Unraveling the Political Polarization on Twitter in the Aftermath of George Floyd's Death: A Computational Text Analysis

Victor Westergren

Solvay Brussels School of Economics and Management,
Université Libre de Bruxelles

Introduction

Since the 1980s, the U.S. has experienced a notable increased in political polarization [1]. It has multifaceted consequences on politics, social interactions and economic decisions. This polarization is rooted in the alignment of partisan and ideological identities with social marker [2]. Furthermore, social protests can act as catalysts in political polarization among the citizens [3].

Research Question

Can social protests following harm to a civilian trigger political polarization among the realm of political elite ?

Focus on:

- The Black Lives Matter movement in 2020.
- The reaction of U.S. governors on Twitter.

Context

- The Black Lives Matter movement began in 2013 after George Zimmerman was acquitted in the shooting of Trayvon Martin.
- The movement gained widespread attention in 2014 following the police killing of Michael Brown, sparking protests across the U.S.
- It reached its peak in 2020 after George Floyd's murder, with protests spreading from Minneapolis to nationwide and international demonstrations within days.
- Twitter, as the world's largest micro-blogging platform, amplified the movement by providing space for organizing protests and allowing opinion leaders to shape political engagement on issues of racism, justice, and policing.

Data

- 28,359 tweets from May 1 to October 31, 2020.
- Tweeted by 46 governors from 46 different states in the U.S.
- Data on the party affiliation, gender, age for each governor.
- Data on the number of likes, comments and retweets for each tweet.
- Data on the number of protests, Covid-19 deaths and cases, lockdown stringency at the state and day level.

Metrics

Challenge: Converting text to numbers:

- Sentiment Score: More positive/negative words result in higher/lower scores.
- Ideological Score: Word frequencies reflect political leanings (positive for Republican, negative for Democrat).

Empirical Strategy

To assess the causal impact of the nationwide outbreak of Black Lives Matter protests, I use a regression discontinuity design in time and I estimate the following regression :

$$y_i = \beta_0 + \beta_1 * (day_i - c_0) + \delta * T_i + \beta_2 * (day_i - c_0) * T_i + \varepsilon_i \quad (1)$$

where $day \in [c_0 - h, c_0 + h]$ with h representing the bandwidth.

- T_i is equal to 1 if tweet i is tweeted after May 28, 2020, and 0 otherwise.
- y_i is the sentiment or ideological score of tweet i. day_i is the day tweet i is tweeted, c_0 is the cut-off, namely May 28^{th}, 2020. ε_i is the error term.
- The parameter δ represents the estimated discontinuity and gives the local average treatment effect.

Results

Table 1: Main Results

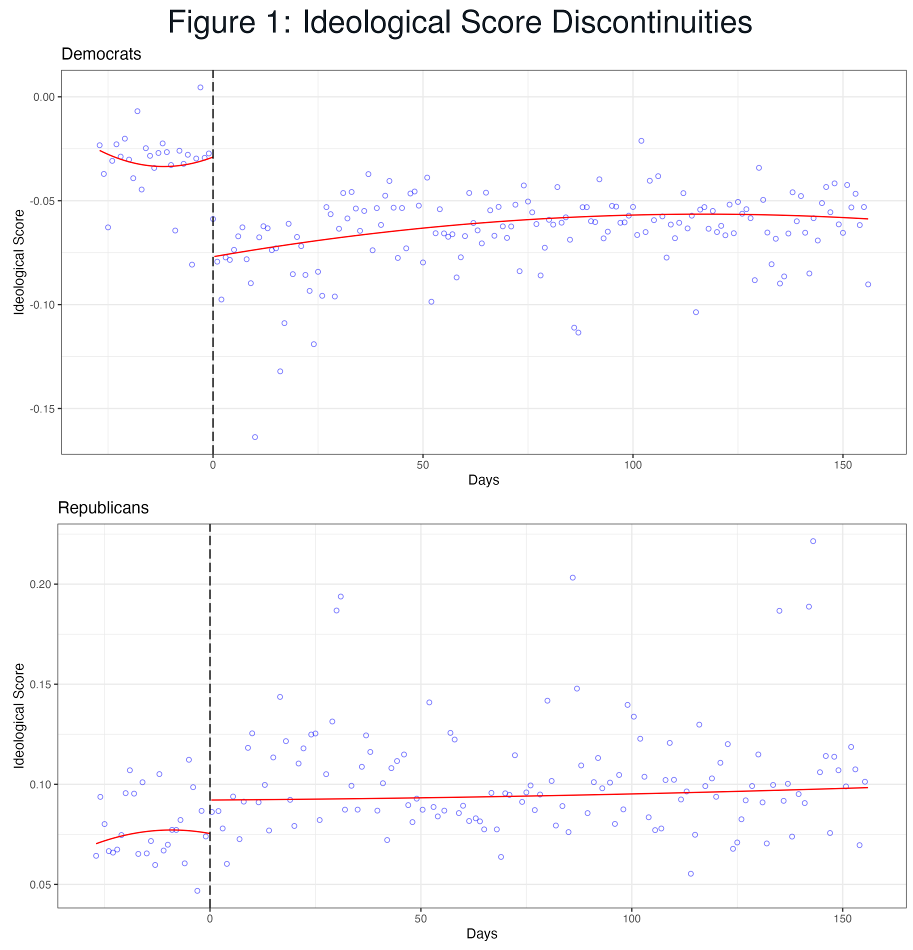
	Average Sentiment Score				Ideological Score			
	Full Sample (1)	*Democrats* (2)	*Republicans* (3)	*Difference* (4)	*Full Sample* (5)	*Democrats* (6)	*Republicans* (7)	*Difference* (8)
Conventional	0.004	−0.075***	0.005	−0.080*	−0.019***	−0.057***	0.020***	−0.077***
	(0.024)	(0.025)	(0.039)	(0.046)	(0.006)	(0.007)	(0.007)	(0.01)
Bias-Corrected	0.024	−0.056**	0.031	−0.088*	−0.018***	−0.060***	0.022***	−0.082***
	(0.024)	(0.025)	(0.039)	(0.046)	(0.006)	(0.007)	(0.007)	(0.01)
Robust	0.024	−0.056*	0.031	−0.088*	−0.018**	−0.060***	0.022**	−0.082***
	(0.027)	(0.029)	(0.045)	(0.053)	(0.007)	(0.008)	(0.009)	(0.012)
Control	0.003	−0.077***	0.000	−0.077*	−0.019***	−0.054***	0.022***	−0.076***
	(0.025)	(0.025)	(0.039)	(0.046)	(0.006)	(0.007)	(0.007)	(0.01)
Kernel	Triangular	Triangular	Triangular	✗	Triangular	Triangular	Triangular	✗
Bandwidth	mserd	mserd	mserd	✗	mserd	mserd	mserd	✗
N below	1932	1903	815	✗	3304	1942	1495	✗
N above	2083	1807	937	✗	3368	1966	1565	✗

