 election and the June 1992 election. By "effect of the riot," authors are referring to a "bundled treatment" encapsulating the effect of a riot through various channels such as media coverage, interpersonal experiences of trauma or psychological effects, public statements by politicians, and changing property values, to name a few Enos et al. (2019a). Support for other university-level education policies were not considered "public goods"

Throughout the paper, the researchers use geocoded data analysis to investigate the source of this shift and trace it back to the mobilization of African American and Liberal White voters following the LA Riots. The "policy shifts" referenced here are actually local shifts in referendum voting on public goods targeted at urban dwelling racial minorities after the 1992 riots. These policies were put on the ballot before the riots erupted. Though the riot itself was a nonrandom event, the release of the video of police officers brutalizing an unarmed Black man (Rodney King) that ultimately triggered the riot was considered by the researchers to be unrelated to the election timeline. The researchers conducted a difference-in-difference analysis of pre and post riot policy voting to control for secular trends in policy support. They further explored the validity of this causal claim by examining the spatial correlation between how much support for a certain policy changed based on how far from the epicenter of those voters were. Ultimately, they found that the closer voters were to the epicenter of the riots, the more likely they were to vote for policies that provided liberal relief to minority urban communities.

The authors rely on a single theoretical assumption to guide their study, which requires closer scrutiny. They believe that increased support for public school funding over university funding is evidence of a liberal shift in political behavior. They arrive at this assumption after a series of complicated logical leaps. First they stipulate that rioting is a political act demanding redress for political grievances. Next, they draw on scholarly interpretations of the 1992 LA riots as ”collective action against poor economic and social conditions, triggered by police brutality.” To bolster this point, they offer the statistic that ”67.5 percent of African Americans in LA County viewed the riots as a protest against unfair conditions” Baldassare (1994). This is potentially problematic for two reasons– first, it assumes a monolithic view of the African-American community, which runs counter to the work the authors do later in the ecological inference weighting process to de-bias the supposed liberalism of Black voters in LA; and second, it offers no such evidence to suggest that White voters viewed the riot in this same light, yet White voters are a key subset of the population studied. Finally, continuing with the authors' logic, they suggest that support for spending on public goods is ”associated with African-Americans and racial minorities generally and is often implicated in the social welfare demands of riot participants” Enos et al. (2019a). On the other hand, the authors offer that ”attitudes about university spending are, at most, weakly linked to attitudes about African Americans and that funding higher education would not as widely be seen as a method of addressing problems made apparent by the riot” Enos et al. (2019a). This is some of the paper's most vague reasoning unsupported by empirical evidence, and yet, the entire crux of the finding that violent protest does, indeed, mobilize voters to liberally shift their political views rests on this essential juxtaposition of the needs of African Americans with public school funding and not university funding.

It is worth considering the methods the authors use to support this idea. Race imputations and ecological inference are two of such methods the authors use to enable their causal inferences about the effect of the riot.

2.1 Race Imputations

The authors' racial imputation procedure has 3 steps:

(1) They matched the census surname race probability file to the voter file; 89 percent of individuals have an exact match. For the remaining 11 percent , they performed a fuzzy match to identify the closest surname; this reduces error from typos in the voter file and multiple forms of the same surname. After this step, 38 individuals remain with no surname match within our threshold of string distance;

(2) They geolocated each registered voter's address, located that address within a census block, then merged that census block ID to a file of race by census block. Due to geolocating errors, roughly 130,000 individuals were placed in census blocks with zero population;

(3) The final step involves a Bayesian update in which they took the census information as a prior and then updated it using the surname probabilities, producing a posterior of racial probabilities.