Dependent Variable: Average Sentiment Score (1)–(4); Ideological Score (5)–(8).

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

Note: Standard errors in parentheses. The conventional coefficient reports the coefficient associated to the discontinuity when the degree of the polynomial is set to 1. The bias-corrected coefficient adjusts for a polynomial of degree 2 and the Robust coefficient implements the robust standard errors with the bias-corrected estimate. Control indicates the conventional estimated discontinuity where I control for age.

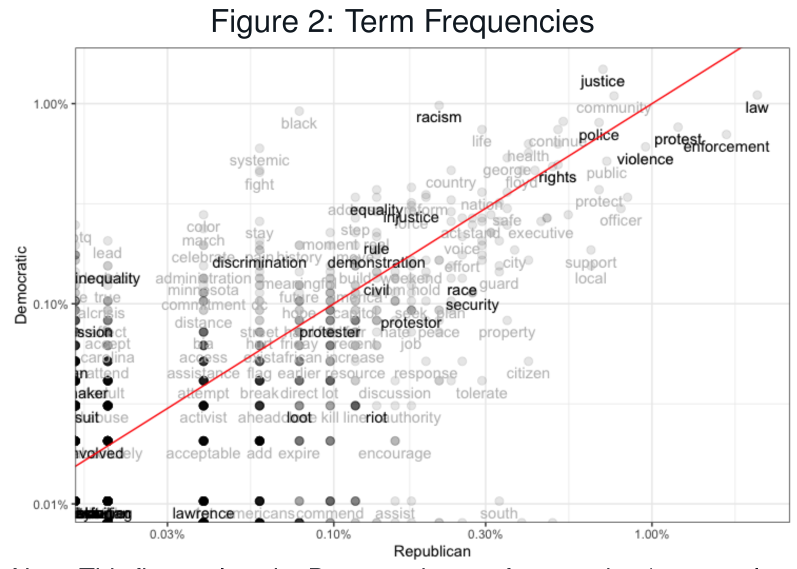
Figure 1: Ideological Score Discontinuities



Note: This figure represents the ideological score discontinuities. The uppermost graph illustrates the plot for the Democrats. The lowermost graph illustrates the Republicans' plot. For each graph, the blue bins are the local averages in the ideological score, estimated by a uniform kernel. The red lines can be obtained with the predicted values of y conditional on x with a quadratic fit.

Discussion

Figure 2: Term Frequencies



Note: This figure plots the Democratic term frequencies ($y-axis$, log-scale) against the Republican term frequencies($x - axis$, log-scale). The red line is the first diagonal. The terms lying above the first diagonal were more frequently used by Democrats while the terms lying below the first diagonal were more frequently used by Republicans.

Democrats

- Employed more terms associated to their ideology such as *racism*, *discrimination*, *justice*.
- Employed these terms with a more negative tone.
- This implies that issues such as racism, discrimination, and justice are significant concerns for the Democratic Party in the U.S.

Republicans

- Employed more terms associated to their ideology such as *law enforcement*, *security*, *protection* to address the protests.
- These terms are addressed in a neutral stance.

→ *Political polarization deepened as Republicans called for increased security after the protests, while Democrats saw them as a reminder of ongoing discrimination in the U.S.*

Acknowledgements

This paper has been written in the context of my Master thesis under the supervision of Professor Pierre-Guillaume Méon. I would like to thank Anaïs Couronné, Mathieu Duchateau, David Mainus and Emmanuelle Van erck for their support and their help. I would also like to thank Professor Pierre-Guillaume Méon for his guidance and feedback.

References

[1] Levi Boxell, Matthew Gentzkow, and Jesse M Shapiro. "Cross-country trends in affective polarization". In: *Review of Economics and Statistics* (2022), pp. 1–60.

[2] Shanto Iyengar et al. "The origins and consequences of affective polarization in the United States". In: *Annual review of political science* 22 (2019), pp. 129–146.

[3] Tyler T Reny and Benjamin J Newman. "The Opinion-Mobilizing Effect of Social Protest against Police Violence: Evidence from the 2020 George Floyd Protests–CORRIGENDUM". In: *American Political Science Review* 116.3 (2022), pp. 1161–1164.