This final step is aligned with the Bayesian Improved Surname Geocoding Method (BISG) developed by the Rand Corporation andc validated by Health Services Research in 2015 Grundmeier et al. (2015). While this method greatly improves the estimation of race and ethnicity information, there is still uncertainty introduced by the process. For example, the exact algorithm the researchers use is unknown. Some algorithms are better than others since they incorporate more sources of race-based information. Studies of race imputation in regards to electronic health records have shown that even powerful algorithms are susceptible to exact string matching. For example, Roblin and colleagues (2010) developed an algorithm to electronically abstract race/ethnicity information from electronic health records notes. The algorithm was found to be highly reliable in identifying white, black and Asian/pacific islander race based on specific strings of characters Mapel et al. (2010). However, the algorithm requires strings to match exactly and cannot overcome misspellings or abbreviations.

The authors of this paper treated all these concerns thoughtfully and conducted robustness checks to allocate different weights to offset potential bias. However, they ultimately imputed the race of the voter using the highest probability, even if the probability was not the majority. This begs the following question: why not maintain the uncertainty of race instead of assigning it to the greatest possible probability? This seems like an unnecessary corrupting of data for the sake of causal inference.

2.2 Ecological Inference Model

The authors use an ecological inference (EI) model to distill precinct-level voting data down to a racialized individual level.

There are three core assumptions undergirding an EI model:

(1) parameter variation is characterized by a truncated bivariate normal distribution;

(2) that the parameters are uncorrelated with the regressors; and

(3) there is no spatial autocorrelation.

The first assumption is satisfied, given that there IS spatial autocorrelation (this is what it means: The term 'spatial autocorrelation' is highly suggestive of its meaning: 'auto' as in 'self'; 'correlation' as in the statistical use of that term to measure a 'relationship' – hence a measure of the relationship between the value of a variable at a location and the same variable but at another location separated by some specified distance (or, in the case of type (3) variables, some measure of 'lag' separation between areas). Positive spatial autocorrelation is the tendency for sites or areas separated by a specified distance or 'lag' to have similar values of the variable (i.e., both values are high or both are low) Haining (2015) According to the authors, even when the third assumption is violated, they say the model performs "exceedingly well." Though they refer to other literature (Cho, 1998) to validate this point, this is still cause for concern. A violation of any key assumption seems to be a problem, even though the authors concern themselves more with maintenance of the second assumption– that the parameters are uncorrelated with regressors. The authors interpret that as meaning "no aggregation bias." Aggregation bias leads to the "ecological fallacy" — the conclusion that what is true for the group must be true for the sub-group or individual. The authors interpret this as referring to the fact that voters of a particular race living in neighborhoods where they are the majority would support public schools at the same or similar rate to voters of that same race in a more heterogeneous neighborhood Enos et al. (2019a). They believe this is a relatively safe assumption for African American voters (borne out by the fact that African Americans in the LA Basin registered as Democrats 95 percent of the time), but less so for White voters. Previous research (Enos, 2017) suggests that Whites in heterogeneous precincts are more liberal than Whites in homogeneously White neighborhoods, due to the residential sorting or the effects of segregation on voting Enos and Celaya (2018). In order to address this, the authors apply a weighting system suggested by King (1997 b) in which they apply a weight to each precinct that is inversely proportional to the size of the ecological inference standard error. They present both weighted and unweighted difference-in-differences results, which are remarkably similar in magnitude: " The weighted average value of the difference-in-differences estimate for whites is 0.029, and for African Americans, it is 0.071. The unweighted value for whites and for African Americans are 0.028 and 0.076, respectively" Enos et al. (2019a). We are to assume that the confidence intervals are similar in the unweighted values.

3 Replication

I successfully replicated Figure 1 of the paper, which depicted the main findings from the experiment. The code for this can be found in the Appendix and on my Github Repository.

3.1 Figure 1 Replicated

These histograms represent the distribution of EdDiff for all voters, White voters, and African-American voters for 1,676 precincts in the Los Angeles Basin. Positive values represent an increase in support for public schools, net of changes in support for university funding. The dashed vertical line is the weighted mean of the difference-in-differences. These histograms show that that there was a statistically significant increasing willingness to pay for public schools relatives to universities.

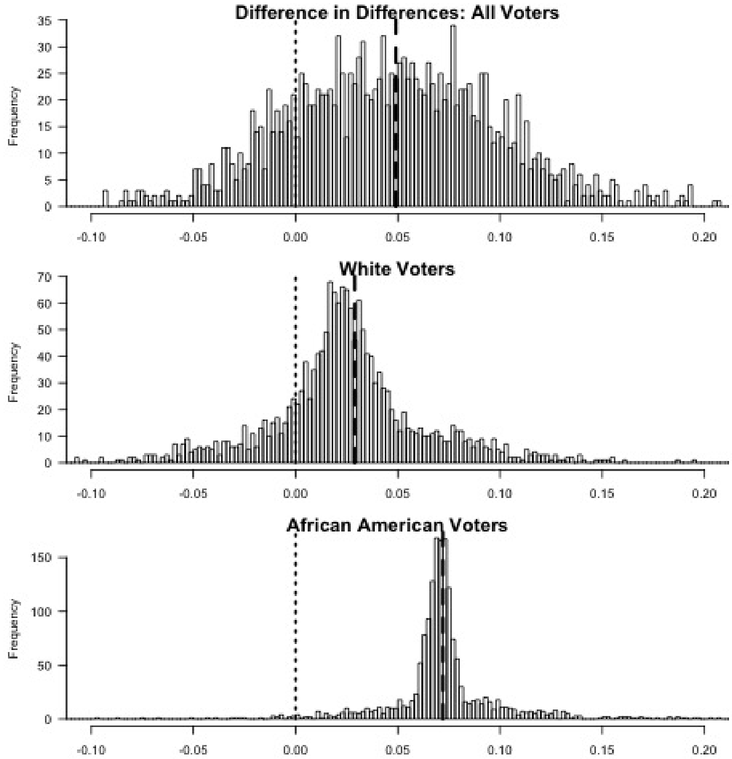

Figure 1: Reproduced via Replication

4 Extension

For my extension, I ran a similar difference-in-differences model on Asian American voters specifically and found that Asian American voters became slightly less liberal (or less in favor of k-12 education, as the authors define it) and voted more in support for increased university funding. This indicates that the riot had a negative shock for Asian American voters. The weighted mean is -0.0043 and the 95 percent Confidence Interval is [-0.0059, -0.0027]. Their distribution is depicted below.

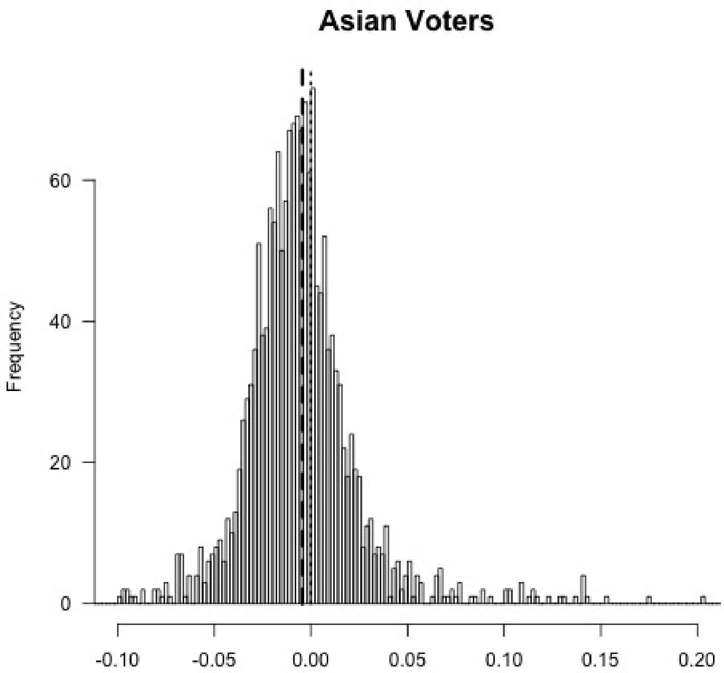

Figure 2: Asian Voters Experience a Decrease in Willingness to Fund Public Schools Net of Changes in Support for University Funding.

My extension aims to reveal the importance of embracing heterogeneous treatment effects. Yes, the indicator for EdDiff overall was positive, indicating that the riot succeeded in changing the electorate's political views towards greater redistribution of public goods like k-12 education; but stopping the story there obscures the small, but meaningful impact the riot had on inter-minority group splintering. Though Asians only make up less than 10 percent of the population in LA in 1990 according to the US Census, understanding minority groups' disparate experiences is essential to understanding systemic and institutionalized racism in America. Tensions between the Korean American and African American communities in South Central LA long predated the riot and were exacerbated by media coverage of racialized violence in the poverty-stricken neighborhood. According to research from the University of California, Riverside, of the over 1 billion dollars in property damage, Korean-owned property suffered between 35 to 40 percent of that destruction Chang (2016). Understanding the effect of the riot on Korean American voter perspectives would have helped illuminate more nuanced pathways forward to re-mediate racial conflict among minorities.

5 Conclusion

While Enos, Kaufman, and Sands' results have been replicated, confirmed, and extended, questions still remain as to whether the indicators chosen were, indeed, the right indicators to measure the change of political behavior as a result of the 1992 riot. The results depend on a series of non-empirical assumptions, which should, perhaps, have been treated with more sociological scrutiny. Anecdotally speaking, the riot did have a significant impact, and though this study aims to quantify this impact through causal inference, the correlations and juxtapositions upon which the causation depends must be examined through the lens of identity and power. To suggest that African American rights and demands are not associated with the pursuit of higher education is a damaging claim. How are other damaging racial stereotypes evoked at the finding that Asian Americans were less supportive of k-12 funding and more supportive of higher education funding? Embracing heterogenous treatment effects helps uncover some of the nuance that is so crucial to understanding the complicated and thorny history of race in America.

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Table 1: Example table of descriptive statistics of the main variables.

Variables	Categories	Unit	Rep	Mean	St. Dev.	Min	Max
Variable 1	Category A	$	8	0	0	0	0
	Category B	lb	8	22,411.20	6,325.90	13,819	31,201
	Category C	$	8	5,869.60	4,609.90	-464.1	12,744.10
Variable 2	Category A	$	8	1,777.40	144.5	1,642.30	1,912.60
	Category B	lb	8	21,444.80	5,146.90	15,096	28,032
	Category C	$	8	4,138.50	2,644.10	22.2	7,932.70
Variable 3	Category A	$	8	2,346.80	190.8	2,168.30	2,525.20
	Category B	lb	8	18,343.30	2,460.70	15,269.00	21,524.10
	Category C	$	8	3,699.20	2,549.80	1,299.10	8,709.80
Variable 4	Category A	$	8	2,288.80	186.1	2,114.80	2,462.90
	Category B	lb	8	23,450.40	4,172.50	20,045.00	32,363.00
	Category C	$	8	6,619.80	1,918.40	4,479.70	10,633.90
	CASE #1			14	6.61	6.9	27.9
	CASE #2			22.8	7.73	10.2	31.4

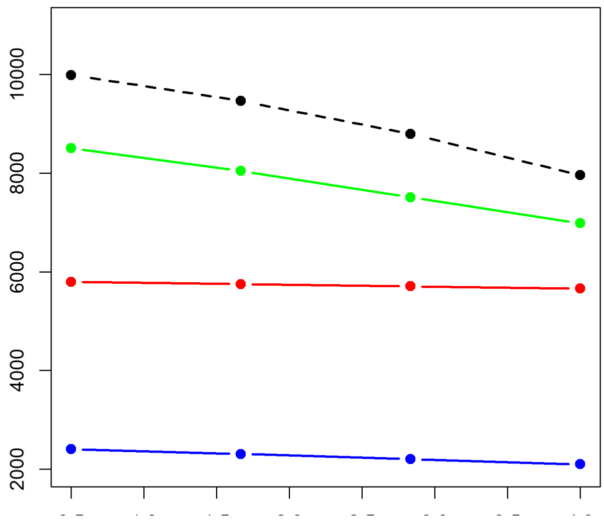

Figure 3: Example figure.